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Student preferences for assignment systems: Results from a discrete choice experiment in Irish universities

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Abstract:
Data from a discrete choice experiment is used to explore preference heterogeneity associated with assignment systems between students in three universities in Ireland. The motivation for the study arises from recent technological advances which have led to a significant increase in the use of online assignment systems in disciplines such as economics and statistics. Despite this, little research exists to understand student preferences for online assignment systems and whether similarities emerge between students across universities. To investigate this issue, we employ latent class and random parameters logit models to explore both observed and unobserved heterogeneity in students' tastes. Our findings reveal that significant heterogeneity in preferences is evident within and between students across the universities. The implications of this finding for the design of assignment systems are discussed.

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I. INTRODUCTION

Technological innovation has had a large impact on the teaching landscape within higher education institutions throughout the world. Many commentators suggest that we are just beginning to see an enormous change in how educational programmes are delivered and assessed (Auletta, 2012; Tabarrok, 2012). Universities such as Harvard and MIT have devoted millions of dollars to develop free online courses that can be taken by students located throughout the world. In Ireland, the use of online delivery in flexible learning models has been noted as strategically important in the future of higher education (HEA, 2011). The HEA also suggest that an expansion in the use by students of online tools in higher education will be one of the key factors in ensuring a high quality learning experience in the future (HEA, 2009).

Technological innovation has already had a large impact on how assignments in disciplines such as economics are delivered and graded. Many universities use learning platforms such as Blackboard which allow individual lecturers to devise their own online assignments while the use of course specific online assignment services such as Aplia or MyEconLab has also become widespread. While some research has been done on the effectiveness of online assignments, very little is known about how students value online assignments and whether differences emerge between students in different universities.

This paper fills this gap and uses a discrete choice experiment (DCE) to explore possible heterogeneity in preferences for features of assignment systems, including online delivery, within and between students in three universities in Ireland. This study represents one of the few applications of the DCE methodology to the area of education, despite the widespread application of the methodology to other areas such as environmental economics, health economics, and transportation. We analyse of preferences for features of assignment systems across commerce students in National University of Ireland, Galway (NUIG), University of Limerick (UL) and University College Cork (UCC). As part of our analysis we explore whether the university to which a student is affiliated is a determinant of the preferences that students hold for the different features of assignment systems. We also examine if other observable characteristics can explain heterogeneity in preferences. We employ models that are capable of accommodating both observed and unobserved preference heterogeneity, namely the latent class (LC) model and the random parameters logit (RPL) model.

While little research of this kind has been conducted previously on exploring student preferences, a few exceptions are noteworthy and relevant for this paper. Huybers (2011) uses the Best-Worst Scaling technique to analyze student responses on course evaluations from two intermediate economics classes in Australia. The study found that three attributes related to assessment and feedback were regarded by students as the most important features of the course, although helpful feedback was found to be unimportant to students. Cunningham et al. (2006) used conjoint analysis to elicit students' preferences regarding the design of a medical education programme in Canada. The attributes used were mainly related to the education programme as a whole and Cunningham et al. found that two groups of students could be identified with a Latent Class modeling framework. A large majority of students (86%) preferred a problem-based approach with small group tutorials led by expert tutors who did not teach didactically while a much smaller group of students preferred large group lectures, explicit learning objectives and streaming options based on learning preferences. While both of these studies use stated preference techniques, a potentially more robust analysis of preferences can be obtained through the use of a Discrete Choice Experiment (DCE), given the strong theoretical underpinnings of the method.[1] Furthermore, these studies did not explore how preferences differ across students in different universities. From an Irish perspective, studies eliciting student attitudes to assessment and assignment methods in higher education are sparse. O'Neill et al (2007) provides some evidence of student responses to various assignment types such as reflective practice, learning journals and problem-based learning in fields such as sociology, humanities and engineering. The analysis is, however, limited to brief qualitative exploration and the issue of online assignment systems is not explored.

To investigate these issues the remainder of our paper proceeds as follows. Section II presents a description of the data and survey design. Section III provides an overview of our econometric methodology. The results are reported in Section IV while Section V presents our discussion and concluding remarks.

