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Recovering costs through price and service differentiation: Accounting for exogenous information on attribute processing strategies in airline choice

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ABSTRACT: The entry of low cost airlines has thrown out a challenge to all airlines to find ways of attracting passengers, through a mix of fare discounting, greater frequency, improved flight times and no-frill's levels of on-board service. All of these competitive strategies have an impact on cost recovery. As airlines seek business in an increasingly heterogeneous passenger market, a greater understanding of what matters to potential passengers in choosing an airline grows in importance. Which attributes really do matter to specific classes of passengers? Traditional studies of passenger airline choice assume that all attributes matter, but some to a lesser extent. What happens to the empirical evidence on willingness to pay when specific attributes are totally ignored by particular passengers? In this paper, we examine the impact of individual-specific attribute processing strategies (APS) on the inclusion/exclusion of attributes on the parameter estimates and behavioural outputs of models of airline service and fare level choice. Current modelling practice assumes that whilst respondents may exhibit preference heterogeneity, they employ a homogenous APS with regards to how they process the presence/absence of attributes of stated choice (SC) experiments. We demonstrate how information collected exogenous of the SC experiment on whether respondents either ignored or considered each attribute of the SC task may be used in the estimation process, and how such information may be used to provide outputs that are APS segment specific. Accounting for the inclusion/exclusion of attributes has important implications on the willingness to pay for varying levels of service.

KEY WORDS: ***Airline choice, stated choice experiment, willingness to pay, attribute processing strategy***

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1. Introduction

The entry of low cost airlines has thrown out a challenge to all airlines to find ways of attracting passengers, through a mix of fare discounting, greater frequency, improved flight times and no-frill's levels of on-board service. All of these competitive strategies have an impact on cost recovery. As airlines seek business in an increasingly heterogeneous passenger market, a greater understanding of what matters to potential passengers in choosing an airline grows in importance. Which attributes really do matter to specific classes of passengers? Traditional studies of passenger airline choice assume that all attributes matter, but some to a lesser extent. What happens to the empirical evidence on willingness to pay when specific attributes are totally ignored by particular passengers?

Stated choice (SC) experiments have become a popular method to model choice behaviour in aviation contexts. The behavioural outputs of SC models, including willingness to pay (WTP) estimates for specific service levels have been used extensively to derive demand forecasts for new and existing modes (e.g., Jovicic *et al.*, 2003), and to model influences on airline choice (e.g., Hensher *et al.* 2001). Given the growing risks resulting in large financial losses if an airline fails to deliver services that attract greater numbers of passengers to fill the low-fare seats, it has become increasingly important that stated choice models be capable of accounting for the greater diversity of preferences of the market in respect of fares and levels of service. Central to this new challenge is the role that attribute processing strategies play in establishing the relevance or otherwise of specific attributes. The majority of SC studies have assumed that all attributes are relevant to some degree.

The paper is organised as follows. We begin with an overview of the appeal of stated choice methods and the need to take into account the attribute processing strategies of respondents. The next section outlines the econometric model. A brief overview of the empirical data is given followed by the set of model results comparing traditional SC models with those conditioned using information on the attribute inclusion/exclusion strategies used. The substantive implications of the analysis are set out followed by some conclusions and directions for ongoing research.

2. Accommodating Attribute Processing Strategies in Stated Choice Experiments

A key reason why stated choice methods are popular is their ability to mimic decisions made in real markets that otherwise could not be observed. With a greater diversity of levels of service and fares, the ability to identify preferences under a wide range of service offerings and to infer the willingness to pay for specific service levels, and to narrow the candidate set to trial in real markets, is very appealing. Realism is captured through respondents being asked to undertake similar actions as they would in real markets. However, for any individual respondent, realism may be lost if the alternatives, attributes and/or attribute levels used to describe the alternatives do not realistically portray that respondent's experiences or, in terms of 'new' or 'innovative' alternatives, are deemed not to be credible (Wittink and Cattin, 1989).

