ITLS

WORKING PAPER

ITLS-WP-19-14

Experience as a conditioning effect on choice – Does it matter whether it is exogenous or endogenous?

By
David A. Hensher, Camila Balbontin and William H. Greene

Institute of Transport and Logistics Studies (ITLS),
The University of Sydney Business School, Australia

July 2019

ISSN 1832-570X

INSTITUTE of TRANSPORT and LOGISTICS STUDIES

The Australian Key Centre in Transport and Logistics Management

The University of Sydney

Established under the Australian Research Council's Key Centre Program.

NUMBER: Working Paper ITLS-WP-19-14

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ABSTRACT: Hensher and Ho (2017) proposed a way to condition the utility of each alternative in a choice set on experience with the alternatives accumulated over previous periods. The paper found that the overall statistical performance of the mixed logit model improved significantly, suggesting that this conditioning idea has merit. Experience was treated as an exogenous influence linked to the scale of the random component, and to that extent it captures some amount of the heterogeneity in unobserved effects, purging them of potential endogeneity. The current paper continues to investigate the matter of endogeneity versus exogeneity. The proposed approach implements the control function method in the representative component of the relative utility expressions in a choice model. These methods have been investigated by Wooldridge (2005), Train and Petrin (2010), Train and Wilson (2009) and Guevara and Hess (2019), amongst other authors. We develop two choice models, both using stated preference data. The paper extends the received contribution in that we allow for the endogenous variable to have an impact on the attributes through a two stage method, called the Multiple Indicator Solution, also implemented in a different context by Guevara et al. (2019) for a single (crowding) attribute, in which stage two is the popular control function method. In the first stage, the entire utility expression associated with all observed attributes is conditioned on the prior experience with an alternative. Hence, we are capturing possible correlates associated with each and every attribute and not just one selected attribute. We find evidence of potential endogeneity. The purging exercise however, results in both statistical similarities and differences in time and cost choice elasticities and mean estimates of the value of travel time savings. We are able to identify a very practical method to allow for possible endogeneity under heteroscedastic conditioning that will encourage researchers and practitioners to use such an approach in more advanced non-linear discrete choice models as a matter of routine.

KEY WORDS: ***Experience, exogeneity, endogeneity, mode choice applications, choice elasticities, value of travel time, control function, experience model residuals, error components, multiple indicator solution, non-linear choice models, heteroscedastic conditioning***

AUTHORS: **Hensher, Balbontin and Greene**

Acknowledgements: This paper contributes to the research program of the Volvo Research and Education Foundation Bus Rapid Transit Centre of Excellence. The research contribution is also linked to an Australian Research Council grant DP140100909 (2014-2016) on 'Integrating Attribute Decision Heuristics into Travel Choice Models that accommodate Risk Attitude and Perceptual Conditioning' and ARC-DP grant (2017-19) DP170100420 on Business Location Decisions.

CONTACT: INSTITUTE OF TRANSPORT AND LOGISTICS STUDIES (H73)

The Australian Key Centre in Transport and Logistics Management

The University of Sydney NSW 2006 Australia

Telephone: +612 9114 1824

E-mail: business.itlsinfo@sydney.edu.au

Internet: http://sydney.edu.au/business/itls

DATE: July 2019

Introduction

Modal experience is an aggregation of many past influences on travel choice. As such there is the risk of endogeneity bias (EB) when experience is included as a conditioning variable in a choice model. EB can arise from a number of sources such as measurement error, missing attributes and simultaneity (Louviere et al. 2005), and is observed when a specific variable included in the observed effects is correlated with the error term associated with the utility expression containing the explanatory variable of interest. Although the reference to endogeneity is often used in multiple ways within the discrete choice literature, the correct interpretation within a model that assumes a utility expression commonly of the additive form V + ε, is that ε is independent of V. If there are some interaction effects that are not accounted for, then one or more variables may appear in both V and ε, and hence the terms are no longer uncorrelated. For example, if there is a price/quality trade-off and only price appears in V, then the interaction between price and quality resides in ε. Then price is in both V and ε and they are no longer independent. This issue can occur for any variable.

To ensure that the experience expression is purged of its potential endogeneity bias (that is, the part that may be correlated with the random error), it is necessary to test the extent to which experience has a systematic influence on the random errors, which suggests that it is impacting on the random component, and hence needs to be separated out through a mechanism to purge the correlation with the random errors. This can be done by identifying a proxy 'index' for the excluded explanatory variables that are correlated with experience, but not with the random error. By including the estimated proxy variable, its statistical significance can be used to establish the presence of statistically significant effects that are correlated with experience and which if excluded would end up in the random errors. This is a very appealing and practical way of purging this correlation to accommodate endogeneity, or simply as evidence of no endogeneity bias.

The paper is organised as follows. We begin with a summary of the choice model form that includes conditioning the utilities of alternatives by modal experience along the lines of Hensher and Ho (2017). This is followed by a discussion of the control function approach which has existed in the economics literature for many years and which is growing in popularity in the discrete choice analysis field. Two data sets are briefly overviewed followed by model results with and without control functions for each mode, as well as an error components treatment for the data sets. We present willingness to pay (value of travel time savings) and travel cost and travel time elasticities, and use the evidence to suggest the extent of potential bias in not accounting for potential endogeneity. The implications on practice are summarised, highlighting whether endogeneity matters or not in the data sets investigated.

The Mode Choice Model Form

Hensher and Ho (2017) reviewed the literature on the various definitions and ways that the construct 'overt experience' can be incorporated in a choice model. All of the studies provide evidence to support the role that experience (as a proxy construct) plays in informing and influencing preferences and hence choices. The proposed approach assumes that there is merit in conditioning the entire observable utility expression on some representation of experience linked to each of the available alternatives. Intuitively, a positive experience with an alternative is expected to increase its overall utility relative to other alternatives and vice versa for a negative experience, *ceteris paribus*. Consequently, experience will have an influence on the marginal utility of each attribute that contributes to the overall level of utility.

This approach to incorporate experience as a latent construct is analogous to the approach developed by Swait and Adamowizc (SA, 2001a,b) to accommodate the notion of 'complexity', in which the theoretical context is aligned with information theory in order to provide a measure of information content or uncertainty. Information theory refers to an approach taken to quantify the amount of information contained in an experiment or phenomenon (e.g., Soofi 1994). Experience is a source of accumulated information quantity. Swait and Adamowizc assume that complexity affects the utilities only through the stochastic component and that differences in complexity generate differential consistency levels in preferences across individuals. This will be reflected in the standard utility expression $V_{qj}+\varepsilon_j$ by affecting the variances of the assumed distribution for the random components. As shown in SA (2001b), under the usual distributional assumptions associated with the logit model form, the complexity conditioning expression, or in our case, an experience conditioning expression, is the scale function μ(E), where μ is inversely related to the variance of the errors. Also, so long as experience is a function of object attributes *X* and decision maker characteristics, the resulting model does not have the Independence from Irrelevant Alternatives property. This is referred to as the Heteroscedastic MNL model, similar to the idea presented in Hensher and Rose (2012). The proposed approach is appealing in that it conditions all of the observable sources of influence on the relative utility associated with each alternative[1]. Thus, this is a way of recognising that each alternative is processed conditioned on the experience of a sampled traveller with each alternative.