[1] See Louviere et al (2010) for more detail.

II. STUDY DESIGN AND DATA DESCRIPTIONS

The study began with the designing and pre-testing of the DCE survey instrument. We began by assembling a focus group of second year commerce students at NUIG to ascertain the relevant attributes of assignment systems that students considered to be important. Following this and a review of the relevant education literature, we established six attributes and their respective levels. The attributes and their associated levels are outlined in Table 1.

|Table 1 about here|

The first attribute that was identified as important was the nature of feedback. This attribute referred to the extent to which students received detailed explanations from their instructor about any errors they made on their assignments. This attribute was presented at three levels - high, moderate and low. The second attribute is the relevance of the assignments for end-of-term exam preparation and referred to the proportion of questions on assignments that helped students prepare for exams. This attribute was also presented at three levels in the DCE - high, moderate and low. Our third attribute was assignment form. With this attribute we wished to understand how students rated traditional paper-based assignment systems against the newer online methods of conducting assignments. Additionally, we presented this attribute in a manner that enabled us to explore student preferences between online systems that enabled graphical manipulation, which can be important for subjects such as economics, and online systems that did not enable graphic manipulation. To allow for this, this attribute consisted of three levels, as described in Table 1.

The fourth attribute was the availability of practice assignments which students could complete prior to answering similar questions on their formal graded assignment. This attribute was presented at two levels; practice assignments were either available or not. The fifth attribute was the speed of getting assignment results; this ranged from fast (receiving results within 24 hours) to slow (receiving results more than one week after submitting an assignment). The final key attribute in the DCE is a cost attribute. This attribute is necessary to determine the implicit prices that the students are willing to pay for the different levels of the other attributes. This was described as an additional once-off payment that students would be required to make for the assignment system in a particular course, over and above any other university charges that they are currently required to pay. As is common in DCEs students were reminded prior to completing the experiment to bear in mind their own financial situation when considering the alternatives on the various choice cards.

We adopted a Bayesian efficient design, based on the minimization of the Db-error criterion to develop our choice cards (Scarpa and Rose, 2008). For each choice task, respondents were asked to choose between two experimentally designed alternatives and a status quo option that did not vary over the choice cards and had a zero cost. Each student was asked to complete 12 choice cards. The questionnaire and the choice cards were pretested in a pilot survey that was conducted with 55 students at NUIG. The pilot study revealed that students had no difficulties in completing the choice cards. We also estimated some basic conditional logit models after the pilot study and the results were in line with our expectations.

To understand whether student preferences were similar between universities we conducted the main DCE with students in the previously mentioned universities. The students were all second year commerce students. It is reasonable to expect some differences in preferences for assignment systems across the different universities as the use of online assignments varies between UCC, UL and NUIG. The NUIG students had used the Aplia service in first year economics (which they had purchased either by buying the textbook for the course or by paying about €40 for the service itself) and had used a free online assignment system delivered via Blackboard in a second year economics course. The UL students had also used the Aplia service (which was only available by buying the textbook) and had also used a free internal online assignment system (SULIS). Most of the UCC students were familiar with MyEconLab but they had not used this or any other service to submit assignments online. In total we got responses from 122 NUIG students, 66 UL students and 141 UCC students.

Table 2 presents summary statistics on the characteristics of the students in our sample.

|Table 2 about here|

In general, approximately 40 percent of the students in NUIG and UL are male, while for UCC there is almost an even proportion of males and females. There were a much smaller proportion of mature students in the UCC cohort compared to NUIG and UL. Approximately half of the students in each three university find that the cost of higher education is a substantial economic burden. Finally, a much smaller proportion of students in UL had received a B+ grade or higher in a previous economics course compared to NUIG and UCC. Without in-depth knowledge of the grade distribution of commerce students in Ireland, it is difficult to firmly suggest the representativeness of the sample to a national level. However, the age and gender profile of the different samples do fit the programme profiles in the respective universities.

