Understanding the Education Choices of Public Sector Employees: The Relative Importance of Time and Money

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Abstract
Australian workers are constantly reminded of the desirability of upgrading their skills in a rapidly changing work landscape. However, comparatively little is known about the relative importance of the factors impacting on the employees’ decisions to undertake further education. This paper presents the results of an experimental choice analysis of workers’ decisions to undertake formal courses of study. This novel approach affords the opportunity to consider factors beyond the economic domain. Results include the development of a model of employee preferences and estimates of willingness to pay for study programs.

1. Introduction
Substantial recent attention has focussed on the imperative of lifelong learning in the context of a rapidly changing and more competitive work environment. In addition, large scale and widespread economic change in Australia has been associated with increased rhetoric about the importance of education and training, as vehicles to cope with the constant state of flux that typifies the contemporary work environment (Burke, 2000; McKenzie, 1999). Particular emphasis in policy making has been placed on the role of education and training in developing a flexible workforce which is capable of adapting quickly to changing market conditions and thus, capitalising on opportunity as it presents itself (Dawkins, 1988). To this end many organisations emphasise the continued development of their employees’ ‘human capital’ through further education and training. Moreover, in the context of increased importance of ‘user pays’ principles, significant research efforts have been devoted to examining employees’ participation in further education and training.

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*The authors wish to acknowledge the comprehensive and insightful comments made by two anonymous referees, although any errors or omissions remain the responsibility of the authors.
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However, it is apparent that the extant literature and empirical evidence is retrospective in nature; concentrating primarily on who gets the education and training (Kilpatrick and Allen, 2001; Lilliard and Tan, 1992; Long, Ryan, Burke, and Hopkins, 2000). Attention has thus focussed on the demographic factors associated with the distribution of education and training (see, for instance, Kilpatrick and Allen, 2001) despite Pryor’s (1990) contention that an understanding of these variables and their contribution to the decision process is of little use to policy makers and organisations, since these variables are not malleable. Moreover, Long et al.’s (2000) analysis of the distribution of education and training amongst workers highlighted the fact that ‘within person’ factors are nowhere accounted for in the economic literature. On the other hand, the psychology literature abounds with such empirical work (see, for instance, Fishbein and Stassen, 1990; Maurer, 2001; Noe and Wilk, 1993; Tharenou, 2001).

This study employs a technique that can accommodate both economic and psychographic factors. Experimental choice analysis is used to investigate the relative importance of factors considered by individual employees in the context of education and training and this is combined with empirical measurement of the importance of individual attitudes. The paper presents a model of employee preferences for formal courses of study, and subsequently ascertains estimates of their willingness to pay. The paper itself comprises six main parts and is organised as follows. Section two presents a detailed explanation of the theoretical underpinnings of the methodology including considerations of model estimation. Section three outlines the design of the choice sets and is followed in section four by survey results and willingness to pay estimates. A brief discussion of the limitations of the work and management and policy implications follows in section five. The paper concludes with some brief remarks and directions for future research.

2. Choice Modelling Approach

One way to examine the preferences of employees in the context of education involves conceptualising the course of study as a ‘product’ and offering individuals choice sets where the product attributes vary. This technique is termed choice modelling and can be traced back to the seminal work of Louviere and Hensher (1982) and Louviere and Woodworth (1983). Carroll and Green (1995) maintain that choice modelling itself simply represents an extension of conjoint analysis, which stems largely from the theoretical contributions of Luce and Tuckey (1964), Kruskal (1965), Carroll (1973), Roskam (1968) and Young (1972). However, this relationship is contested within the literature, with Louviere (2000) and Wassenaar, Chen, Cheng and Sudijanto (2003) highlighting the distinctive nature of discrete choice modelling.

The behavioural basis of choice modelling is random utility theory developed by Thurstone (1927) and extended by McFadden (1974). Random utility theory assumes that the probability of an individual choosing a particular good from an array of goods is dependant on the utility of the good relative to the utilities of other alternative goods. It further suggests
that consumers seek to maximise utility when they make choices. According to random utility theory, the utility of a good is made up of an observable component that is a function of a vector of attributes and individual characteristics along with an unobservable error component. Thus, random utility theory based choice models allow inferences to be made about preferences for choice attributes, based on stated preferences. Since random utility theory concedes that there is an unobservable component to utility, assumptions must be made about this random component. Most commonly, an independently and identically distributed error term is assumed, implying that a multinomial logit model can be employed to analyse the observable component of utility. Following Morrison (1996, pp. 9-10), a typical multinomial logit model with probability of choosing a given option, $P_i$, is given by:

$$P_i = \frac{\exp (\lambda V_i)}{\sum \exp (\lambda V_j)}$$  \[1\]

where $V$ represents the observable and systematic component of utility for a particular alternative, and $j$ takes values from one to $n$. The scale parameter, $\lambda$, is inversely related to the variance and is arbitrarily equated to unity in most cases.

Blamey et al. (1999, p. 341) note that the resulting linear-in-parameters utility function for the $j$th alternative can be specified by:

$$V_j = \text{ASC}_j + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k + \gamma_1 S_1 + \ldots + \gamma_p S_p$$  \[2\]

where $\beta_1$ to $\beta_k$ is the vector of coefficients attached to the vector of attributes $(x)$ describing the study product. In equation [2] socioeconomic variables of individual $S$ are included by interaction with the alternative-specific constant [ASC]. The ASC, [i.e. the ASC for the $j$th alternative] is usually derived by estimating a set of $j-1$ constants as per conditional logit models. Here constants take on a value for alternative $j$ but are otherwise assigned a value of zero. Accordingly, the ASC captures the mean effect of unobservable factors in the error term and results in a 0.5772 mean for unobserved utility (Ben-Akiva and Lerman, 1985). Moreover, the average probability of each alternative is equated to the proportion of respondents choosing an alternative after accounting for parameter estimates, other than the ASC (Hensher, et al. 2005).