Beginning with the standard utility expression associated with the j^{th} alternative contained in a choice set of $j = 1,\ldots,J$ alternatives, we assume that an index defining overt experience with the j^{th} alternative and q^{th} individual, referred to as E_{qj}, conditions the utility expression. The functional form can be denoted by equation (1), also Equation (9) in SA (2001b):

$$U_{qj}^{*} = \mu(E_q)U_{qj} = \mu(E_q)(V_{qj}+\varepsilon_{qj}), \quad (1)$$

where U_{qj}^{*} is the standard utility expression, U_{qj}, conditioned on the overt experience (and other possible influences) with an alternative. This conditioning is a form of heteroscedasticity. E_q recognises that individual-specific experience, proxied by some metric such as overt prior frequency of use, conditions the marginal (dis)utility of each and every attribute, observed and unobserved, associated with the j^{th} alternative in a pre-defined choice set. In equation (1), the random variables $\mu(E_q)\varepsilon_j$, for all q and j contained in an individual's choice set are IID Gumbel but with scale factors $\mu(E_q)$ that can vary as required across the sample. Dividing both the left and right hand sides of (1) by $\mu(E_q) > 0$ produces the standard basis of the random utility choice model. The probability behind random utility maximisation is unchanged by the positive scale factor, as shown in (2).

$$\begin{aligned}\Pr[U_{qj}^{*} > U_{qj'}^{*}] &= \Pr[U_{qj} > U_{qj'}] \\ &= \Pr[V_{qj} - V_{qj'} > \varepsilon_{qj} - \varepsilon_{qj'}] \\ &= \Pr[\mu(E_{qj})(V_{qj} - V_{qj'}) \geq \mu(E_{qj'})(\varepsilon_{qj} - \varepsilon_{qj'})]\end{aligned} \quad (2)$$

Given the IID property of the error difference, it follows that the probability of choosing an alternative is an MNL-like model with the observed sources of utility $\mu(E_q)V_{qj}$ as given in equation(3).

$$\Pr_{qj} = \frac{\exp\left[\mu(E_{qj} \mid \gamma_j)\cdot V_{qj}(X_{qj} \mid \beta)\right]}{\sum_{j' \in J_q} \exp\left[\mu(E_{qj'} \mid \gamma_{j'})\cdot V_{qj'}(X_{qj'} \mid \beta)\right]} \quad (3)$$

where we have parameters γ_j and β, and the observed variables *E* and *X* associated with each alternative and each individual. γ_j is the parameter set associated with the expression for experience

[1] It is also possible to condition each attribute separately by experience to obtain unique conditioning parameter estimates for each observed attribute, as we have done in other studies.

(see equation 4 and 5). By making the parameters in the scale function vary across the alternatives (for identification), we have transformed the MNL model in (2) to one in (3) in which the utility functions are nonlinear in the parameters. We used slightly different specific functional forms of heteroscedastic conditioning for the datasets given that the experience in one of the SP data sets was measured as a binary variable (i.e., if they had or not experienced that mode of transport). However, all the functional forms are equivalent to the log-sum formulation which is convex and strictly monotonically increasing.

Given differing definitions of experience in the considered data sets, we have used alternative measures of experience as follows. The functional form for one of the SP data sets where experience in mode *i* was measured as a binary variable, is given in equation (4):

$$E_{q,i} = \ln\left(1 + \exp\left(\gamma_{q,i} \cdot DummyExp_{q,i} + \beta_i \cdot Z_q\right)\right) \quad (4)$$

where $DummyExp_{q,i}$ represents a dummy variable that equals to 1 if mode *i* has been experienced by individual *q*, and 0 otherwise; $\gamma_{q,i}$ is the parameter estimate associated with the experience dummy variable which is estimated as random; z_q represents any statistically significant socioeconomic characteristics such as the respondents' age to recognise the residual heterogeneity effect after individual experience has been accounted for; and β_i is the parameter estimate associated with the socioeconomic characteristics, considered as fixed parameters.

For the other SP dataset, the functional form is represented by equation (5):

$$E_{q,i} = \ln\left(1 + \exp\left(\gamma_{q,i} \cdot \ln\left(FR_{q,i} + a\right)\right) + \beta_i \cdot Z_q\right) \quad (5)$$

where $FR_{q,j}$ is usage frequency, defined by the number of times the q^{th} individual used mode *i* over a previous fixed period; and a is a fixed constant defined by the modeller[2]. The behavioural rationale for including socio-economic variables in the conditioning function is that commuters, for example, in different age and income groups may respond to travel time and travel cost differently. This is essentially an interaction effect.

The functional forms in equations (4) and (5) have the advantage that they will always have a positive value. This is particularly important considering $\gamma_{q,i}$ are estimated as random parameters, which implies their values might be positive or negative. It is crucial that $E_{q,i}$ is positive to maintain the sign of the utility function. The functional forms adopted ensure the conditioning form will be positive when allowing for fixed and/or random parameters.

In summary, when we allow for this form of heteroscedasticity, the standard logit model takes the revised form shown in equation (6), where V_{qj} is linear-in-parameters and the functional form of $E_{q,i}$ will depend on the dataset as shown in equations (4) and (5).

$$\Pr_{jq} = \frac{\exp\left[ASC_j + E_{q,j} \cdot \left(\sum_n \beta_{n,q,j} \cdot x_{n,j}\right)\right]}{\sum_{j'=2}^{J} \exp\left[ASC_{j'} + E_{q,j'} \cdot \left(\sum_n \beta_{n,q,j'} \cdot x_{n,j'}\right)\right]} \quad (6)$$

[2] Alternative combinations of the constant and functional forms were investigated, with the form presented here found to provide a superior overall model fit and significance levels.

The model form is non-linear-in-parameters since the parameter associated with the experience effect (γ_j) interacts with the parameters β associated with attributes X_{qj}. This non-linear-in-parameter model, the elasticities, willingness to pay and their confidence intervals[3] are estimated using PythonBiogeme (Bierlaire 2017)[4].

Control Function

There are a number of ways to set up a discrete choice model that embeds the presence of endogeneity associated with a specific inclusion in the representative component of a utility expression. Some key papers on this topic are applications by Train and Wilson (2009), Petrin and Train (2010), Guevara, and Ben Akiva (2010) and Guevara and Hess (2019), Guevara et al. (2019) and a mainstream econometric review by Wooldridge (2015). The main focus of Petrin and Train (2010) and Guevara and Ben Akiva (2010) is on endogeneity induced by conditioning the attribute levels in a stated preference experiment on revisions in a reference alternative (in contrast to exogenously fixed attribute levels of market chosen alternatives). The current paper focuses on the potential endogeneity induced by including accumulated experience in using each of the modes in a mode choice application. As set out above, experience, proxied by exogenous frequency of use has similar features to a reference alternative that is fixed and hence it might not induce endogeneity, but is worthy of consideration.

There are (at least) three classes of estimators for choice models with endogenous attributes: (1) Berry et al. (1995) and similar. These require instrumental variables and market share data. (2) Full maximum likelihood estimation (FIML). These are extremely complicated, and usually infeasible. A partial solution has been devised for some cases using maximum simulated likelihood. (3) Control function (CF) estimators which are growing in popularity in traveller behaviour research, although they are well known in econometrics (see Wooldridge (2015) for a review). CF estimators are usually devised rigorously from the underlying theory of the model, with Petrin and Train (2010) being a good example of progress. Other studies (e.g., Guevara and Hess 2019) appear to be based on more ad hoc intuition of variables that should be exogenous, like instrumental variables (IVs); however control functions are not IVs. We recognise however that the appropriate CFs for an endogenous variable in a choice model might be difficult if not impossible to devise, so some *ad hoc* creativity might be necessary. Wooldridge (2015) writes along these lines. In this paper we have adopted the control function approach.

Control functions are statistical methods to correct for endogeneity problems by modelling the endogeneity in the relevant random components. The approach differs in important ways from other models that try to account for the same econometric problem. Instrumental variables, for example, attempt to model an endogenous variable *X* as an often invertible model with respect to a relevant and exogenous instrument *Z*. Panel data use special data properties to difference out unobserved heterogeneity that is assumed to be fixed over time. Control functions were introduced by Heckman and Robb (1985a), although the principle can be traced back to earlier papers such as Heckman (1979). A particular reason why they are popular is because they work for non-invertible models (such as discrete choice models) and allow for heterogeneous effects, where effects at the individual level can differ from effects at the aggregate. Classical examples using the control function approach are the Heckit model and the Heckman (1979) correction (linked to selectivity bias).