In establishing the attributes and attribute levels to be built into a stated choice experiment, careful consideration of candidate attributes is required to avoid possible inclusion of irrelevant or improbable product descriptors, or exclusion of relevant attributes, within the choice sets shown to respondents (Hensher *et al.*, 2005). Additionally, for quantitative variables, typical of those applicable to airline service levels, pivoting the attribute levels of the SC task from a respondent's current or recent experience[1] is likely to produce attribute levels within the experiment that are consistent with those experiences, and hence, produce a more credible or realistic survey task for the respondent.

Typically, SC studies have focussed on single pre-specified experimental designs with a fixed number of alternatives, attributes and attribute levels. Although significant research effort has been committed to the design of statistically efficient choice experiments (e.g., Bunch et al., 1994; Huber and Zwerina, 1996, Kanninen, 2002; Kuhfeld et al., 1994), whilst minimising the amount of cognitive effort required of respondents (e.g., Oppewal et al., 1994; Wang et al., 2001); there has been inadequate recognition that respondents might process SC tasks differently. That is, there may exist heterogeneity in the attribute processing strategies (APS) employed. This is borne out by the not uncommon observance of lexicographic choice behaviour in segments of respondents completing SC surveys and therefore should be tailored to be as realistic as possible at the level of the individual respondent.

Adaptive-Choice-Based-Conjoint (e.g., see Toubia, et al., 2004) customises the attribute levels of a SC experiment shown to a respondent using the previous choices made. This, however, is not the same as customising the actual alternatives or attributes in order to make the choice task more realistic or believable to the individual respondent. Rose and Hensher (2004) address the mapping of alternatives in terms of their presence or absence in reality to choice experiments at the individual respondent level, however, research addressing the presence or absence of attributes at the individual level is noticeably absent. This is somewhat surprising given that in real markets, there exists heterogeneity in the information held with regards to the attributes and attribute levels of alternatives amongst decision makers as well heterogeneity in terms of the salience of and preference for specific attributes.

Whilst advances in the econometric modelling of discrete choices, such as mixed logit models, may help in uncovering preference heterogeneity for attributes, these models assign non-zero parameter estimates to individual decision makers, even though their marginal (dis)utility for an attribute may be zero. Whilst this might apply to only a small number of decision makers, a bias in the population parameter estimates is still likely to exist. Therefore, the econometric models used to derive stated choice outputs such as willingness to pay need to be conditioned to assign a zero parameter estimate to those individuals who either ignore an attribute or do not have that attribute present.

In the following sections we show how we can use exogenous information on the APS strategies employed by individual respondents undertaking SC tasks and how we can

[1] If a respondent has never flown, then specific design conditions can be introduced to offer service and fare levels that are sensible, comprehensible and deliverable within the application context. Within a computer-aided personal interview environment for data collection, the tailoring of the SC instrument to each respondent is very straightforward.

use such information to condition the parameter estimates derived from the econometric models.

3. Model Development

Consider a situation in which q=1,2,…,Q individuals evaluate a finite number of airline service alternatives. Let subscripts j and t refer to alternative j=1,2, …,J and choice situation t=1,2, ...,T. Random utility theory (RUT) posits that the utility for alternative j present in choice situation t may be expressed as:

$$U_{jtq} = q_q^{'} x_{jtq} + e_{jtq} \tag{1}$$

where

U_{jtq} is the utility associated with airline service alternative j in choice situation t held by individual q, x_{jtq} is a vector of values representing attributes belonging to alternative j, characteristics associated with sampled decision makers q, and/or variables associated with context of the choice situation, t, and e_{jtq} represents unobserved influences upon utility. $q_q^{'}$ is a vector of parameters such that $?=?_1,?_2,\ldots,?_K$ where K is the number of parameters, corresponding to the vector x_{jtq}.