The complexity of the ‘product’ that is education and training and of the individual decision making context, suggests that the choice modelling technique offers significant advantages in analysing ‘consumers’ choices in this context. Choice modelling draws upon the homo economicus assumption, but allows for a number of other interaction terms to be specified. It also recognises the restricted nature of the individual’s decision process and, despite its experimental nature, more closely approximates a ‘real life’ choice situation than alternative techniques like traditional or adaptive conjoint analysis. Furthermore, the iterative experimental design process that cumulatively draws on instances of qualitative data collection can accommodate the gathering of information specific to the organisational
context. Thus, in-depth interviews and focus groups are commonly employed to inform development of meaningful product attributes and levels. In sum, this approach employs an expanded notion of human agency that largely preserves the rational choice paradigm, but offers the option of adding psychological and social considerations.

Model Estimation Considerations

Earlier, we observed that choice experiments are founded on random utility theory where utility comprises both observable and unobservable components (McFadden, 1974). By adopting a Gumbell extreme value error term the choice probabilities correspond to the convenient closed-form multinomial logit model (Rolfe and Bennett, 2000, p. 5). However, one of the consequences of this assumption is the independence from irrelevant alternative property, which requires that the ratio of choice probabilities for any two alternatives is independent from the observable utility of other alternatives. Violations of the irrelevant alternative property assumption can be detected using a test developed by Hausman and McFadden (1984). Alternatives are omitted from the choice sets to test for significant changes in parameter estimates.

In reality, violations of this property are common and occur for many reasons, not the least of which is the existence of heterogeneous preferences. Louviere et al. (2000, p.138) observe that although the majority of studies do not progress beyond the MNL model, non-trivial research efforts have centred upon the relaxation of this restrictive assumption in a manner that is ‘...behaviourally enriching, computationally tractable and practical.’ In practice, violations might arise where respondents have not made consistent choices because they found it difficult to frame their choices (Rolfe and Bennett, 2000).1 Whilst Blamey et al. (1998) offer options for dealing with the problem of independence of alternative violations, the assumption itself makes it difficult to statistically predict between close alternatives (Hair, et al., 1998). Accordingly, a number of more advanced models, such as the nested logit or mixed logit, which relax this IIA assumption have recently gathered popularity in the literature (see, Hensher, et al., 2005, for examples).

Models such as the nested logit model may also be employed in an effort to avoid serial correlation which may be associated with the multinomial logit models. Multinomial logit models assume that each choice observation used in estimating the model is treated as independent. Clearly, this is a questionable approach in an experiment where an individual participant contributes a number of choice observations to the total. However, as shown by Hensher and Greene (2003, p. 160), in the case of instantaneous stated choices, such as this one, the choices are elicited without the influence of an extended period of accumulated experience that is often attributed to state dependence.

An additional technical matter relates to the overall goodness of fit of any estimated choice model. One approach to dealing with this is illustrated by

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1 Rolfe and Bennett (2000) also observe that there are a number of other reasons why violations might occur.
Lockwood and Carberry (1998) and Morrison and Bennett (2000) and involves using the unrestricted log likelihood \([Lu]\) and restricted log likelihood \([Lr]\) of the model to generate a goodness of fit statistic. The significance of parameters is assessed using a statistic \(\chi^2\) calculated using equation 3, below:

\[
\chi^2 = -2 \left[ L_r - L_u \right]
\]  

[3]

An overall goodness of fit indicator widely employed in studies of this type (see, for example Mazzanti, 2003; Whitten & Bennett, 2001; Morrison, Bennett & Blamey, 1998), despite some contention about its usefulness (Hensher et al. 2005, p. 337), is \(\rho^2\), is described by equation 4, below:

\[
\rho^2 = 1 - \left[ \frac{L_r}{L_u} \right]
\]  

[4]

Here, a good fit is described by \(\rho^2 > 0.2\) and values approaching 0.4 are considered a very good fit (Hensher and Johnson, 1981). Lockwood and Carberry (1998, p. 6) observe that comparisons between models requires a superior goodness of fit measure which accounts for the number of degrees of freedom. One option offered by Hensher and Johnson (1981) is to employ an adjusted \(\rho^2\) presented in equation 5, below:

\[
\rho^2 = 1 - \left[ \frac{L_r}{N(C-1-K)} \right] / \left[ \frac{L_u}{N(C-1)} \right]
\]  

[5]

where, \(N\) describes the number of choices, \(C\) is the number of choice options\(^2\), and \(K\) depicts the number of variables in the model.

### 3. Designing Choice Sets

The initial task of the researcher in designing choice sets is to identify those attributes that are simultaneously significant to the research question, important in the decision of most respondents, and controllable within the context of the experiment. In the present context this was accomplished by an iterative process involving focus sessions, interviews and survey pre-testing (see, for instance, Lockwood and Carberry, 1998).\(^3\) This process generated three main attributes of interest: the financial cost of the study program to the employee, the leisure time forgone to complete the study course, and the extent to which the study program led to career advancement. By presenting choice sets that offer different combinations of attribute levels to workers it is possible to ‘unbundle’ the relative importance of each attribute in the choice. When presenting choice sets to respondents, the researcher can use ‘labelled’ or ‘unlabelled’ formats. An unlabelled experiment such as the type employed in this case, focuses the participant’s attention on the attributes themselves. By way of contrast, a labelled experiment invokes ‘brand names’ or ‘policy options’ to further specify the choice context (Blamey, et al., 1998). An example of a choice set for a study ‘product’ used in this instance appears in table 1.