III. METHODOLOGY

We use the econometric framework of the random utility model (RUM) as developed by McFadden (1974) to analyse the DCE data. The basic idea of this model is that utility for individual *n* is made up of an observable component $\beta' x_{ni}$ and a random component ε_{ni}. Therefore, the total utility U_{ni} associated with individual *n's* chosen alternative *i* is represented by:

$$U_{ni} = \beta' x_{ni} + \varepsilon_{ni} \qquad (1)$$

Where β' represents a vector of coefficients used to describe preferences for the *x* attributes. Different discrete models can be estimated depending upon the assumptions made about the random component of utility. We focus on two model specifications which fall under the mixed logit (ML) umbrella. In ML models the probabilities are the integrals of the multinomial logit probabilities over a density of parameters:

$$Prob_{ni} = \int \left(\frac{\exp(\beta' x_{ni})}{\sum_j \exp(\beta' x_{nj})} \right) f(\beta|\theta) d\beta \qquad (2)$$

The ML probability is the weighted average of the logit formulas at different values of β with the weights given by the density $f(\beta)$. In the above equation θ represents the parameters that describe the density function. We can specify different behavioural forms of the ML model depending on the specification of $f(\beta)$. We employ a latent class (LC) logit model and a random parameters logit model (RPL), which are both able to accommodate preference heterogeneity in the analysis of DCE data (Stithou et al.,2012).

The LC and RPL models reported in this paper are estimated using a panel specification which takes accounts of the fact that several observations are drawn from the same respondent. Therefore we define a sequence of choices y_n which is observed for a particular respondent as $y_n = < y_{nt=1,\dots\dots\dots,} y_{nt=T} >$ for the T choice occasions. In the case of the LC model we assume that β takes C possible values labelled $\beta_1 \dots \dots \dots . \beta_c$ with probability $Prob_c$. so that the LC choice probability becomes:

$$Prob_{y_n} = \sum_{c=1}^{c} Prob_c \prod_{t=1}^{T} \left(\frac{\exp(\beta'_c x_{nit})}{\sum_J exp(\beta'_c x_{njt})} \right) \qquad (3)$$

In the LC model, respondent *n* is probabilistically assigned into a particular class *c* based on their preferences for the good under consideration. The expected probability of alternative *i* being chosen is the expected value (over classes) of the class specific probabilities. The share of the population probabilistically assigned to class c is $Prob_c$, which can be estimated in the model along with the β' for each class.

In the RPL model, the parameters vary over the decision-makers in the population with$f(\beta)$. Therefore, for the RPL models, the unconditional choice probability represents the integral of the logit probabilities over all possible values of β_n. As a result the choice probability can be represented by a product of logits:

$$Prob_{yn} = \int \prod_{t=1}^{T} \left(\frac{\exp(\beta_n{}' x_{ni})}{\sum_j \exp(\beta'_n x_{nj})} \right) f(\beta_n) d\beta \qquad (4)$$

where T is the number of choices observed for each respondent.

There has been a debate on whether unobserved taste heterogeneity is more suitably accommodated through a continuous distribution (e.g. RPL model) or finite distribution (e.g. LC model) resulting in a number of studies that have compared the two (e.g., Greene and Hensher, 2003; Hynes et al., 2008; Provencher and Bishop, 2004; Scarpa et al, 2007). In the RPL model, preferences are assumed to be unique to each individual.

Provencher and Moore (2006) use the analogy of each respondent having their own ‘fingerprint' to describe the assumption underlying a continuous distribution of preferences. In LC models, it is assumed that there are groups (or classes) of respondents with homogenous preferences. Given that the LC and RPL models can potentially provide differing information, we chose to present the results from both model specifications in this paper.

IV EMPIRICAL RESULTS

Table 3 presents the results from the LC model specification which combines the student samples from across the universities. Within the LC model taste heterogeneity is accounted for by simultaneously assigning students into behavioural groups and estimating the choice model[2]. Another benefit of this approach is that we are able to analyse the preference variation across students and universities conditional on the probability of membership to a latent segment (Hynes et al., 2008).