The probability that alternative j will be chosen is given as multinomial logit[2]:

$$P(j \mid J) = \frac{e^{V_{jtq}}}{\sum_J e^{V_{Jtq}}} \tag{2}$$

where

$$V_{jtq} = q_q^{'} x_{jtq}\,. \tag{3}$$

Assuming a sample of choice situations, t = 1, 2, ..., T, has been observed with corresponding values x_{jtq}, and letting j designate the alternative choice situation t, the likelihood function for the sample is given as

$$L(q) = \prod_{t=1}^{T} P(j \mid J) \tag{4}$$

and the log likelihood function of the sample as

$$L^*(q) = \ln\left[L(q)\right] = \ln\left[\prod_{t=1}^{T} P(j \mid J)\right]$$

[2] We limit the derivation to multinomial logit, although the same inferences apply to more advanced choice models.

$$= \sum_{t=1}^{T} \ln\left(P(j \mid J)\right). \quad (5)$$

Equation (5) may be re-written to identify the chosen alternative j:

$$L^*(q) = \sum_{t=1}^{T}\left[V_{jt} - \ln\left(\sum_{J} e^{V_{Jt}}\right)\right]. \quad (6)$$

Given that ? is unknown, it must be estimated from the sample data. To do this, we use the maximum likelihood estimator of ? which is the value of $\hat{q}$ at which L(?) is maximised. In maximising equation (6), it is usual to use the entire set of data for V_{jt}. Assuming that over a sample of choice situations, t, not all k variables within the x_{jtq} vector are considered in the decision process, the value of $\hat{q}$ conditioned on the assumption that all x_{jtq} are considered, will likely be biased. For those choice situations in which an attribute, k, is excluded from consideration in the choice process, $\hat{q}_k$ should be equal to zero. Note that this is not the same as saying that the attribute itself should be treated as being equal to zero.

In cases where attribute k is indicated as being excluded from the decision process, rather than set the value for the k^{th} element in the x_{jtq} vector to zero and maximising equation (6), the algorithm used in searching for the maximum of equation (5), excludes that x from the estimation procedure altogether and automatically assigns to it a parameter value of zero. The parameter estimate, $\hat{q}_k$, is then estimated solely on the sample population for which the variable was not excluded. In this sense, the process is analogous to selectivity models (which censors the distribution, as distinct from truncation). To demonstrate, consider a simple example in which there are only two variables, x_1 and x_2, associated with each of J alternatives. Denote N as the number of attribute processing strategies such that n = 1 represents those decision makers who consider only x_1 in choosing between the J alternatives, n = 2 represent those decision makers who consider only x_2, and n = 3 represent those decision makers who consider both x_1 and x_2. The likelihood is defined by the partitioning of observations based upon subset membership defined above. The likelihood function is therefore given as:

$$L^*(q) = \sum_{t=1}^{T}\sum_{n=1}^{N} \ln\left(P(j \mid J)\right). \quad (7)$$

The derivatives of the log likelihood for groups n_1 and n_2 have zeros in the position of zero coefficients and the Hessians have corresponding rows and columns of zeros. This partitioning of the log-likelihood function may be extended to any of the logit class of models, including the nested and mixed logit models. In the next section, we discuss the empirical application in which we estimate models of the form described above.

4. Empirical Application

The data was collected as part of a larger study examining differences between the temporal partitioning of the administration of stated choice data (see Rose *et al.* 2004). The sample was drawn from residents of Sydney and administered in early 2004. The empirical setting for the study is a labelled SC experiment, the context of which was the choice of airline carrier for an interstate holiday in Australia. The experiment involved four alternatives, three labelled alternatives and a no choice alternative. Each labelled alternative was described by four attributes, each further described by four attribute levels. Within the labelled experiment, three existing airlines were named as part of the experiment. The first airline, which we report as Airline A, represents the dominant domestic airline carrier in Australia. The second airline, (Airline B) is an international carrier that is perceived within the Australian domestic airline market as the budget carrier. The third alternative airline (Airline C) is a dominant international airline that competes with Airline A in terms of offering similar service levels within the marketing mix.