\(^2\) All respondents are assumed to face the same number of choices.

\(^3\) This process involved reducing the upper level of the cost attribute from an initial $20,000 as suggested by one participant, to the level of $8,000 which was agreed as a realistic upper limit.
Table 1  Example of a Choice Set

<table>
<thead>
<tr>
<th>Option</th>
<th>Cost to you (pa)</th>
<th>Leisure Hours Lost Per Week</th>
<th>Career Impact</th>
</tr>
</thead>
<tbody>
<tr>
<td>Option A</td>
<td>0</td>
<td>0</td>
<td>Maintain current position</td>
</tr>
<tr>
<td>Option B</td>
<td>8000</td>
<td>6</td>
<td>Advance in other industry or sector</td>
</tr>
<tr>
<td>Option C</td>
<td>No study</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

In addition to the specification of attributes and levels, the status quo must either be overt to the respondent and researcher or, alternatively, the survey must be designed so that this information can be gleaned from responses (Hair, Anderson, Tatham, and Black, 1998). In the current context, the inclusion of the ‘no study’ option was assumed to entail specific transaction implications. The base case price can therefore legitimately be coded as zero, along with a zero coding for time. Dhar and Simonson (2003) provide a comprehensive discussion of the theoretical and practical implications of the inclusion of the ‘no choice’ option. Clearly, in the current context, if a respondent chooses ‘no study’ s/he pays nothing and forfeits no leisure time. On the other hand, the interpretation of the career impact attribute is more problematic. In the preamble to the choice sets that outlines the hypothetical choice scenarios, it was explained that choosing the ‘no study’ option would enable the individual to maintain his/her current position in the short term, as opposed to option one or two, which gave rise to the employee maintaining this position in the long term, advancing to other positions, or other organisations. The coding of all attributes and other socio-economic data used in the modelling process is summarised in table 2.

Table 2  Coding of Attributes and Other Variables

<table>
<thead>
<tr>
<th>Variable/ constant</th>
<th>Definition</th>
<th>Coding</th>
</tr>
</thead>
<tbody>
<tr>
<td>PRICE</td>
<td>Cost per annum to the individual ($)</td>
<td>0, 2500, 5000, 8000</td>
</tr>
<tr>
<td>TIME</td>
<td>Number of leisure hours per week required to complete the study program.</td>
<td>0, 6, 12, 15</td>
</tr>
<tr>
<td>ADVANCE</td>
<td>The study program leads to career advancement.</td>
<td>Dummy variable with career &gt; 1 taking the value of 1.</td>
</tr>
<tr>
<td>CI</td>
<td>Alternative specific constant.</td>
<td>Constrained to be equal across V1 and V2</td>
</tr>
<tr>
<td>NOW</td>
<td>Employees who were studying at the time of survey.</td>
<td>Dummy variable, taking the value of 1 for ‘yes’</td>
</tr>
<tr>
<td>MANAGE</td>
<td>Employee’s position level, ranging from base level (1) to executive (7).</td>
<td>Dummy variable with levels &gt; 3 taking the value of 1.</td>
</tr>
<tr>
<td>SCIENCE</td>
<td>Employee’s position type classified as scientific.</td>
<td>Dummy variable with science (level 3) taking the value of 1.</td>
</tr>
<tr>
<td>AGE</td>
<td>Respondent’s age at time of survey.</td>
<td></td>
</tr>
<tr>
<td>ENJ</td>
<td>Respondent’s additive score (1-5) on items designed to measure enjoyment of study.</td>
<td>Dummy variable, with scores &gt; 3 taking the value of 1.</td>
</tr>
<tr>
<td>OV</td>
<td>Respondent’s additive score (1-5) on their perception of the degree to which organisational values support participation in study.</td>
<td>Dummy variable, with scores &gt; 3 taking the value of 1.</td>
</tr>
</tbody>
</table>
A main effects fractional factorial design was generated to produce choice sets using SPSS Conjoint. This yielded 16 choice options. A foldover design was then used to generate alternative choice options, which were paired to provide the choice sets.

Foldover designs generally maximise the number of tradeoffs between options but ‘…[t]he high efficiency in terms of maximising tradeoffs comes at the cost of high cognitive burdens on participants- there are no easy choices’ (Lockwood and Carberry, 1998). Each survey included only eight choice sets on the grounds that 16 choices was likely to prove excessively burdensome for respondents. Whilst orthogonal designs such as these currently predominate the literature, there appears to be a fundamental shift away from this approach, towards the employment of more efficient designs (see, for example, Bunch, et al., 1994; Burgess and Street, 2005; Huber and Zwerina, 1996; Kanninen, 2002; Kuhfeld, et al., 1994; Lazari and Anderson, 1994; Sandor and Wedel, 2002). This reflects the fact that whilst orthogonal designs represent a statistical and theoretical ideal, ensuring orthogonality over an entire data set is problematic, since a design can only be considered orthogonal if the entire fractional or full factorial are used (Hensher, et al., 2005, p. 126). In this context, Hensher, et al., (2005, p. 126) provide some insight into the extent of the problem: ‘One wonders how many carefully crafted orthogonal designs have in reality maintained their statistical properties after data are collected and used in model estimation’.