The CF method is described in Heckman and Robb (1985), Guevara and Ben-Akiva (2010), Petrin and Train (2010), and Antolin et al (2014) amongst other papers. It involves two stages. First, the

[3] The reader is referred to (Bierlaire, 2017) for more information on the sensitivity analysis. 500 draws have been used for the sensitivity analysis simulations.
[4] The models presented could also be estimated in Nlogit6.

endogenous variable is regressed on exogenous instruments; then, the residual (or a function of it) is incorporated into the utility function as an additional explanatory variable denoted the control function (Louviere et al., 2005; Guevara and Ben-Akiva, 2010). As with maximum likelihood, this approach requires that the relationship between the endogenous regressors and the instrument be correctly specified. Suppose you have an endogenous variable in a regression model, but you use OLS anyway. If you are interested in the predictions (or residuals which have the same effect in a linear model) from the linear CF model, the fitted values, 'are not' systematically biased. This is an important point because in a discrete choice model, the parameter estimates, themselves, are never of interest. So other than testing whether the parameters are zero or not, it is generally dubious to interpret the parameters on a CF. In most cases, the parameter is an uninterpretable multiple of a correlation coefficient. By that construction, the parameter is only zero if the correlation is zero, which in turn, implies something about exogeneity. But, the specific value is not meaningful, and even the sign is up for grabs.

A general advantage of the control function approach is that the test that the coefficient on the CF is zero is broadly equivalent to a test of exogeneity. This is easy to show for the linear regression model (OLS vs. 2SLS), but is true for other applications as well such as binary logit. Forming the joint likelihood for the extreme value type 1 (EV1) terms in the logit choice model and the normal variables in the ancillary equations is complex. An alternative approach is to make the joint (EV1, Normal) into a conditional EV1| Normal times a normal, then integrate the normal out using simulation. This is how all of the received treatments have proceeded. Another way is to add appropriate control variables to the full model, then break it up into components the way that Guevara and Hess, and Train and Wilson do. In general, one cannot be optimistic about a FIML treatment of the full model, and an alternative strategy is required.

Antolin et al. (2014) note that the conventional estimator of the coefficient on the endogenous variable is biased; however this fails to account for the fact that the coefficients on all of the variables are biased. There is an issue that appears generally to be overlooked. Even if the coefficient estimators on all the variables in the choice model are, indeed, inconsistent, it does not follow automatically that estimators of willingness to pay and elasticities are also inconsistent. This remains to be investigated. A straightforward related case in point concerns omitted higher order lagged values in a dynamic regression. The inconsistency of the individual coefficient estimators does not translate into any systematic bias in forecasts.

In this paper we propose to estimate three models with two data sets. The first model (M1) assumes that experience is exogenous and conditions the representative component of each of the utility expressions. This is a standard heteroscedastic conditioned mixed logit model (HCML). The second model (M2) is the same re-estimated HCML model with control functions defined as the residuals from the experience model, added into the utility expression but not conditioned on reported modal experience. Where the experience variable is continuous (data set 2) we use OLS, and for the binary experience variable (data set 1) we use a binary logit model where the residuals are Y (1,0) minus the predicted choice probability. The third model (M3) has the same form as M2 but includes an error component that allows the error to vary across respondents but not within respondents.

A recent paper by Guevara et al. (2019) has suggested the Multiple Indicator Solution (MIS) method (Guevara and Polanco, 2016) to address the problem of endogeneity due to omitted crowding in public transportation choice models. The proposed MIS method relies on having at least a pair of suitable indicators (for crowding in their example). The indicators are measured variables that depend on the omitted variable causing endogeneity and may be collected in RP or SP experiments. Prior experience with an alternative is an example. The authors suggest that 'The relative easiness in collecting such data makes the MIS an attractive tool for the correction of endogeneity in public transportation choice models.' They applied the MIS method in two stages: First, one of the indicators is included in the utility of the choice model. By this modification, the endogeneity of other variables is eliminated, and the included indicator becomes the only endogenous variable. Then, in a second stage, the problem is solved by using the second indicator as an instrument for the first one. This is very similar to what Hensher and Ho (2017) suggest as the first stage, using experience. In this paper, we extend Hensher and Ho (2017) by conditioning, at the first stage, the *entire* utility expression associated with all attributes in a utility expression, on the prior experience with an alternative. This captures possible correlates associated with *each and every attribute* and not just one selected attribute (i.e., crowding in Guevara et al. 2019). The second stage, implemented in the current paper, is the control function method. Standard errors for the two stage approach can be computed, if required, using bootstrapping (Hensher et al. 2015) or standard formulae for two-stage estimation (Karaca-Mandic and Train 2003), both of which provide very similar standard errors.

The Empirical Setting

Data Set 1: Stated Preference Mode Choice – Northwest

The Northwest dataset was collected as part of a larger study to evaluate public transport investment options (train and bus) in the northwest of Sydney (Hensher and Rose, 2007). The sample covered residents that made trips within the region (intra-regional) and outside of the region (inter-regional). If an individual made intra-regional trips, the stated preference survey presented three public transport modes plus a car alternative if it was available to a respondent. If an individual made inter-regional trips, the survey included five public transport modes plus a car alternative if available. Each alternative was described by access, egress and main mode attributes. The survey included existing public transport modes (bus, existing M2 busway and existing train line) and non-existing ones (new heavy rail systems, new light rail and dedicated busway systems along the same corridor). Individuals in this sample have not experienced the non-existing modes so we do not include experience or residuals for these modes. Figure 1 presents an illustrative choice screen. The Northwest dataset used in this research has 453 respondents with each facing 10 choice sets, giving a total sample size of 4,530 observations.

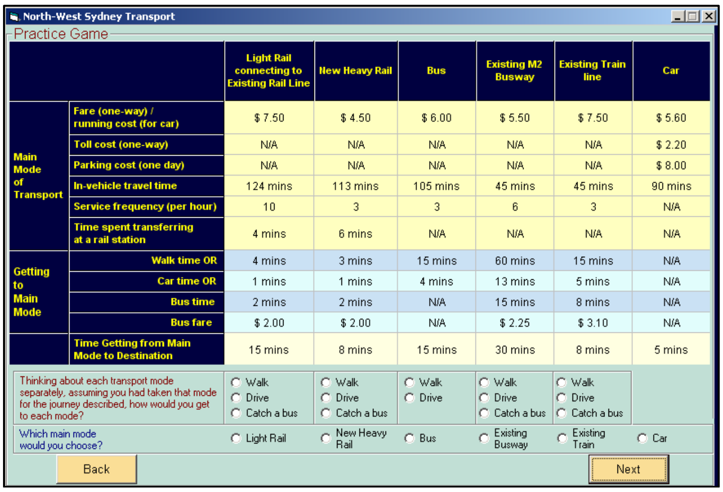


Figure 1: Illustrative screenshot of Northwest Sydney choice experiment (Hensher and Rose 2007)

Data Set 2: Stated Preference Mode Choice – Metro Rail

The Metro Rail dataset was collected to evaluate the New South Wales government proposal to build a new Metro rail system for Sydney (Hensher et al., 2011). The stated preference survey included four alternatives: bus, metro, train and car where metro was the only alternative that at the time did not exist (i.e., respondents did not have any experience with it). Each mode was described by access, main mode and egress attributes. Figure 2 presents an illustrative choice experiment screen. This dataset has 1,519 respondents, where each was given six sequential stated choice tasks to assess, giving a total of 9,114 observations.