In order to decide the number of classes with different preferences, we use the information criteria statistics developed by Hurvich and Tsai (1989). In particular, we report the Akaike information criterion (AIC) and the Bayesian Information Criteria (BIC). The number of classes that minimize each of these statistics suggests a preferred model although Scarpa and Thiene, (2005) argue that the decision on the number of latent classes to choose also involves some discretion on behalf of the researcher to ensure that the chosen model contains sensible parameter estimates. We report the LC model estimates for 4 classes as the BIC criterion suggested that this was the best model and we obtained mostly sensible estimates. While the AIC suggested that a 5 class model is preferable, one of its classes had a positive price parameter and another class displayed mostly non-significant attribute coefficients.

|Table 3 about here|

The four-class LC model specification suggests that 27% of respondents are probabilistically assigned to class 1, 26% to class 2, 20% to class 3 and 27% to class 4. The coefficients representing the attributes vary significantly across the four classes, indicating a

[2] A more basic conditional logit model was also estimated but the results are not reported for reasons of brevity.

substantial degree of heterogeneity across our sample with regard to assignment system preferences. All classes have negative and significant cost coefficients and positive and significant coefficients on the feedback and exam relevance dummies, except for the moderate feedback level which is not significant in class 1. As expected, the magnitude of these coefficients varies across the four classes.

More interestingly, we also observe that there is variation in preferences with regard to the form that assignments are delivered. Students probabilistically assigned to class 1 and 2 show a significant preference for paper-based assignment systems while those assigned to classes 3 and 4 favour online assignment systems. We also observe heterogeneity across the student sample in relation to preferences for the speed of getting assignment results back. Students probabilistically assigned to class 1 and 2 show no significant preferences for quicker speed of result assignment while those in classes 3 and 4 exhibit a significant desire for receiving results quickly.

The results in Table 3 illustrate the wide heterogeneity across the student sample in their preferences for various attributes of assignment systems. Of central interest in this paper is to understand if and how preferences for assignment systems vary across universities. To investigate this we estimated the model with the university dummies as covariates explaining class membership in the LC model. As the covariate terms in Table 3 highlight students from UCC are more likely than NUIG students to belong to classes 1 or 2 compared to class 4 (the base class). However, we find no such evidence with regard to UL students. The results suggest that UCC students have a preference for paper-based assignments and are indifferent to the speed of receiving their assignment result relative to students probabilistically assigned to class 4. This might be explained by the greater use of in-class exams rather than take-home assignments in UCC coupled with the lower usage of online technology in assessment submission compared to students in UL and NUIG.

The socioeconomic variables in our dataset such as gender and the dummy for finance burden were also considered as possible determinants of class membership in the model. However, they were not significant when included. Thus, we decided to keep these variables as interactions with the status quo option within the estimated model itself. In the case of class 1, we found that male and mature students are significantly less likely to choose the status quo option whereas students who indicate that financing study is a great burden are more likely to choose the status quo option. In the case of class 2, we find that men are significantly less likely to choose the status quo option compared to female students probabilistically assigned to this class. In the case of classes 3 and 4 male students assigned to these classes are significantly more likely to choose the status quo option compared to female students probabilistically assigned to these classes. Additionally, mature students in classes 3 and 4 are significantly less likely to choose the status quo. Finally, we note that students who state that financing study is a great burden are significantly more likely to choose the status quo in class 3, while those students who state that financing study is a great burden in class 4 are significantly *less* likely to choose the (zero cost) status quo option. Presumably the benefits of the attribute levels associated with the non-status quo alternatives outweigh the costs associated with moving away from the status quo option.

In Table 4 we present the WTP estimates for the latent class model. We present the class specific estimates and also the weighted average of WTP. This is estimated by multiplying the class specific WTP estimates by the probability of class membership and adding the resulting estimates.

|Table 4 about here|

There is a substantial degree of heterogeneity in WTP estimates between the classes. High exam relevance is consistently associated with the highest WTP estimate of all the attributes across the classes (albeit it is only significant at the 10 per cent level in the case of class 3). Second, there are differences between the classes in terms of the preferences for online versus paper-based assignments. In particular, students probabilistically assigned to class 1 and class 2 have a WTP to avoid online assignments, while students assigned to classes 3 and 4 have a positive WTP for online assignment students compared to paper-based assignments. This has implications in terms of delivery of assignments because it suggests that variation in assignment form is required to satisfy the range of student preferences. Third, apart from class 3, students do not show a strong preference for the highest level of the attribute that captures the speed with which they receive their assignment results. We also note that for class 3 in particular very large WTP estimates are retrieved. This may be a function of the large number of parameters that are estimated in the LC specification, which can result in extreme values being obtained.