In addition to the demographic variables and the attributes themselves, the survey instrument gathered data on the respondents’ psychographics in this context in an attempt to capture preference heterogeneity as described by Boxall and Adamowicz (2002). Such an approach is not novel and has previously been employed by Ashok, et al. (2002), Ben-Akiva, et al. (1999) and Morikawa, et al. (2002). Specific psychographic items for inclusion in the survey were developed from interrogation of data gathered from semi structured interviews, focus groups and a review of the psychological literature. Following Hayes and Darkenwald (1990), respondents were asked to rate the strength of their agreement with a range of attitudinal items. A five point Likert scale was employed with a value of one representing strongly disagree, and a value of five depicting strong agreement.

The survey contained 22 items of this type, and a principal component analysis was employed to reduce this number to a manageable set of constructs for inclusion in the choice modelling process. The challenge was to include for analysis only those items that were meaningful and represented core psychological constructs. The principal component analysis allowed for items to be subsequently removed if they loaded without interpretable meaning.

4 The extent of cognitive burden often associated with stated choice experiments is, however, somewhat contentious in the literature. Recent empirical work by Hensher (2004), for example maintains that it is not the number of choices and attributes per se that make an experiment burdensome, but rather the selection of inappropriate attributes, levels and alternatives that complicates the respondent’s decision task. Brazell and Louviere (1998) subjected respondents to up to 96 choice situations without any appreciative ‘cognitive burden’ being detected.
Exploratory principal component analysis (using SPSS version 11) was undertaken to statistically determine the subscale structure of attitudes to study. Notwithstanding the statistical concern for ensuring orthogonality in econometric models such as these, the principal component analysis of the attitude variable employed a non-orthogonal approach (oblique rotation) as relationships between factors was assumed (Tabachnick and Fidell, 1983). This method is common in studies that utilise similar psychological variables (see for example, Hart, Wearing and Headey, 1993). To ensure more stable principal component structures a criterion of five subjects per item is optimal – a ratio of 6.45:1 easily met this criteria. Three ‘rules of thumb’ criteria were used to derive factors, eigenvalues of one (Rummel, 1970; Stevens, 1986), scree tests and ‘...smaller factors are retained only if they have sufficient substantive meaning to be interpretable’ (Rummel, 1970, p. 362). Applying these criteria resulted in a number of items being discarded from the analysis; only those factors with greatest explanatory power were retained.

The principal component analysis process described above subsequently revealed four pertinent factors in the study data set: ENJOYMENT, PERCEIVED ORGANISATIONAL VALUES, IMPORTANCE, and PERCEIVED BEHAVIOURAL CONTROL. However, the subsequent model estimation process confirmed the significance of only the first two of these variables. These were dummy coded in this choice application as per table 2.

The questionnaire was distributed on-line as this mode of delivery offered several advantages over mail based surveys in this context, notwithstanding the differences in response rates and speed of response reported in the literature (see, for instance, Cobanoglu, Warde & Moreo, 2001; Dillman, 2000). This delivery mode enabled the utilisation of extensive and difficult ‘skip patterns’ without confusing the participant. The use of drop down menus served to reduce respondent error, and, use was made of ‘pop-up boxes’ to instruct participants and refresh their memory about the particular scenario under consideration. The survey was pre-tested in both paper-based and on-line formats and some minor changes were made, mainly in an attempt to reduce its length.

4. Results
Data collection occurred in December 2004. The population was employees of a Victorian State Government Department, comprising 1702 employees in various locations around the state. All employees in the population were emailed on the organisation’s intranet. The email included pertinent information about the study, and a link to the questionnaire web-site. There were two versions of the questionnaire, each with eight choice sets.5 The overall response rate was 21.38 percent with details summarised in table 3.

5 An additional experiment examining a training product was conducted simultaneously although only data pertaining to the formal ‘study’ product is reported here.
Table 3  Survey Response Rates

<table>
<thead>
<tr>
<th></th>
<th>Formal Study Product</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total distributed</td>
<td>851</td>
</tr>
<tr>
<td>Returned</td>
<td>182</td>
</tr>
<tr>
<td>Incomplete/excluded</td>
<td>40</td>
</tr>
<tr>
<td>Usable responses</td>
<td>142</td>
</tr>
<tr>
<td>% usable responses</td>
<td>78%</td>
</tr>
<tr>
<td>Number of choices</td>
<td>3817</td>
</tr>
</tbody>
</table>

The socio-economic and demographic data gathered as part of the experiment can be used to assess the representativeness of the sample. The sample was not representative of the organisation’s employee population at the five percent level. Some response bias was not unexpected, given the nature of the topic since, a priori, we expected that those with higher levels of education would exhibit increased propensity to complete the survey.

**Choice Models**

In the first instance, a basic multinomial logit model was computed using a specialised computer program, LIMDEP, designed to analyse models employing limited dependent variables. The indirect utility functions specified for the basic model were as follows:

\[
V_1 = C_1 + \beta_1 \text{Price} + \beta_2 \text{Time} + \beta_3 \text{Advance}
\]

\[
V_2 = C_1 + \beta_1 \text{Price} + \beta_2 \text{Time} + \beta_3 \text{Advance}
\]

\[
V_3 = 0
\]

The resulting linear model is referred to as Study Model One. In the interests of comprehensiveness, additional functional forms for each of the attributes PRICE, TIME and ADVANCE were trialled in an effort to improve the predictive capabilities of the model. These functional forms were limited to quadratic transformations due to the inclusion of zero values for each of the attributes which precluded the consideration of logarithmic and inverse functions.