Given that the experiment was a labelled choice experiment, the smallest possible experimental design (capable of estimating non-linear main effects in the marginal utilities of each attribute) consists of 16 treatment combinations (see Rose and Bliemer, 2004). Rather than generate a design with 16 treatment combinations, a $4^{(3\times4)}$ orthogonal fractional factorial experimental design with 40 treatment combinations was generated. This design allows for the estimation of non-linearities in the marginal utilities over the attribute levels for all main effects. The attributes and attribute levels are shown in Table 1.

Table 1: Attribute and attribute levels

Attribute	Attribute levels
Ticket Price	\$79, \$99, \$119, \$139
Flight Time (minutes)	40, 50, 60, 70
Departure Time	6.00am, 10.00am, 12.00pm, 8.00pm
Flight Time Variability	±5%, ±7.5%, ±10%, ±12.5%

In addition to the attribute columns, two additional orthogonal blocking columns were generated as part of the experimental design. The first blocking column of two levels, divided the design into two orthogonal halves. The second blocking column of four levels, divided the design into four orthogonal quarters. These two blocking columns were used to establish two of three experimental conditions. The first experimental condition, involving neither blocking column, consisted of respondents completing the entire design in a single session (i.e., respondents completed all 40 choice sets in one sitting). The second experimental condition, using the first blocking column, saw respondents complete the entire experiment over two sessions, completing each half fraction of the experiment as determined by the blocking column, spaced one week apart. The second blocking column was used in the third experimental condition, with respondents asked to complete each of the four quarters in separate sessions spanning a four week time frame. In each condition, the order of choice sets was randomized so as to avoid order effect biases. A second non-labelled choice experiment involving mobile phone choice was also conducted at the same time using the same principles described above (see Rose *et al.,* 2004).

Two hundred and thirty two (232) first and second year marketing undergraduate students were recruited to complete the experiment. Recruited students were randomly assigned to one of the three experimental conditions. Of the 232 students, 61 were randomly assigned to the first experimental condition, 81 to the second experimental condition and 90 to the last experimental condition. Greater numbers of students were assigned to each successive experimental condition so as to compensate for expected attrition over sessions. Table 2 shows the number of respondents completing each experimental condition of the study and the number of observations thus obtained. Percentages shown represent the within condition completion/non-completion rates.

Table 2: Attribute and attribute levels

Condition (choice sets per condition)	Number of choice sets completed	Number of respondents	Number of choice observations
1 (40)	40	61 (100%)	2440
2 (20)	40	55 (67.9%)	2200
2 (20)	20	26 (32.1%)	520
3 (10)	40	34 (37.78%)	1360
3 (10)	30	29 (32.22%)	870
3 (10)	20	12 (13.33%)	240
3 (10)	10	15 (16.67%)	150
		Total	7780

Table 3 shows the demographic breakdown of the sampled respondents by experimental condition.

Table 3: Demographic breakdown of sample

Condition (choice sets per condition)	Number of choice sets completed	Age (average)	Gender (female)
1 (40)	40	20.54	47.46%
2 (20)	40	20.30	64.00%
2 (20)	20	20.97	65.63%
3 (10)	40	20.38	61.54%
3 (10)	30	19.9	65.52%
3 (10)	20	19.9	72.73%
3 (10)	10	20.3	58.33%

Upon completing the choice tasks for a session, sampled respondents were asked which attributes they had ignored in making the choices that they had made whilst undertaking the choice experiment. The response metric for this question was a simple binary yes/no for each attribute. Although we use a simple binary indicator to define the inclusion or exclusion of an attribute in an individual's attribute processing strategy, we do not attribute the reason for the response herein, which could be due to cognitive burden or simply relevance (see Hensher, 2004). Table 5 summarises the number of times each attribute was stated as being ignored over choice observations. Ticket price was ignored in the choice process the least number of times and flight time variability the most number of times. Over the sample, flight time and departure time were ignored approximately the same number of times. Significantly, a check of the data showed no respondent ignored all attributes in making their choices.