We now turn to the estimates of the Random Parameter Logit (RPL) model. RPL models are more suitable for estimating preference structures where each individual's preference is completely unique to themselves (hence the analogy with fingerprints). For our RPL model we allow random variation in the non-cost attributes. We specify all the non-cost attributes with a log-normal distribution except for assignment form. Our hypothesis is that for attributes such as exam relevance, students should prefer assignment systems that have higher exam relevance. Therefore, it seems intuitive that the distribution of these attribute levels are bounded on the positive side of zero. On the other hand, for the assignment form attribute, it is plausible that paper-based systems may be preferred to online systems by some students and, therefore, we allow the distribution of heterogeneity for the assignment form levels to take a normal distribution. It is possible that those who prefer paper assignments might regard them as better preparation for the end of course examination than assignments delivered online.

As with many DCE studies we specify the cost coefficient as fixed. While this implies the strong assumption of the same marginal disutility of income for every respondent, specifying the cost coefficient as random leads to the risk of retrieving extreme WTP estimates and can lead to estimation problems. Furthermore, by specifying the cost coefficient as fixed, it ensures that the distribution of WTP takes on the same distribution as the non-cost attribute (Doherty et al., 2013).

Table 5 presents the results from the RPL model. This model estimates one coefficient for the mean of the random distribution and one for the standard deviation of the distribution. Associated with each of these is an estimate of the standard error so one can draw inferences about the significance of the coefficients. If the estimate of the standard deviation is not statistically significant but the mean coefficient is, then one can infer that the preference parameter is constant across the population. If the mean coefficient is not significant, but the standard deviation estimate is, one can infer that there is a diversity of preferences for the attribute which are both lower and higher than the mean value. Ultimately, however, as Rigby and Burton (2003) point out, for an attribute to be declared as having no impact on choices, both the estimate of the mean and the standard deviation would have to be not significantly different from zero.

|Table 5 about here|

We find a high degree of preference heterogeneity for the non-cost attributes as signified by the significant standard deviations for all the attributes. The largest standard deviation relative to the mean value is for an online assignment form without a graphical interface. While the mean coefficients are not statistically significant for the moderate level of feedback and the moderate level of exam relevance attributes, this points to a high degree of heterogeneity surrounding these coefficients, which are causing the mean value to be not statistically significant. In terms of the fixed coefficients, we find that cost is negative and statistically significant. We interacted the alternative specific constant with several demographic variables similar to what we did for the LC model. Our results suggest that if you a male or mature student you are significantly less likely to choose the status quo option. On the other hand if you think that financing study is a great burden you are significantly more likely to choose the status quo option.

As previously noted, a key focus of our analysis is to explore differences in student preferences across the three universities. To examine this, we explored whether university type is able to explain the heterogeneity surrounding the random coefficients. Our results show that university type explains some of the variation in relation to the feedback and assignment form attributes. In particular, being a student at UL appears to explain some of the heterogeneity surrounding the feedback levels while, in the case of high feedback, being a student at UCC explains this to a lesser extent. There are also significant coefficients for both of these universities in the case of assignment form. For instance, some of the heterogeneity for these attributes is explained by being a student of UL or UCC. In addition these students have a stronger preference for paper-based assignments than NUIG students. This is not surprising for UCC students but it is hard to know why UL students have a stronger preference for paper-based assignments than NUIG ones.

In Table 6 we present the retrieved WTP estimates from the RPL model. Once again we find that students are willing to pay the most for assignment systems with high exam relevance. Furthermore, while students prefer online assignment systems overall, their WTP values are almost identical for online systems with graphical interface and those without graphical interface.

|Table 6 about here|

A somewhat unexpected result is the large degree of heterogeneity surrounding the nature of the moderate feedback attribute level as signified by the large standard deviation of WTP relative to the mean estimate. On the other hand, for assignment systems that come with practice questions, the standard deviation is relatively narrow. These results provide an interesting overview of the diversity of preferences regarding the features of assignment systems that we explore in this study.