The theoretical validity of the Study Models is adjudged on two grounds. Firstly, the overall significance of the models [in this case chi-square] is supportive of the view that the model is statistically significant. Secondly, the extent to which independent variables are significant and meet a priori expectations can also be used to indicate significance (Morrison and Bennett, 2000). In the context of the aforementioned models, all formulations fulfil these criteria.

Violations of the IIA property should be tested in this type of analysis. The previously described Hausman and McFadden (1984) test conducts comparisons between a full multinomial model and a model with an alternative removed. The Hausman and McFadden (1984) test can only be used under certain circumstances- usually if parameter estimates are all generic (Hensher, et al., 2005). If the parameter estimates do not vary significantly across the two models the IIA assumption holds. The Hausman and McFadden test revealed no significant violations of IIA at the five percent level in any of the Study Models, with the exception of Model Five.
Prior research in this area suggests that socio-economic and attitudinal factors play an important part in choices of this type. Accordingly, a number of additional models were trialled. These models included a variety of socio-economic, psychographic and demographic variables. Since these type of variables do not differ across the choice sets they cannot be used to predict the option chosen (Blamey 1999) and are included in either of two ways. Firstly, they can be included through interactions with the ASC\textsuperscript{6}. Secondly, they can be interacted with attributes in the choice sets. Details of each model are provided in table 4.

Table 4 Study Interaction Models (Significant variables only)

<table>
<thead>
<tr>
<th>Study Model 1: Linear</th>
<th>Study Model 2: Price Interactions:</th>
<th>Study Model 3: Time Attribute: Interactions</th>
<th>Study Model 4: Advance attribute: Interactions:</th>
<th>Study Model 5: Linear with ASC\textsuperscript{6} Factor &amp; demographic</th>
</tr>
</thead>
<tbody>
<tr>
<td>CI</td>
<td>0.5923*** (5.123)</td>
<td>1.0601*** (6.985)</td>
<td>0.59605*** (5.150)</td>
<td>0.65032*** (5.551)</td>
</tr>
<tr>
<td>PRICE</td>
<td>-0.00028*** (-15.666)</td>
<td>-0.00035*** (-4.856)</td>
<td>-0.00022*** (-15.688)</td>
<td>-0.0002923*** (-15.681)</td>
</tr>
<tr>
<td>TIME</td>
<td>-0.07345*** (-8.650)</td>
<td>-0.13886*** (-8.580)</td>
<td>-0.02626 (-9.56)</td>
<td>-0.07663*** (-8.822)</td>
</tr>
<tr>
<td>ADVANCE</td>
<td>1.0945*** (9.876)</td>
<td>1.2176*** (10.570)</td>
<td>1.1002*** (9.906)</td>
<td>2.2364*** (6.632)</td>
</tr>
<tr>
<td>AGE*ASC</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MANAGE*ASC</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ENJ*ASC</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>OV*ASC</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PRICE*MANAGE</td>
<td>0.000116** (3.142)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PRICE*SCIENCE</td>
<td>-0.00017*** (-5.580)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>PRICE*TIME</td>
<td>0.00002*** (4.754)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TIME*AGE</td>
<td></td>
<td></td>
<td>-0.00171** (-2.171)</td>
<td></td>
</tr>
<tr>
<td>TIME*MANAGE</td>
<td></td>
<td>0.03957** (2.428)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ADVANCE*MANAGE</td>
<td></td>
<td></td>
<td>1.1593*** (6.428)</td>
<td></td>
</tr>
<tr>
<td>ADVANCE*SCIENCE</td>
<td></td>
<td></td>
<td>-0.37967** (-2.633)</td>
<td></td>
</tr>
<tr>
<td>ADVANCE*AGE</td>
<td></td>
<td></td>
<td>-0.04178** (-4.802)</td>
<td></td>
</tr>
<tr>
<td>ADVANCE*NOW</td>
<td></td>
<td></td>
<td>0.87860*** (4.690)</td>
<td></td>
</tr>
<tr>
<td>Rho 2 ($\rho^2$)</td>
<td>0.19698</td>
<td>0.22253</td>
<td>0.20106</td>
<td>0.22720</td>
</tr>
<tr>
<td>Adjusted Rho 2 ($\lambda$)</td>
<td>0.19529</td>
<td>0.21982</td>
<td>0.18997</td>
<td>0.22451</td>
</tr>
<tr>
<td>Observations</td>
<td>1152</td>
<td>1152</td>
<td>1152</td>
<td>1152</td>
</tr>
<tr>
<td>Chi-Square</td>
<td>2278.134</td>
<td>2247.5681</td>
<td>2222.1242</td>
<td>2241.6534</td>
</tr>
</tbody>
</table>

In this case, the ASCs were constrained to be equal across V1 and V2, since the experiment employed an unlabelled format. In this instance, the constant simply represents the propensity to enter the market for a study program.
In the basic linear model (Study Model One) all attributes were highly significant and signed as expected. In the interests of completeness, quadratic transformations were trialled, but the increased complexity of these models yielded little in terms of model fit. Instead, the linear model was employed to trial attribute and ASC interactions.