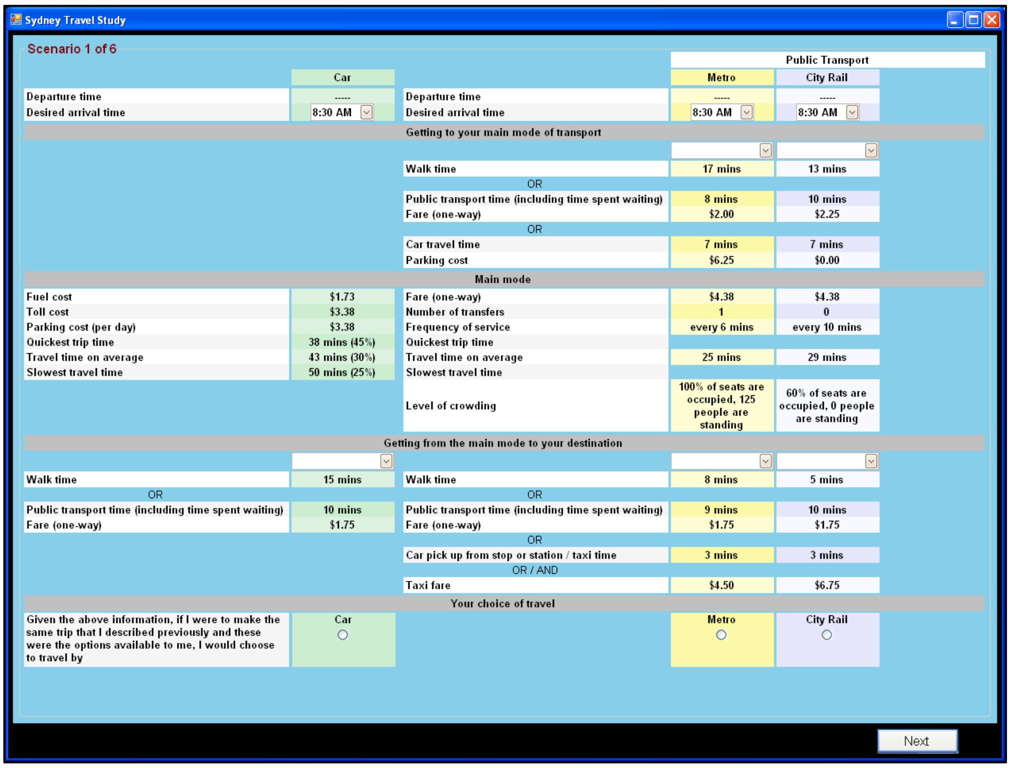


Figure 2: Illustrative screenshot of Metro Rail Sydney choice experiment (Hensher et al. 2011)

Comparison of the two datasets

Table 1 presents summary statistics for each dataset, some of which will be included in the control function or choice models. As can be seen, respondents have relatively higher personal income and lower household size in data set 2, with the other socioeconomic characteristics being similar across the data sets; however, some data items were not captured in both data sets. The last three rows in Table 1 describe the nature of captured experience in the surveys. In the Northwest survey, experience is represented by a binary variable – if they used that mode or not in their most recent trip. In the Metro Rail survey, respondents were asked about the mode chosen in their most recent trip and how many similar one-way trips they had made during the last week. Therefore, the survey only captures the number of trips for the mode chosen in a most recent trip.

Table 1: Summary statistics of the two datasets: mean and standard deviation (in parentheses)

Variable	Northwest (DS1)	Metro Rail (DS2)
Socio demographics:		
Age (years)	42.85 (46.28)	43.21 (15.82)
Female	57%	56%
Weekly working hours	26.49 (20.22)	26.38 (55.46)
Personal income before tax ('000$)[5]	45.15 (39.70)	54.96 (42.64)
Number of household cars	-	1.54 (1.01)
Number of household residents	3.51 (1.83)	2.76 (1.63)
Car driver licence (dummy)	-	-
Work trip (dummy)	49%	-
Education trip (dummy)	11%	-
No car (dummy)	14%	11%
Travel characteristics:		
PT Travel time	55.31 (19.59)	25.72 (12.02)
Car Travel time	56.66 (27.67)	44.06 (23.27)
PT Travel cost	6.21 (2.81)	3.83 (1.63)
Car Travel cost	22.41 (15.75)	20.28 (11.71)
Experience:		
Description	If they used that mode in their most recent trip	Number of trips made during the last week for the mode used in their most recent trip
Public Transport	70%	2.54 (2.31)
Car	30%	2.26 (2.05)

Model Estimation and Results

The first modelling task was to estimate the control functions for each dataset, using Nlogit version 6.0 (for details see Hensher et al. 2015). The estimated residuals are then included in the mode choice model as explanatory variables, with the models fitted assuming that the parameters used to compute the control functions are known. Given that the asymptotic variances are estimated and hence not known, by not accounting for this additional variance, by construction, the computed standard errors at the second step (i.e., mixed logit estimation) are smaller than would otherwise be the case. Bootstrapping is a way of correcting for this additional variance, resulting typically, but not always, in lower t-values (higher standard errors). Alternatively, Karaca-Mandic and Train (2003) provide standard formulae to correct the standard errors when the number of observations differ between the control function and the choice model. In our applications, we use the exact same samples and hence both bootstrapping and a simplified specification are permissible (see Kuksov and Villas-Boas (2008), although we stay with bootstrapping.

As explained above, we estimated three different models for the SP datasets:

- M1: Experience assumed to be exogenous and conditioning the representative component of the Utility expressions – HCML model

[5] The data was collected in various years between 2007 and 2009 and income refers to the reported income in the year of data collection.

- M2: Re-estimated HCML model with additional explanatory variables defined as the residuals from the experience model control function, added into the utility expression but *not* conditioned on reported modal experience.
- M3: Same as M2 but adding an error component that allows the error term to vary across but not within individuals. This last form only makes sense when individuals respond to more than one choice task, as applies to SP datasets or longitudinal RP data.

The control functions presented below include only socio-demographics of the respondents, to avoid any possible confounding between the modal attributes and the residuals, considering the residuals will then be included together with modal attributes to explain respondent preferences.

Data Set 1: Stated Preference Mode Choice – Northwest

The results for Data Set 1 are summarised in Table 2-5. The overall statistical fit of the choice models is very acceptable with the AIC index reducing as we move from M1 to M3. The parameter estimates associated with the residual variables are all statistically significant, suggesting that endogeneity associated with experience exists. The error components have statistically significant variance effects for all modes except new busway, suggesting that after introducing of residuals derived from control function, there remain other sources of unobserved variance distinguishing the random errors between the modes. We provide, in Table 3, the t-values before and after accounting for revised standard errors through bootstrapping.

Our particular interest is the implication of controlling for possible endogeneity for key behavioural outputs – does it make a difference? An interesting result is the almost identical mean estimate for VoT in M2 for public transport ($9.21) in comparison with M1 ($9.21 under experience exogeneity) when we introduce the control function residuals as explanatory variables; however when we add in the error components to M2 (as M3), we obtain a higher mean VoT ($10.4). The car evidence suggests that controlling for endogeneity in M2 modifies the mean VoT slightly (from $30.9 to $28) with an even lower estimate ($22.3) after allowing for error component effects. Despite the range of evidence, there is no statistical difference around the mean estimates for all three models when we account for the confidence limits at the 95 percent level.

When we look at the direct elasticity estimates, however, we do not obtain the same finding; rather the mean direct elasticities are in the main, consistently higher in Model M3 when we allow for endogeneity and error components, although not in all cases, but are often similar when we allow only for the residuals from the control functions. When we consider the confidence limits at 95 percent confidence we are inclined to conclude that there are no statistically significant differences and that testing for and accounting for endogeneity appears to make little difference to the behavioural evidence based on the exogeneity assumption; however practitioners tend to op for use of mean estimates and hence we would suggest that the evidence in M3 be used.