CONCLUSION

The increased utilization of technological tools in assignment delivery has already led to massive changes in the delivery of assignment systems, and these changes are likely to intensify in the future as more students take online courses. A student might take a free online course in say, microeconomics, while also buying a particular assignment system to help her/him be successful in the course. It seems plausible that the evolution of assignment systems will enable students to select from a range of choices to suit their learning experience. We are aware that some of the leading textbook publishers are developing more sophisticated online assignment systems such that a particular error by a student will prompt the computer to suggest a specific way for that student to get the correct answer. The era in which all students sat through the same lecture and did the same assignments may be over. As it stands, however, little research has been conducted into students' preferences for features of assignment systems particularly whether they differ between students attending different universities. This paper contributes to filling this gap in the literature.

From a methodological perspective, our study illustrates the advantages of the DCE method over other stated preference techniques such as contingent valuation as well as the standard end-of-course evaluations that generally simply ask categorical or Likert-style questions about particular features of the course. We are able to learn far more about the nuances of preferences for a good such as an assignment system using a DCE. The cost of conducting a DCE with students is relatively low and we think there is considerable scope for using DCEs to learn more about other features of the education process or to test whether our results would be replicated with students in other faculties and universities.

Overall, we found that assignments that had a high level of exam relevance were most valued by students across the universities. This is hardly surprising given that many students are orientated towards examinations. We found that there was a diversity of preferences between students in the different universities as regards some attributes of assignment systems. This was most apparent in the case of assignment form. We found that UCC and UL students had a stronger relative preference for paper-based systems compared to NUIG students. This is a noteworthy finding and in the case of UL students unexpected given that UL students had similar exposure to online assignment systems as students in NUIG. On the other hand the results appear consistent with the experience of UCC students given that these students have not been exposed to the same extent as NUIG and UL students to online assessment. Our results suggest that different experiences obtained at different universities influence some, but not necessarily all, students' preferences for assignment systems. It would be interesting to conduct further investigation to decipher whether this finding is apparent in other forms of teaching or assessment delivery.

The LC model produced higher willingness-to-pay estimates than the RPL model, which is a not uncommon finding in papers that have compared both modeling approaches.. Morey et al. (2006) argue that an advantage of the LC model is that it is can generate potentially very useful information for policy makers simply by identifying groups of like-minded users with particular demands.

From an educational perspective, the results suggest that there is scope to design alternative assignment systems to satisfy differences in preferences. In fact the idea of "students as consumers of education" suggests that student preferences for the delivery of their education will become increasingly important. Our study may also have marketing implications with respect to assignment delivery tools as we illustrate varying prices for assignment systems based on their attributes. The differences in preferences across universities may also help to inform different pricing strategies and prove more efficient in the market for these types of products.

More generally, the advances of technology may also mean that universities compete globally for students, as geographical proximity becomes less important. While this study explored preferences for assignment systems using the DCE methodology, obviously many other applications of the method can be applied in the area of education. This could include deciphering preferences for how students wish their degree to be delivered - such as through face-to face contact, online delivery or blended learning methods - and assessing whether differences emerge based on observable characteristics including the students' own educational experience. Such information could provide potential for universities to achieve a competitive advantage, as universities increasing compete for students.