In order to gain a more comprehensive insight into the role of salient factors we constructed interactions with the attributes in the choice modelling. The PRICE attribute was interacted with a range of demographic variables to produce Study Model Two. The significance of the PRICE*MANAGE term at the one percent level and its positive sign suggests that those who are managers are more inclined to select a high cost option. The negative sign and significance at the one percent level of the PRICE*SCIENCE variable however, indicates that those who are scientists had a lower propensity to choose more expensive study alternatives ceteris paribus. This may reflect the fact that these employees are already well qualified in this organisation and are therefore more price-sensitive to qualifications that add to their existing high educational standing.

Study Model Three was developed to include TIME interactions and showed that there was a reduced tendency to choose more time consuming options amongst respondents who were older. On the other hand, managers were more inclined to choose an option requiring greater time commitment.

Study Model Four which included ADVANCE interactions, supported the findings of previous research in this field (see, for instance, Long, et al. 2000). More specifically, those currently studying whilst in the workforce, and those at higher levels within the organisation are most inclined to choose an option leading to career advancement, whilst older respondents and scientists are less likely to do so.

Earlier in this paper, we described the development of four variables that were refined by principal component analysis to capture relevant psychographic dimensions of the choice faced by employees. These comprised measures of the enjoyment of formal education [ENJOYMENT]; the respondent’s ranking of the importance of study, the extent of their perceived behavioural control over the choice, and the respondent’s perceptions of organisational values in the context of education [ORGANISATIONAL VALUES]. As with socio-economic variables, these data can only be brought into the models as interaction terms. This was accomplished by interacting the attitudinal variables with the ASC and retaining only those of statistical significance (at five percent level or better) in the mode, in this case the ENJOYMENT and ORGANISATIONAL VALUES variables.

Model Five was based on the linear equation and allowed for interactions between the ASC and socio-economic and psychographic variables. Once again the chi-square test was generally supportive that the model is statistically significant. The model explained more than twenty percent of the variation in the data. Again, the AGE*ASC variable was negative and significant at the one percent level, with older employees less likely to choose any of the study options. Respondents who were managers (MANAGE*ASC) were more inclined to choose a study option (significant at the one percent level). In this instance, the (MANAGE*ASC) attribute
might feasibly be conceptualised as a proxy for income, since in this public sector organisation remuneration bands are strongly enforced.

Study Model Five, whilst conceptually more complex, modestly improved the fit of the model. The sign of all attributes meets a priori expectations and coefficients are significant at the one percent level or better. ENJOYMENT and ORGANISATIONAL VALUES variables were positively signed, indicating that workers who scored highly on these psychological factors were more likely to choose a study option. That is, workers who enjoyed studying along with those who perceived that the organisation supported and encouraged further study were more positively predisposed to choose a study option from the choice sets.

**Welfare Estimates**

Since Study Model Five exhibited a superior fit of the data, it forms the logical basis for further calculations. This model has the added advantage of including a number of significant ‘within person’ variables in the analysis and therefore extends our understanding of the individual’s decision making process. The choice modelling process allows for the calculation of the specific trade-offs between product attributes made by individuals.\(^7\)

Put differently, the models allow the calculation of the relative importance of attributes in the choice to participate in a study program. Implicit prices embody these trade-offs. They are derived by examining the marginal rate of substitution between the cost to the individual (PRICE) attribute, and the other attribute under consideration. This involves calculating the implicit price of leisure time forgone (TIME). All non-price attributes can feasibly be treated in this way, although in the current context the dummy coding of the ADVANCE variable renders any meaningful interpretation of such estimates for this attribute problematic. It is therefore omitted from these calculations. In the case of the linear function the implicit price of leisure time simply reduces to:

\[
\text{Implicit Price}_{(\text{LINEAR})} = \frac{\beta_{\text{TIME}}}{\beta_{\text{PRICE}}}
\]  

Here, \(\beta\) is the coefficient attached to the product attribute. Confidence intervals for implicit price estimates can be calculated using a technique attributed to Krinsky and Robb\(^8\) (1986). Results for the implicit price of a one hour per week increment in the TIME attribute and related confidence intervals are reported in table 5.

<table>
<thead>
<tr>
<th>Table 5</th>
<th>Estimated Marginal Rates of Substitution for TIME Attribute</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(Based on Study Model 5)</td>
</tr>
<tr>
<td>TIME (Study Model 5)</td>
<td>Mean</td>
</tr>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>TIME (Study Model 5)</td>
<td>-$255.55</td>
</tr>
</tbody>
</table>

\(^7\) Some care should be taken in interpreting these figures. For example, Hensher, et al. (2005) argue that multi-nomial logit models commonly tend to over-estimate willingness to pay.

\(^8\) This procedure employs a large number of random draws from a multivariate normal distribution relating to the estimated parameters. In the current context 5000 random draws were simulated using SPSS.
The negative sign of the implicit price of leisure time implies that in order to give up one additional hour of leisure to undertake a course of study, employees would need to be offered, on average, $255.55 in compensation ceteris paribus. Whilst this estimate may at first glance appear inordinately high when compared to Value of Travel Time Savings, closer scrutiny reveals several plausible explanations. Firstly, the two situations are not strictly analogous since time spent studying implies the application of non-trivial cognitive effort and an element of risk of unsuccessful completion attended by associated psychological costs. Secondly, time spent studying a work-related course involves redistribution of leisure time of which there is a limited supply. Thirdly, the status quo in this organisation provides employees with time off to study, so that they have not previously been expected to forgo their own leisure time to undertake study. Their point of reference is therefore skewed.