Table 5: Number of observations in which an attribute was not considered
(percentage of choice observations in which an attribute were excluded from the choice process shown in brackets)

Attribute	**Number**
Ticket Price	850 (10.93%)
Flight Time (minutes)	1540 (19.79%)
Departure Time	1510 (19.41%)
Flight Time Variability	5130 (65.94%)

4.1 Empirical Results

Table 6 presents the model results for the experiment. The first two models were estimated using all data irrespective of whether a sampled individual indicated whether they had ignored an attribute throughout the experiment or not. This represents current practice whereby it is assumed that all attributes are relevant (to varying degrees) to all sampled respondents. The final two models are estimated using the procedure described earlier. Models 1 and 3 are MNL models, models 2 and 4 are mixed logit (ML) models. All four models were estimated using the pooled choice data from all three experimental conditions, irrespective of whether all 40 choice sets were completed or not.

For all four models, all parameters associated with the design attributes are specified as generic random parameter estimates. With the exceptions of the flight time variability parameters of models 1 and 2, all parameters associated with the design attributes are statistically significant and of the expected sign. In specifying the ML models, the parameters associated with the design attributes were drawn from a constrained triangular distribution. Hensher and Greene (2003) have shown that for the triangular distribution, when the mean parameter is constrained to equal its spread (i.e., $\beta_{jk} = \beta_k + |\beta_k| T_j$, where T_j is a triangular distribution ranging between -1 and +1), the density of the distribution rises linearly to the mean from zero before declining to zero again at twice the mean. Therefore, the distribution must lie between zero and some estimated value (i.e., the β_{jk}). As such, all individual specific parameter estimates are constrained to be of the same sign. Empirically the distribution will be symmetrical about the mean which not only allows for ease of interpretation, but also avoids the problem of long tails often associated with drawing from a log-normal distribution. The random parameter estimates of the ML models were drawn using 500 Halton draws.

Comparison of models 1 and 2, and 3 and 4 reveal significant differences in the parameter estimates. The parameter estimates for the ticket price and flight time attributes for models 1 and 2 suggest that when the attribute processing strategy is not accounted for, the sample population is much more sensitive to both increases in price and flight times than when the inclusion/exclusion strategy of sampled respondents is considered during the modelling process. The flight time variability parameter estimates which were not significant and of the incorrect sign when the attribute inclusion/exclusion strategy is ignored, become highly significant and of the correct sign when estimated only for those who considered the attribute. This suggests that including or excluding attributes is an important segmentation criterion. The departure time attribute, which was effects coded, produces similar population moments whether all data is used in the estimation process or only data for those who considered the attribute during the choice experiment.

Table 6: Summary of Empirical Results for Models 1 through 4
(Random Parameters mean = spread parameter)

	Full Data				**Partial Data**			
	MNL		**ML**		**MNL**		**ML**	
	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio	Coeff.	t-ratio
Ticket Price	-0.054	-52.87	-0.107	-32.26	-0.036	-41.41	-0.035	-32.69
Flight Time	-0.027	-18.78	-0.041	-20.13	-0.016	-14.67	-0.022	-16.04
Flight Time Variability	0.483	0.78	0.378	0.46	-6.488	-11.26	-9.905	-12.56
Departure Time (6am)	-0.533	-17.36	-0.686	-17.29	-0.424	-8.26	-0.452	-8.29
Departure Time (10am)	0.437	14.16	0.617	14.49	0.488	9.86	0.448	8.78
Departure Time (12pm)	0.089	2.96	0.121	3.31	0.159	3.21	0.123	2.39
Non-Random Parameters								
Constant A	7.171	50.33	14.814	33.88	4.650	41.08	5.220	32.69
Constant B	7.245	50.97	14.865	34.17	4.731	41.66	5.304	33.08
Constant C	6.952	49.48	14.451	33.87	4.490	39.75	5.061	31.82
Model Fits								
LL(0)	-10785.370		-10785.370		-10785.370		-10785.370	
LL(B)	-8538.611		-8158.476		-9502.17		-9441.21	
Chi-square	4493.519		5253.788		2566.401		2688.324	
R^2	0.199		0.243		0.118		0.124	
Observations	7780		7780		7780		7780	
Direct Marginal Effects								
Ticket A	-2.9889		-3.37678		-2.04641		-1.73769	
Ticket B	-2.92352		-3.32594		-1.99911		-1.69864	
Ticket C	-3.09845		-3.66612		-2.0957		-1.69864	
Flight Time A	-0.82258		-0.85364		-0.44935		-0.56842	
Flight Time B	-0.80993		-0.84029		-0.44123		-0.55751	
Flight Time C	-0.85125		-0.90675		-0.46243		-0.5891	
Flight Time Variability A	0.02344		0.01285		-0.12247		-0.17398	
Flight Time Variability B	0.0235		0.01303		-0.12057		-0.17116	
Flight Time Variability C	0.02567		0.01465		-0.12802		-0.1813	
Departure Time (6am) A	-0.10316		0.0108		-0.06899		-0.01171	
Departure Time (6am) B	-0.10942		0.01673		-0.07106		-0.01283	
Departure Time (6am) C	-0.1043		0.00672		-0.06637		-0.0073	
Departure Time (10am) A	0.08469		-0.01244		0.07954		0.02069	
Departure Time (10am) B	0.08983		-0.00901		0.08192		0.02207	
Departure Time (10am) C	0.08563		0.0195		0.07652		0.02732	
Departure Time (12pm) A	0.01718		-0.00188		0.02582		0.0049	
Departure Time (12pm) B	0.01822		-0.00278		0.0266		0.00451	
Departure Time (12pm) C	0.01737		0.0013		0.02484		0.0046	