Table 2: Control Functions Northwest dataset (Binary logit models)

	Bus experience (1,0)	**Train experience (1,0)**	**Busway experience (1,0)**	**Car experience (1,0)**
Constant	-1.438 (16.71)	-1.619 (10.32)	0.272 (1.39)	-1.097 (6.27)
Household income in $1000	0.006 (4.75)	-0.001 (0.72)	0.003 (2.10)	-0.006 (4.87)
Number of residents in household	0.085 (4.58)	0.073 (3.61)	-0.173 (5.60)	-0.100 (3.92)
Age of respondent	-	0.005 (2.08)	-0.018 (6.54)	0.007 (2.78)
Gender (male)	0.133 (1.74)	0.622 (8.82)	0.103 (1.34)	-0.866 (11.71)
Work hours per typical week	-0.019 (7.48)	-0.004 (1.78)	-0.014 (5.45)	0.032 (13.24)
Log-likelihood	*-2328.12766*	*-2585.93926*	*-2292.63818*	*-2607.08154*
Restricted log-likelihood	*-2363.26425*	*-2635.93202*	*-2337.31579*	*-2764.48741*
Sample size		*4,530*		
Adjusted R-squared	*0.015*	*0.019*	*0.019*	*0.057*
AIC/n	*1.032*	*1.147*	*1.017*	*1.156*

*Note: experience is a binary variable if they have used that mode in their most recent trip

Table 3: Northwest data Model Results (t values in brackets)

			M1		M2		M2 bootstrapping		M3		M3 bootstrapping	
Parameters:	**Acronym**	**Alternatives**	**Mean**	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**
Alternative Specific Constant New Light Rail	ASCLR	New Light Rail	1.520 (9.27)	-	1.920 (8.76)	-	1.920 (5.29)	-	6.600 (8.82)	-	6.600 (41.20)	-
Alternative Specific Constant New Heavy Rail	ASCNHR	New Heavy Rail	1.680 (10.40)	-	2.030 (9.30)	-	2.030 (5.97)	-	6.800 (8.98)	-	6.800 (43.00)	-
Alternative Specific Constant New Busway	ASCNBW	New Busway	0.608 (3.13)	-	0.872 (3.56)	-	0.872 (2.25)	-	5.740 (7.58)	-	5.740 (27.10)	-
Alternative Specific Constant Bus	ASCBS	Bus	0.876 (4.90)	-	1.280 (5.40)	-	1.280 (2.93)	-	4.270 (5.01)	-	4.270 (11.10)	-
Alternative Specific Constant Busway	ASCBW	Busway	-0.266 (1.72)	-	0.133 (0.50)	-	0.133 (0.37)	-	4.320 (5.94)	-	4.320 (24.00)	-
Alternative Specific Constant Train	ASCTR	Train	-0.517 (3.45)	-	0.101 (0.37)	-	0.101 (0.30)	-	3.950 (5.25)	-	3.950 (21.80)	-
Alternative Specific Constant Car	ASCCR	Car	-	-	-	-	-	-	-	-	-	-
Fare Public Transport	COSTPT	All PT	-0.312 (24.20)	-	-0.313 (22.70)	-	-0.313 (8.19)	-	-0.424 (20.50)	-	-0.424 (12.10)	-
Cost (fuel + toll + parking) car	COSTCR	Car	-0.112 (11.80)	-	-0.089 (9.02)	-	-0.089 (3.30)	-	-0.099 (4.19)	-	-0.099 (4.26)	-
Travel Time Public Transport	TTPT	All PT	-0.048 (30.70)	-	-0.048 (27.10)	-	-0.048 (12.80)	-	-0.073 (26.80)	-	-0.073 (16.00)	-
Travel Time Car	TTCR	Car	-0.058 (13.40)	-	-0.041 (8.49)	-	-0.041 (3.91)	-	-0.037 (3.82)	-	-0.037 (5.42)	-
Age of Individual Bus	BAGE_BS	Bus	0.007 (7.25)	-	0.003 (2.78)	-	0.003 (0.91)	-	-0.001 (0.63)	-	-0.001 (0.35)	-
Age of Individual Car	BAGE_CAR	Car	-	-	-	-	-	-	-	-	-	-
Experience Bus	BEXPBS	Bus	-0.154 (0.75)	-1.610 (6.64)	1.090 (5.73)	-1.140 (7.55)	1.090 (4.95)	-1.140 (5.10)	0.612 (3.59)	-0.235 (1.99)	0.612 (4.50)	-0.235 (1.04)
Experience Busway	BEXPBW	Busway	-0.068 (0.56)	-0.957 (6.81)	1.040 (5.07)	0.342 (2.13)	1.040 (6.13)	0.342 (1.51)	0.291 (1.66)	-0.271 (2.03)	0.291 (2.51)	-0.271 (1.19)
Experience Train	BEXPTR	Train	-0.374 (1.89)	1.840 (7.25)	1.260 (6.63)	0.114 (0.69)	1.260 (7.93)	0.114 (0.91)	0.478 (3.02)	-0.109 (0.82)	0.478 (5.04)	-0.109 (0.74)
Experience Car	BEXPCR	Car	1.400 (3.53)	3.980 (4.98)	1.900 (5.56)	3.620 (5.61)	1.900 (4.02)	3.620 (10.10)	1.780 (2.73)	1.870 (5.12)	1.780 (5.67)	1.870 (5.22)
Residuals Bus	BRES_BUS	Bus	-	-	3.510 (8.80)	-	3.510 (6.99)	-	3.580 (4.00)	-	3.580 (13.40)	-

Residuals Busway	BRES_BW	Busway	-	-	2.690 (3.21)	-6.600 (12.30)	2.690 (10.10)	-6.600 (11.20)	1.820 (2.61)	-1.740 (3.07)	1.820 (8.25)	-1.740 (6.74)
Residuals Train	BRES_TR	Train	-	-	3.580 (5.54)	5.890 (14.30)	3.580 (13.90)	5.890 (16.70)	2.700 (4.81)	-2.710 (4.77)	2.700 (8.82)	-2.710 (8.43)
Residuals Car	BRES_CR	Car	-	-	2.270 (6.18)	-	2.270 (3.36)	-	6.090 (5.00)	-	6.090 (30.10)	-
Error Components New Light Rail	BEC_LR	New Light Rail	-	-	-	-	-	-	-	1.720 (11.20)	-	1.720 (6.08)
Error Components New Heavy Rail	BEC_NHR	New Heavy Rail	-	-	-	-	-	-	-	1.740 (12.00)	-	1.740 (6.67)
Error Components New Busway	BEC_NBW	New Busway	-	-	-	-	-	-	-	-0.490 (1.44)	-	-0.490 (1.58)
Error Components Bus	BEC_BUS	Bus	-	-	-	-	-	-	-	2.660 (13.70)	-	2.660 (8.32)
Error Components Busway	BEC_BW	Busway	-	-	-	-	-	-	-	-1.420 (7.63)	-	-1.420 (3.85)
Error Components Train	BEC_TRAIN	Train	-	-	-	-	-	-	-	-1.720 (8.14)	-	-1.720 (7.86)
Error Components Car	BEC_CAR	Car	-	-	-	-	-	-	-	5.240 (11.10)	-	5.240 (12.80)
Number of Parameters Estimated			19.00		25.00				32.00			
Log Likelihood at convergence			-5710.32		-5244.84				-4473.39			
Log likelihood at zero							-7838.25					
AIC/n			1.21		1.11				0.95			

Table 4: Northwest data Value of Travel Time ($/person hour)
Note: CI confidence intervals

	M1			M2					M3				
	Mean	CI		Mean	CI		CI bootstrapping		Mean	CI		CI bootstrapping	
PT Value of travel time ($/person hr)	9.22	7.48	11.90	9.21	7.65	11.5	7.53	11.80	10.40	8.72	12.50	8.72	12.60
Car Value of travel time ($/person hr)	30.90	14.00	87.60	28.00	12.1	74.1	11.40	88.20	22.30	8.05	48.80	12.80	40.00