It is also possible to calculate the mean willingness to pay (WTP) for a number of specific scenarios in this manner. This can be useful because it allows the researcher to consider specific product designs, or policy options. Welfare change in the form of compensating surplus can be estimated directly from the choice modelling data. Hanemann (1984) offers the following technique:

\[
W = \left[ \ln \sum_{j \in C} e^{\epsilon_{j0}} - \ln \sum_{j \in C} e^{\epsilon_{j1}} \right] / \mu^1
\]

where \( \mu^1 \) is the marginal utility of income and \( \epsilon_{i0} \) and \( \epsilon_{i1} \) describe utility before and after the change. \( C_i \) is the policy relevant choice set for respondent \( I \).

Blamey, et al. (1999, p. 342) observe that if the choice set contains a single before and after option the estimate of welfare change reduces to:

\[
W = [\epsilon_{i0} - \epsilon_{i1}] / \mu^1
\]

Moreover, the welfare change associated with adjusting a single attribute can be estimated from the ratio of marginal utility for the attribute in question and the price attribute (Hensher and Johnson, 1981). Results relating to alternative product scenarios are summarised in table 6. These WTP estimates include mean values and confidence intervals at the five percent and ninety-five percent levels estimated using a similar technique to that applied to the earlier implicit price estimation.

**Table 6 Willingness to Pay Estimates: (Study Model 5)**

<table>
<thead>
<tr>
<th></th>
<th>0 hours of Leisure</th>
<th>6 hours of Leisure</th>
<th>12 hours of Leisure</th>
<th>15 hours of Leisure</th>
</tr>
</thead>
<tbody>
<tr>
<td>Career advancement</td>
<td>$3821.38</td>
<td>$2280.74</td>
<td>$765.57</td>
<td>-$17.39</td>
</tr>
<tr>
<td></td>
<td>($2988.20 to $4805.49)</td>
<td>($1431.86 to $3193)</td>
<td>($238.52 to $1821.13)</td>
<td>($1148.33 to $1129.58)</td>
</tr>
<tr>
<td>No career advancement</td>
<td>-$1534.33</td>
<td>-$3069.75</td>
<td>-$3820.77</td>
<td>-$3820.77</td>
</tr>
<tr>
<td></td>
<td>(-$1968.42 to $1159.48)</td>
<td>(-$3911.85 to $2319.07)</td>
<td>(-$4876.57 to $2845.44)</td>
<td>(-$4876.57 to $2845.44)</td>
</tr>
</tbody>
</table>

*Confidence intervals in parentheses

\(^9\) Value of Travel time Savings is frequently referred to in the transport economics literature that employs a choice modelling approach. It is specified in these studies as the ration between the time coefficient and the price or cost coefficient (Mabit, 2006, p. 1).
The key findings presented in table 6 relates to the trade-offs made by individual workers as revealed in the choice modelling process. More specifically, these trade-offs are expressed in terms of leisure time forgone and the likely impact on an individual’s career. The calculations assign a monetary value to particular study product scenarios with negative prices indicating the monetary payment to the employee required to offset the disutility associated with other attributes (e.g. forgoing excessive leisure hours to undertake study). In this instance, the scenarios tested are defined by the attribute levels in the choice experiment. For example, the top left hand segment of the table describes a study product that entails no impost on the participant’s leisure and yet offers the opportunity to advance the employee’s career. Keeping in mind that the figures in table 6 are mean estimates, we can nonetheless draw some broad conclusions about likely employee behaviour when faced with certain choices of study program. For instance, workers appear prepared to pay on average $3821.38 for a study product that requires no forfeiting of leisure time but that allows career advancement. Put differently, the deterrent effect of leisure time required is ameliorated by the positive impact of the career attribute. The upshot of this is that individuals are still prepared to make a personal monetary contribution for a course of study and to allocate up to twelve hours of their leisure time, but only if there was an optimal impact on their career. The scenarios for which individuals required compensation are indicated by the negative ‘prices’ for these products.

5. Limitations and Implications
Choice modelling, as an experimental stated preference technique is not without its critics when compared to revealed preference techniques. However, its main advantage in the current context is that it can provide \textit{ex ante} information to inform policy makers and organisations alike. This contrasts with much of the research in this area which, as we noted earlier, tends to be retrospective. A number of biases have also been identified\textsuperscript{10} as inherent in this method although as Mitchell and Carson (1989) and Sinden (1988) point out, much of this bias can be minimised with careful experimental design. A related issue is the influence of framing effects (Rolfe, Loch, and Bennett, 2002).

In addition to the possible shortcomings of the method itself, this research in particular has a number of limitations, not the least of which is the fact that the sample was confined to one government organisation, making generalisability problematic. Moreover, as indicated previously, the sample was not unexpectedly skewed and therefore we cannot claim representativeness.

Despite the limitations outlined above, a number of inferences can be drawn from the results of the choice experiment. In particular, these implications resonate within modern work organisations, compelled as they are to ensure employees have sufficient levels of education. Within the organisation that is the subject of this project, all costs of the formal course of study are currently met by the employer, presuming it is adjudged as relevant to the employee’s current or future tasks. Specifically, it appears from the models

\textsuperscript{10} See Morrison, \textit{et al.}, (1996) for a comprehensive discussion of this matter.
and implicit prices reported in this paper that employees are prepared to contribute financially for a formal course of study, but are most concerned with encroachment on their leisure time. Specifically, employees appear to value their leisure far more than the opportunity cost of an hour of labour. Notwithstanding concern about the magnitude of the willingness to pay estimates mentioned previously, some interesting implications flow from these calculations. The average respondent in this study earned $26.70 per hour, but was only prepared to give up an hour of leisure if paid roughly ten times that amount.