In interpreting the parameter estimates for models 3 and 4, it is important to note that the parameter estimates are specific only to sample segments who consider an attribute whilst undertaking the choice experiment. For those who do not consider an attribute, the parameter estimate for that individual is zero. As such the parameter estimates of models 3 and 4 are not inclusive of the entire sampled population. That is, the parameter estimates are specific to each attribute processing inclusion/exclusion strategy. In terms of segmentation and benefits studies, this is an important development. Assuming that respondents only consider attributes which they perceive a benefit when making choice decisions, the parameter estimates shown in models 3 and 4 may be interpreted as those for the specific needs benefit segments. In traditional models, these AP or benefit segments may be lost if the segment is small relative to the size of the total population. This is demonstrated with the flight time variability attribute in which only a small segment of the sampled population considered this attribute in the choice process. When the parameters are estimated ignorant of the attribute processing strategy employed, the flight time variability parameter is not significant (indeed it is of the wrong sign) which would result in the analyst wrongly assuming that the parameter is not important in the choice process for the entire population, when in fact, for a small proportion of the sampled population, the attribute is a highly significant influence on airline choice.

The impact of the attribute processing strategy carries through to the behavioural outputs derived from models of discrete choice. As well as the parameter estimates, Table 6 shows the direct marginal effects for the four estimated models. Supporting our earlier observations, ignoring the attribute processing strategy employed by sampled respondents tends to increase the sensitivities to increases in airline ticket prices and flight times. Indeed, the marginal effects for model 4 are approximately half those for model 2. Non-marginal changes are observed for the marginal effects for the flight time variability attribute when the attribute processing strategy is accounted for in the model estimation process compared to when it is ignored. Only marginal changes are observed within the magnitudes of the departure time effects coded attribute, however several sign reversals are noted.

Figure 1 shows the willingness to pay (WTP) distributions for the flight time attribute estimated from the two ML models reported in Table 6. The estimation procedure assigns a zero parameter estimate to those who did not consider an attribute but assigns a parameter estimate from the assigned distribution for those who did, using the procedures described in Train (2003). For derivation of WTP distributions, this poses problems if one or both of the parameters in the WTP ratio are equal to zero. If the cost parameter is equal to zero, the denominator of the ratio is equal to zero and the WTP measure becomes infinite. This is similarly the case if both parameters are equal to zero. If on the other hand, the parameter located in the numerator of the WTP calculation is zero, the WTP estimate becomes zero. These issues do not arise if the attribute processing strategy is not accounted for in the estimation process. In deriving the WTP distributions shown in Figure 1, we have removed those WTP measures which are infinite or which are equal to zero. We discuss this in a later section. The WTP based on individual parameters are summarised in Table 7 for the mixed logit models. All WTP have a distribution in the positive range (Figure 1).