Table 5: Northwest data Choice Probability Direct Elasticity Estimates

	M1	Confidence Intervals		M2	Confidence Intervals		M3	Confidence Intervals	
New light rail average travel cost	-1.460	-1.720	-1.220	-1.400	-1.720	-1.160	-1.840	-2.330	-1.480
New heavy rail average travel cost	-0.856	-1.720	-0.655	-0.817	-1.720	-0.639	-0.987	-2.330	-0.781
New busway average travel cost	-1.230	-1.460	-1.020	-1.180	-1.460	-0.970	-1.480	-1.920	-1.180
Bus average travel cost	-0.778	-1.460	-0.591	-0.744	-1.460	-0.580	-0.839	-1.920	-0.656
Busway average travel cost	-2.070	-2.370	-1.770	-2.060	-2.420	-1.760	-2.630	-3.100	-2.250
Train average travel cost	-1.720	-2.370	-1.340	-1.730	-2.420	-1.390	-2.040	-3.100	-1.660
Car average travel cost	-1.460	-2.020	-1.010	-1.520	-2.100	-1.070	-1.780	-2.450	-1.200
New light rail average travel time	-1.110	-2.020	-0.761	-1.190	-2.100	-0.824	-1.310	-2.450	-0.827
New heavy rail average travel time	-1.060	-1.290	-0.866	-1.280	-1.590	-1.000	-1.360	-1.860	-1.040
New busway average travel time	-1.010	-1.290	-0.750	-1.210	-1.590	-0.898	-1.150	-1.860	-0.861
Bus average travel time	-0.905	-1.210	-0.691	-1.440	-1.810	-1.110	-1.450	-1.940	-1.120
Busway average travel time	-0.613	-1.210	-0.438	-0.888	-1.810	-0.659	-0.826	-1.940	-0.619
Train average travel time	-1.580	-2.350	-0.847	-1.420	-2.280	-0.564	-1.670	-2.710	-0.139
Car average travel time	-1.070	-2.350	-0.518	-0.961	-2.280	-0.377	-1.070	-2.710	-0.102

*The bootstrapping confidence intervals, which are statistically equivalent to the ones in this table, are presented in Table 10 in the Appendix.

Data Set 2: Stated Preference Mode Choice – Metro Rail

The model results and behavioural outputs are summarised in Tables 6-9. The overall statistical fit of the choice models is very acceptable with the AIC index reducing as we move from M1 to M3. The parameter estimates associated with the residuals variables are all statistically significant, suggesting that endogeneity associated with experience exists. The error components have statistically significant variance effects for all modes after correcting for standard errors through bootstrapping, suggesting that after introducing of residuals derived from control function, there remains other sources of unobserved variance distinguishing the random errors between the modes.

For Data set 2, the VoT evidence differs from data set 1. The correction for endogeneity reduces the mean public transport VoT from $9.59 in M1 to $9.11 in M2, and increasing it after the error components treatment to $9.50, essentially the same as the finding when exogeneity is not allowed for. The same relative directional impact of the mean VoT is also found for car ($13.6 for M1, $8.63 for M2 and $13.7 for M3). Like data set 1, although M2 has a lower mean VoT, the differences at the 95 percent confidence are not statistically significant; however the same comment applies in relation to practitioner selection of behavioural mean estimates in applications.

The mean elasticity estimates vary up and down for M2 and M3 compared to M1, with the direct cost elasticities either remaining the same (car) or decreasing from M1 to M2 but returning to the M1 levels in M3. The travel time elasticities have less of a consistent relativity with some (e.g., train) decreasing between M1, M2 and M3, while car increases noticeably in M3 compared to similar findings for M1 and M2. With the possible exception of car travel time, the confidence limits suggest no statistical difference in the estimated elasticities.

Model 2 mean elasticities are either similar or a little lower than M1, but the M3 results are typically higher.

Table 6: Control Functions Metro Rail dataset (Ordinary Least Squares Regression)

	Bus experience	**Train experience**	**Car experience**
Constant	0.524 (8.93)	1.473 (18.73)	-0.162 (3.33)
Household income in $1000	-0.001 (2.67)	-0.002 (4.07)	0.006 (10.83)
Number of vehicles in household	-0.068 (3.91)	-0.099 (4.48)	0.222 (16.04)
Commuter (dummy)	0.794 (22.03)	1.687 (36.34)	0.595 (17.54)
Gender (female)	0.066 (2.02)	-0.339 (8.18)	-0.119 (3.99)
Work hours per typical week	0.0002 (2.70)	-0.0005 (2.43)	0.0002 (1.72)
Age of respondent	-0.003 (3.30)	-0.010 (8.40)	-0.002 (2.07)
Dependent variable mean (std dev)	*0.596 (1.53)*	*1.261 (2.08)*	*0.604 (1.45)*
Sample size		*9,114*	
Adjusted R-squared	*0.068*	*0.175*	*0.109*

*Note: experience is measured as the number of trips in the last week

Table 7: Metro Rail data Models Results (t values in brackets)

			M1		M2		M2 bootstrapping		M3		M3 bootstrapping	
Parameters:	**Acronym**	**Alternatives**	**Mean**	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**
Alternative Specific Constant Bus	ASCBUS	Bus	-0.804 (3.06)	-	-0.019 (0.05)	-	-0.019 (0.05)	-	-1.070 (1.98)	-	-1.070 (6.39)	-
Alternative Specific Constant Train	ASCTRAIN	Train	-1.220 (5.27)	-	-0.991 (3.01)	-	-0.991 (2.70)	-	-1.420 (3.20)	-	-1.420 (11.70)	-
Alternative Specific Constant Metro	ASCMETRO	Metro	-0.072 (0.31)	-	0.213 (0.64)	-	0.213 (0.56)	-	0.013 (0.03)	-	0.013 (0.11)	-
Alternative Specific Constant Car	ASCCAR	Car	-	-	-	-	-	-	-	-	-	-
Fare Public Transport	COSTPT	Bus, Train, Metro	-0.423 (14.00)	-	-0.406 (12.70)	-	-0.406 (9.81)	-	-0.401 (11.50)	-	-0.401 (11.10)	-
Cost (fuel + toll + parking) car	COSTCR	Car	-0.211 (11.10)	-	-	-	-	-	-0.198 (11.00)	-	-0.198 (9.67)	-
Travel Time Public Transport	TTPT	Bus, Train, Metro	-0.068 (15.00)	-	-0.062 (12.90)	-	-0.062 (9.27)	-	-0.063 (12.10)	-	-0.063 (11.50)	-
Travel Time Car	TTCR	Car	-0.048 (5.59)	-	-0.030 (2.95)	-	-0.030 (1.88)	-	-0.045 (4.54)	-	-0.045 (4.94)	-
Age of Individual Bus	BAGE_BUS	Bus	-0.003 (1.36)	-	-0.001 (0.57)	-	-0.001 (0.32)	-	-0.006 (1.67)	-	-0.006 (1.80)	-
Experience Bus	TAU_BUS	Bus	-0.367 (3.62)	1.470 (7.34)	-0.987 (5.52)	-1.390 (5.42)	-0.987 (4.89)	-1.390 (4.09)	-0.445 (3.59)	-0.519 (4.27)	-0.445 (3.22)	-0.519 (3.81)
Experience Train	TAU_TR	Train	-0.076 (2.06)	-0.807 (13.30)	-0.112 (2.08)	0.700 (10.60)	-0.112 (1.89)	0.700 (8.42)	-0.001 (0.02)	-0.235 (3.02)	-0.001 (0.02)	-0.235 (2.43)
Experience Car	TAU_CAR	Car	-0.906 (6.60)	-2.490 (10.00)	-0.978 (5.56)	-2.190 (8.49)	-0.978 (2.23)	-2.190 (2.36)	-0.346 (3.82)	-0.609 (5.85)	-0.346 (2.75)	-0.609 (3.12)
Residuals Bus	BRES_BUS	Bus	-	-	-0.574 (5.05)	0.650 (4.84)	-0.574 (3.91)	0.650 (2.53)	-0.259 (2.23)	0.004 (0.03)	-0.259 (2.74)	0.004 (0.12)
Residuals Train	BRES_TRAIN	Train	-	-	-0.062 (0.84)	0.739 (8.99)	-0.062 (0.72)	0.739 (6.87)	0.077 (1.23)	0.060 (0.43)	0.077 (1.09)	0.060 (0.75)
Residuals Car	BRES_CAR	Car	-	-	0.078 (0.52)	1.980 (7.49)	0.078 (0.27)	1.980 (4.68)	-0.084 (0.56)	-0.112 (0.37)	-0.084 (0.63)	-0.112 (0.96)
Error Components Bus	EC_BUS	Bus	-	-	-	-	-	-	-	1.270 (4.66)	-	1.270 (6.79)
Error Components Train	EC_TRAIN	Train	-	-	-	-	-	-	-	0.314 (0.91)	-	0.314 (2.21)
Error Components Metro	EC_METRO	Car	-	-	-	-	-	-	-	1.860 (17.50)	-	1.860 (15.80)
Error Components Car	EC_CAR	Car	-	-	-	-	-	-	-	2.550 (9.74)	-	2.550 (11.50)
Number of Parameters Estimated			14.00		20.00				24.00			
Log Likelihood at convergence			-5584.13		-5478.19				-5213.31			
Log likelihood at zero							-13125.44					
AIC/n			1.183		1.161				1.106			