This could be the result of a combination of factors. Firstly, it could be argued that leisure time is decidedly different from work in the eyes of employees, and that it takes on a much greater value. In addition, there are likely to be perceptual factors in operation. That is, the organisation’s allocation of time for study may be seen as indicative of the value that the employer places on the employee themselves and on the skills that will be acquired. The study also collected data on the employees’ perceptions of supervisory and organisational support, and, whilst it is beyond the scope of this paper future results drawn from these data are likely to be illuminating with regard to the role of perceptions.

The obvious implication of these findings is that if organisations want employees to participate in further education, then they must make time available within the working week. Employees were, to varying degrees, quite prepared to contribute financially to their own study programs, but were clearly reluctant to give up leisure time in order to do so.

6. Concluding Remarks and Directions for Future Research

This paper has presented a novel approach to modelling employees’ decisions to participate in formal courses of study in a state government organisation. It reported the development of choice models that allow for the unbundling of the relative importance or part-worth utilities of various product attributes in the employee’s decision process. In addition, it utilised interaction terms to introduce the effects of various demographic, socio-economic and psychographic factors. The results of this stated preference experiment provide broad empirical support for previous revealed preference studies and build upon the qualitative research that formed the basis of this study. More importantly, the models developed include both economic and psychographic variables in some recognition of the complexity of the study ‘product’ and of the decision making context for the worker. This approach assists in gaining understanding of the interplay

11 Barrett and O’Connell (2001) argue employer-provided general education or training may feasibly be perceived as a gift, in a similar manner to the payment of an above market wage that Akerlof examined in his 1982 article. Accordingly, the ‘gift’ of firm-provided general education or training is duly reciprocated by the worker in the form of increased work effort. Similarly, Rousseau’s (1995) psychological contract would conceptualise firm provided general training or education as indicative of the standing of a particular worker in the eyes of their employer. Hence, it would appear realistic to interpret this provision as a signal that the worker will remain with the employer.

12 There may be myriad unobserved factors such as access to suitable programs, family responsibilities and perceived likelihood of success that may further complicate and constrain such decisions.
between the employees’ attitudes and values and the more classical economic considerations of price, time and perception of future benefit, as embodied in the career attribute in this instance.

One of the difficulties in conducting this research was in describing the product of a formal course of study- there are myriad variants of education and training in the workplace, and it is exceedingly difficult to communicate definitive categories of education and training. Nevertheless, the promise of the technique described here is its capacity to enumerate pertinent choice attributes and guide future policy choices from a government and organisational perspective.

### Appendix A: Factor Structure for Study

<table>
<thead>
<tr>
<th>Item</th>
<th>Enjoyment</th>
<th>Organisational Perceived Values or Behavioural Subjective Importances</th>
</tr>
</thead>
<tbody>
<tr>
<td>The expense of a formal course of study is a waste of employers’ money</td>
<td>0.04</td>
<td>0.10 0.07 0.74</td>
</tr>
<tr>
<td>Successful people do not need formal courses of study</td>
<td>0.27</td>
<td>0.00 0.24 0.68</td>
</tr>
<tr>
<td>Formal courses of study are mainly for people with little else to do</td>
<td>0.50</td>
<td>0.24 0.12 0.58</td>
</tr>
<tr>
<td>Formal courses of study can be a waste of time</td>
<td>0.28</td>
<td>0.07 -0.09 0.62</td>
</tr>
<tr>
<td>I dislike participating in education and training</td>
<td>0.81</td>
<td>0.14 0.12 0.27</td>
</tr>
<tr>
<td>I enjoy formal courses of study that allow me to work with others</td>
<td>0.73</td>
<td>0.12 0.12 0.09</td>
</tr>
<tr>
<td>I’m fed up with teachers and classes</td>
<td>0.77</td>
<td>0.12 0.18 0.32</td>
</tr>
<tr>
<td>This organisation values formal courses of study highly</td>
<td>0.03</td>
<td>0.15 0.81 0.02</td>
</tr>
<tr>
<td>Workplace policies encourage employees to participate in formal courses of study</td>
<td>0.07</td>
<td>0.06 0.79 0.00</td>
</tr>
<tr>
<td>My supervisor really has little influence over whether I undertake further formal courses of study</td>
<td>0.21</td>
<td>0.57 0.38 0.35</td>
</tr>
<tr>
<td>It is up to me whether I undertake formal courses of study</td>
<td>0.01</td>
<td>0.85 0.07 0.01</td>
</tr>
<tr>
<td>It is really not up to me whether I undertake formal courses of study</td>
<td>0.16</td>
<td>0.69 0.03 0.22</td>
</tr>
<tr>
<td>Amount of variance explained</td>
<td>22.75%</td>
<td>15.30% 10.54% 10.09%</td>
</tr>
</tbody>
</table>

Extraction Method: Principal Component Analysis.
Rotation Method: Oblimin with Kaiser Normalization.
This factor structure for Study explained 58.68% of the total variance. Chronbach’s alphas for ENJOYMENT and ORGANISATIONAL VALUES were 0.70 and 0.54 respectively. Some cross-loading of factors was evident for particular items, but this was of little relevance since the modelling process found only two of these variables had a significant bearing on the individual’s choices about study.

References


McKenzie, P. (1999), How to Make Lifelong Learning a Reality, Melbourne, ACER.