Table 7: Summary of Empirical WTP values from models 2 and 4

	Willingness to Pay Attribute	Mean	Standard deviation	Range
Full data	Flight Time (minutes)	$25.14	**$7.10**	**$16.20-$76.16**
Attribute exclusion strategy	Flight Time (minutes)	$38.40	**$11.75**	**$3.26-$58.34**

The WTP distributions derived by the ML models were plotted using the kernel densities functions. The kernel density estimator is a useful tool for plotting individual-level parameter estimates and WTP outputs derived from mixed logit models. Similar to the construction of a histogram, the kernel density estimator selects points along the distribution and determines the proportion of sample observation that are 'close' to each point. Unlike histograms however, a weighting function, known as the kernel function, is used to weight each sample observation such that those observations furthest away from the selected point receive smaller weights than closer sample observations. In this way, the kernel density estimator constructs a 'smooth' plot of the sample distribution, necessary for representing continuous type data such as the WTP outputs derived from mixed logit models (see Hensher and Greene, 2003). The *y*-axis of the Figure shows the density, the *x*-axis WTP measured as Australian dollars per minute of flying time. The centre of gravity for the WTP distribution when the entire data is used in the estimation process is much greater than when the information processing attribute inclusion/exclusion strategy is accounted for.

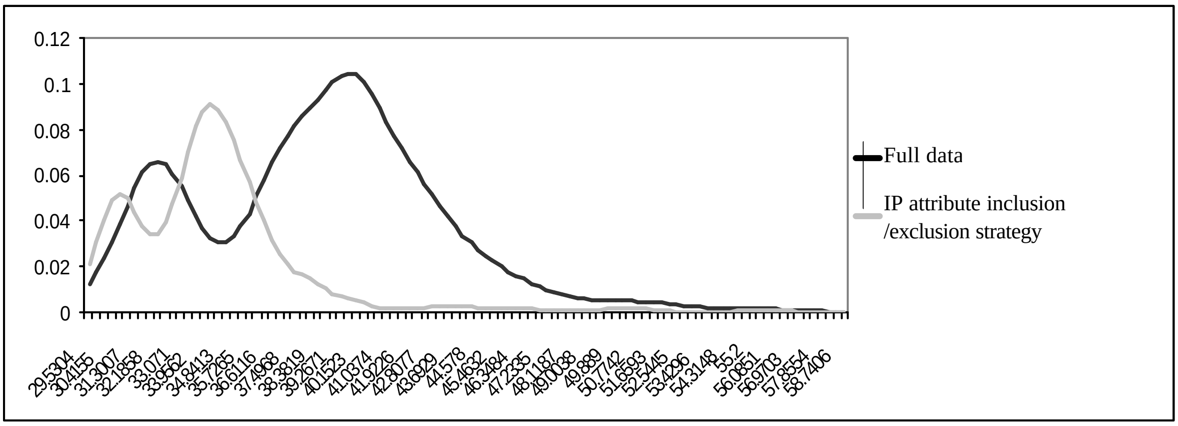

Figure 1: Willingness to Pay Kernel Density Functions for Flight Times

5. Conclusion

This paper has examined attribute inclusion/exclusion strategies and their effect upon the parameter estimates, marginal effects and willingness to pay for specific service levels associated with choice between airline service packages.

The evidence is a powerful reminder of the complexity of information processing strategies that individuals choose in considering service and fare level options in choosing an airline and class of travel. If we had assumed that all actual and potential passengers considered every attribute offered to them in a market research study, then we run the risk of misrepresenting the role of such attributes in influencing specific individual's choices. When we use that information to make inferences, through a choice model, for the population as a whole, we are likely, as shown herein, to over or underestimate the behavioural responsiveness to specific service level changes.

This paper has focussed on one information processing strategy. There are many additional strategies worthy of consideration in ongoing research.

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