Table 8: Metro Rail data Value of Travel Time ($/person hour)
Note: CI confidence intervals

	M1			M2					M3				
	Mean	CI		Mean	CI		CI bootstrapping		Mean	CI		CI bootstrapping	
PT Value of travel time ($/person hr)	9.59	7.62	12.40	9.11	7.14	11.8	6.98	12.40	9.50	7.40	12.40	7.48	12.10
Car Value of travel time ($/person hr)	13.60	6.17	24.20	8.63	0.14	18.7	-0.50	21.20	13.70	6.35	21.40	7.61	22.60

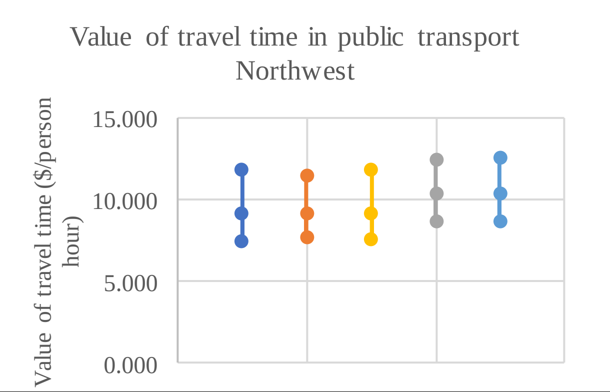
Table 9: Metro Rail data Choice Probability Direct Elasticity Estimates

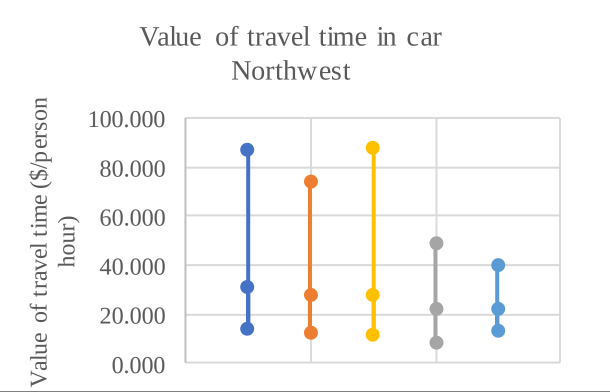
	M1	**Confidence Intervals**		**M2**	**Confidence Intervals**		**M3**	**Confidence Intervals**	
Bus average travel cost	-0.707	-1.080	-0.464	-0.534	-0.917	-0.301	-0.766	-1.190	-0.486
Train average travel cost	-0.418	-1.080	-0.270	-0.348	-0.917	-0.201	-0.459	-1.190	-0.285
Metro average travel cost	-0.921	-1.160	-0.717	-0.872	-1.130	-0.639	-0.949	-1.170	-0.747
Car average travel cost	-0.730	-1.160	-0.571	-0.728	-1.130	-0.562	-0.768	-1.170	-0.605
Bus average travel time	-0.333	-0.440	-0.250	-0.279	-0.387	-0.193	-0.275	-0.371	-0.194
Train average travel time	-0.470	-0.440	-0.345	-0.413	-0.387	-0.295	-0.387	-0.371	-0.270
Metro average travel time	-0.256	-0.583	-0.093	-0.161	-0.476	0.008	-0.569	-0.992	-0.258
Car average travel time	-0.438	-0.583	-0.253	-0.417	-0.476	-0.245	-0.938	-0.992	-0.643

*The bootstrapping confidence intervals, which are statistically equivalent to the ones in this table, are presented in Table 11 in the Appendix.

Comparison of Finding across the Three Data Sets

Figure 3 presents the value of travel time for public transport and car travel for the two datasets. There is an overlap across the three models, suggesting that the values estimated are statistically equivalent in all the models for each dataset. However, there are some differences with regards to their confidence intervals.





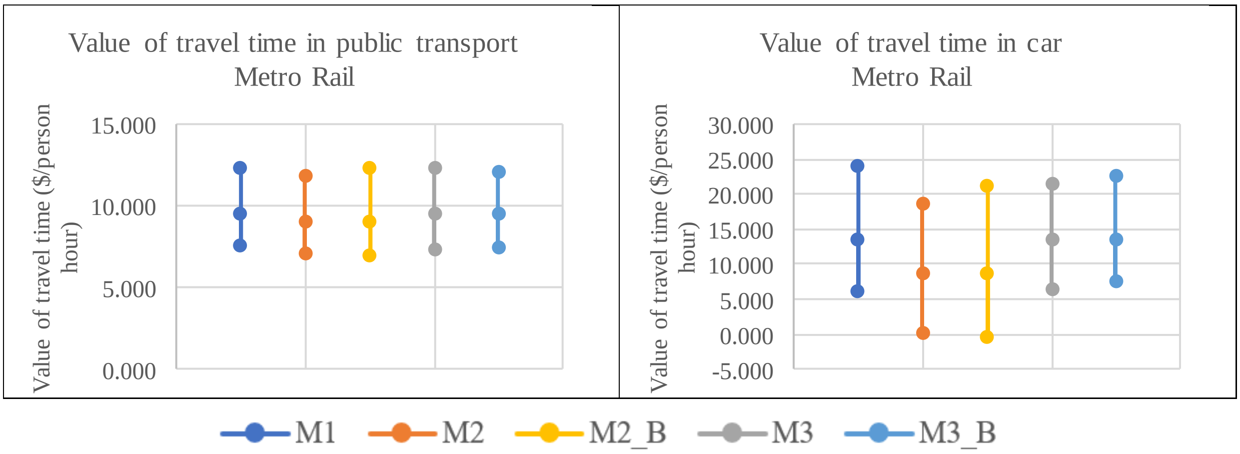


Figure 3: Value of travel time in public transport and car for M1, M2 and M3 in each dataset

Figures 4 to 6 present the elasticities for fare and travel time for the data sets. All the elasticities are statistically equivalent except for the car travel time in the Metro Rail data set 2 (Figure 6) where M1 and M2 are equivalent, but statistically different to M3 – although they are statistically equivalent when comparing the bootstrapping results.

Figure 4 presents the elasticities for cost and travel time in the Northwest dataset. M3 has the lowest elasticities (or largest in absolute terms) in the public transport attributes, but it has higher elasticities in the car attributes relative to M1. When comparing M1 to M2, it seems that most of the fare elasticities are lower in M1 (except for car and train), and most of the travel time elasticities are lower in M2 (except for car and train).