TABLE 1: Description of Attributes and their Levels

Attributes	Levels	Description
Nature of Feedback	High	Complete answers to all of the questions are provided and an explanation of each student's mistakes is also provided
	Moderate	Brief answers to all of the questions are provided
	Low	There is no feedback
Exam Relevance	High	Most of the questions on the assignments help in exam preparation
	Moderate	About half of the questions on the assignment help in exam preparation
	Low	Few of the questions on the assignment help in exam preparation
Assignment Type/Form	online with graphic interface	The assignment is done online using a system with an interface that requires the manipulation of graphs in answering the questions
	online without graphic interface	The assignment is done online but without an interface that allows the manipulation of graphs in answering the questions
	paper assignments	The assignment is done on paper by hand or on a computer and is handed to the lecturer/tutor or handed in to a department office
Practice Assignments Provided	Yes	before each assignment the student has access to a fully worked out practice assignment that has questions that are very similar to those on the graded assignment
	No	There are no practice assignments

Speed of Getting One's Result on an Assignment	Fast	The student can find out her/his mark within 24 hours of the deadline for the assignment
	Moderate	The student gets her/his mark within one week of the deadline
	Slow	The student gets her/his mark more than one week after the deadline has passed
Money cost	0, 5, 10, 20, 35, 45, to 60 Euros	This money is over and above any regular college fees that the students have to pay.

TABLE 2: Summary Statistics

Proportion of Students in Sample (%)	NUIG		UL		UCC	
	Mean	SD	Mean	SD	Mean	SD
Male	0.38	0.48	0.36	0.48	0.49	0.50
Non-Mature (i.e. aged less than 23 years)	0.77	0.52	0.65	0.48	0.90	0.30
Students that feel the cost of higher education is a great burden	0.51	0.49	0.52	0.50	0.46	0.50
Students that received a grade equivalent to a B+ or higher in a previous economics course	0.17	0.37	0.05	0.21	0.18	0.39
Sample Size (n)	122		66		141	

TABLE3: Latent Class model estimates of preferences for assignment attributes

Coefficient	Class 1	Class 2	Class 3	Class 4
Assignment Price	-0.035 (0.01) ***	-0.033 (0.01) ***	-0.006 (.003) ***	-0.085 (0.006) ***
Nature of feedback is high	0.514 (0.22) **	2.106 (0.26) ***	0.592 (0.15) ***	1.311 (0.19) ***
Nature of feedback is moderate	0.116 (0.26)	1.429 (0.21) ***	0.437 (0.18) **	0.851 (0.18) ***
Exam relevance is high	0.650 (0.24) ***	3.663 (0.27) ***	1.230 (0.21) ***	2.461 (0.25) ***
Exam relevance is moderate	0.635 (0.21) ***	2.235 (0.21) ***	0.998 (0.18) ***	1.796 (0.19) ***
Assignment form - online with graphical aids	-0.443 (0.24) *	-0.701 (0.16) ***	0.829 (0.25) ***	0.317 (0.15) **
Assignment form - online with no graphical aids	-0.590 (0.24) **	-0.387 (0.19) **	0.776 (0.21) ***	0.149 (0.15)
Practice assignment is available	0.145 (0.15)	0.678 (0.10) ***	0.343 (0.09) ***	0.492 (0.12) ***
Speed of getting back assignment result is fast	0.397 (0.28)	0.052 (0.16)	0.897 (0.24) ***	0.342 (0.15) **
Speed of getting back assignment result is moderate	-0.337 (0.27)	-0.031 (0.17)	0.651 (0.17) ***	0.229 (0.17)
Alternative specific constant	4.093 (0.52) ***	0.483 (0.44)	-1.22 (0.71)	-0.085 (0.47)
Male	-0.743 (0.16) ***	-1.023 (0.22) ***	0.781 (0.31) ***	0.367 (0.22) *
Mature Student	-2.197 (0.40) ***	0.486 (0.29)	-0.138 (0.32) ***	-1.498 (0.25) ***
Financing study a burden	0.381 (0.13) ***	0.123 (0.20)	0.253 (0.26) ***	-0.530 ** (0.21)
Class Probability				
Constant	-0.534 (0.35)	-0.487 (0.37)	-0.039 (0.31)	-
University of Limerick	0.492 (0.53)	0.461 (0.56)	-0.661 (0.59)	-
University College Cork	1.004 (0.47)***	0.865 (0.48)***	-0.554 (0.57)	-
Estimated class probabilities	0.257	0.25	0.187	0.258
Log likelihood	-2774			
Pseudo R2	0.344			
AIC	5677			
BIC	6084			

* indicates significant at 90% level. ** indicates significant at 95% level, *** indicates significant at 99% level.