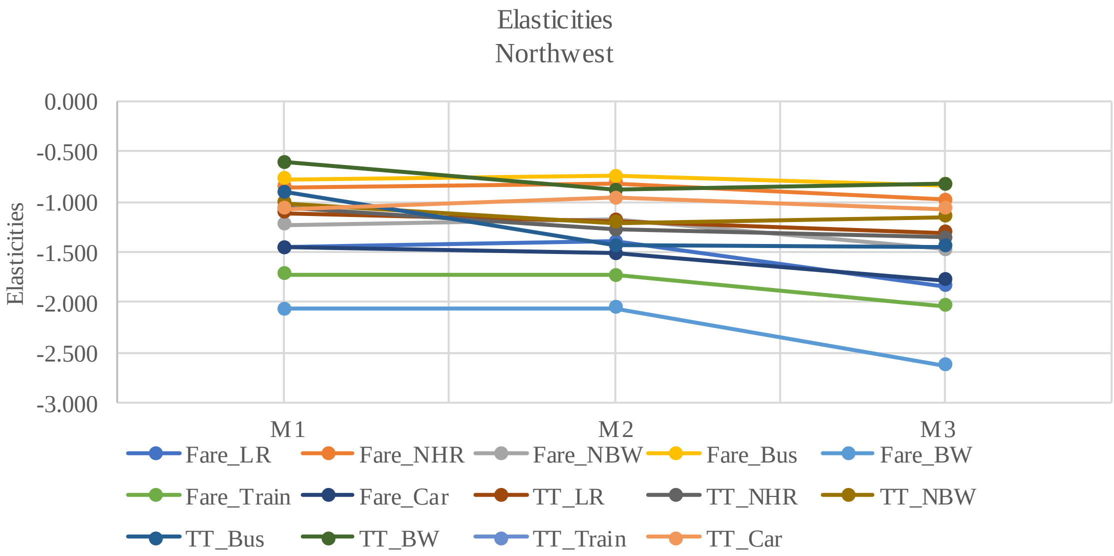


Figure 4: Elasticities for M1, M2 and M3 in the Northwest dataset

Figure 5 presents the elasticities for cost and travel time in the Metro Rail dataset. For all the attributes across all four modes, there is an increase in the elasticity (or decrease in absolute terms) of M2 relative to M1. M3 always estimates lower elasticities (or higher in absolute terms) than M1 and M2, except for the bus and train travel times. Overall, we cannot conclude from both of the tested data sets that there is some directional consistency in the behavioural responses as we move from an exogenous to an endogenous treatment of experience.

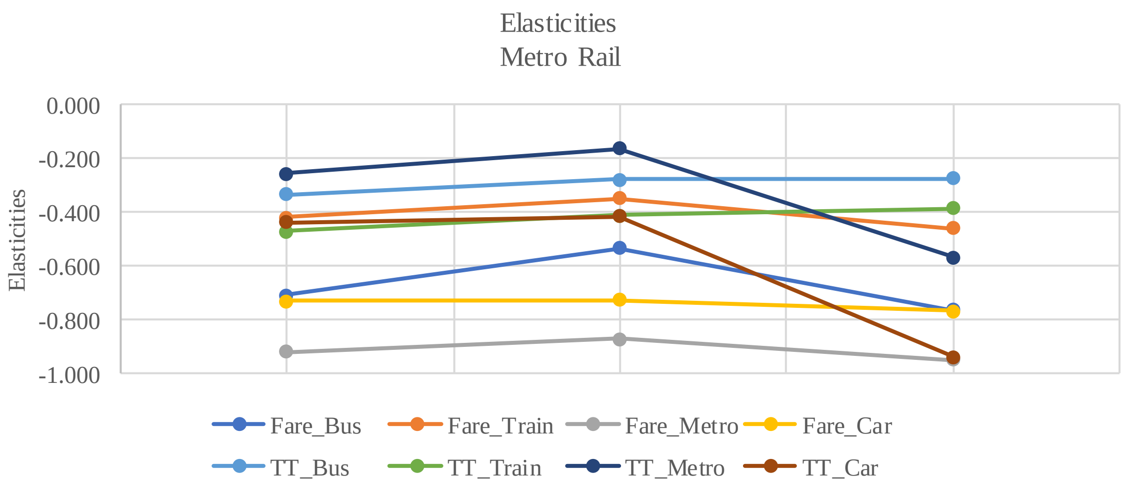


Figure 5: Elasticities for M1, M2 and M3 in the Metro Rail dataset

Conclusions

Endogeneity is assumed to exist if there are some unobserved effects that are not accounted for that occur in the random errors that are correlated with an endogenous explanatory variable. By deriving a proxy variable that conditions on the part of the endogenous explanatory variable that depends on the random errors, then the remaining or residual part of the random errors becomes independent of random error. In this paper we investigated the extent to which treating overt experience, in three data sets, as a strictly exogenous effect, is a behavioural concern.

While we have proposed, and implemented, a way to identify and if necessary purge the model of endogeneity bias, the empirical evidence suggests (for two data sets only) that differences in key behavioural outputs are inconsequential when allowing for the confidence limits of such outputs. However, practitioners tend to use only the mean estimates in applications, and as such the behavioural outcomes can be quite different, although there is no consistency in the direction (i.e., higher or lower) of the difference in mean magnitudes.

Further research should investigate the findings in this paper with other data sets; but in the meantime we suggest that a test of endogeneity bias should be undertaken where this is a potential concern. Fortunately, the test presented in this paper is easy to implement and hence should become common place.

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Appendix

Table 10: Northwest data Choice Probability Direct Elasticity Estimates for the bootstrapping models

	M2	Confidence Intervals		M3	Confidence Intervals	
New light rail average travel cost	-1.400	-1.720	-1.140	-1.840	-2.260	-1.490
New heavy rail average travel cost	-0.817	-1.720	-0.599	-0.987	-2.260	-0.765
New busway average travel cost	-1.180	-1.470	-0.964	-1.480	-1.850	-1.170
Bus average travel cost	-0.744	-1.470	-0.542	-0.839	-1.850	-0.634
Busway average travel cost	-2.060	-2.410	-1.740	-2.630	-3.080	-2.240
Train average travel cost	-1.730	-2.410	-1.280	-2.040	-3.080	-1.620
Car average travel cost	-1.520	-2.150	-1.040	-1.780	-2.460	-1.230
New light rail average travel time	-1.190	-2.150	-0.798	-1.310	-2.460	-0.856
New heavy rail average travel time	-1.280	-1.600	-1.020	-1.360	-1.770	-1.030
New busway average travel time	-1.210	-1.600	-0.876	-1.150	-1.770	-0.848
Bus average travel time	-1.440	-1.850	-1.080	-1.450	-1.820	-1.140
Busway average travel time	-0.888	-1.850	-0.623	-0.826	-1.820	-0.612
Train average travel time	-1.420	-2.370	-0.630	-1.670	-2.930	-0.673
Car average travel time	-0.961	-2.370	-0.301	-1.070	-2.930	-0.418

Table 151: Metro Rail data Choice Probability Direct Elasticity Estimates for the bootstrapping models

	M2	Confidence Intervals		M3	Confidence Intervals	
Bus average travel cost	-0.534	-0.895	-0.303	-0.766	-1.160	-0.503
Train average travel cost	-0.348	-0.895	-0.197	-0.459	-1.160	-0.300
Metro average travel cost	-0.872	-1.110	-0.647	-0.949	-1.170	-0.745
Car average travel cost	-0.728	-1.110	-0.552	-0.768	-1.170	-0.599
Bus average travel time	-0.279	-0.420	-0.184	-0.275	-0.373	-0.194
Train average travel time	-0.413	-0.420	-0.269	-0.387	-0.373	-0.270
Metro average travel time	-0.161	-0.760	0.006	-0.569	-1.020	-0.276
Car average travel time	-0.417	-0.760	-0.180	-0.938	-1.020	-0.581