TABLE 4: WTP Estimates for assignment attributes within Latent Class model

	Class 1	Class 2	Class 3	Class 4	Weighted Average WTP
	WTP (€)	WTP (€)	WTP (€)	WTP (€)	WTP (€)
High feedback	14.62 (6.3)**	63.02 (9.28)***	99.74 (53.25)*	15.34 (1.7)***	42.12
Moderate feedback	3.3 (7.4)	42.7 (6.9)***	73.6 (53.3)	9.96 (1.87)***	27.87
High exam relevance	18.5 (6.9)***	109.6 (11.9)***	207.1 (110.5)*	28.8 (2.03)***	78.29
Moderate exam relevance	18.07(5.9)***	66.8 (8.09)***	168.1 (93.28)*	21.0 (1.84)***	58.2
Assignment form online with graphical aids	-12.6 (7.5)*	-20.9 (5.55)***	139.5 (88.5)	3.7 (1.76)**	18.57
Assignment form online with no graphical aids	-16.8 (7.9)**	-11.5 (6.02)*	130.6(75.6) *	1.7 (1.76)	17.7
Practice assignments available	4.1 (4.08)	20.29 (3.54)***	57.8 (34.8)*	5.7 (1.24)***	18.43
Speed of getting back assignment result is fast	11.3 (7.46)	1.55 (4.65)	151.05 (87.7)*	4.0 (1.73)**	32.56
Speed of getting back assignment result is moderate	-9.6 (8.06)	-0.93 (5.1)	109.6 (71.9)	2.68 (1.92)	18.48

* indicates significant at 90% level. ** indicates significant at 95% level, *** indicates significant at 99% level.

TABLE 5: RPL model

Random Parameters in Utility Functions	**Mean of coefficient**	**Standard Deviation of coefficient**
Nature of feedback is high	0.897 (0.182)	0.744 (0.09) ***
Nature of feedback is moderate	0.778(0.479) ***	0.249(0.29) ***
Exam relevance is high	2.187(0.109) ***	1.66(0.061) ***
Exam relevance is moderate	1.296(0.119)	1.139(0.090) ***
Assignment form - online with graphical aids	0.455 (0.180) **	0.990 (0.123) ***
Assignment form - online with no graphical aids	0.486 (0.163) ***	1.123(0.115) ***
Practice assignment is available	0.230 (0.325) ***	0.033 (0.213) ***
Speed of getting back assignment result is fast	0.677 (0.397) ***	0.327 (0.182) ***
Speed of getting back assignment result is moderate	0.386 (0.677) **	0.208 (0.461) **
Non-Random Parameters in Utility Functions		
Assignment Price	-0.04 (0.001)***	
Alternative specific constant	1.109 (0.194)***	
Male	-0.398 (0.081)***	
Mature Student	-0.4355 (0.109)***	
Financing study a burden	0.199 (0.083)**	
Explaining heterogeneity in means of random coefficients		
High Feedback* UL	0.518(0.211)**	
High Feedback* UCC	0.358(0.190)*	
Moderate Feedback* UL	1.042(0.408)**	
Moderate Feedback* UCC	0.3269(0.377)	
High Exam Relevance*UL	0.149(0.170)	
High Exam Relevance*UCC	-0.122(0.126)	
Moderate Exam Relevance*UL	0.154(0.220)	
Moderate Exam Relevance*UCC	0.115(0.149)	
Online with Graphics*UL	-0.702(0.311)**	
Online with Graphics*UCC	-0.922(0.230)***	

Online without Graphics*UL	-0.512(0.302)*
Online without Graphics*UCC	-1.065(0.224)***
Practice Assignments*UL	-0.059(0.332)
Practice Assignments*UCC	0.024 (0.292)
Fast Speed*UL	-0.5703(0.339)*
Fast Speed*UCC	-0.2200 (0.313)
Moderate Speed*UL	-22.45 (0.75)
Moderate Speed*UCC	-1.453(1.377)
Log likelihood	-3324.79
Pseudo R2	0.2139
AIC	6731.58
BIC	6988.077

* indicates significant at 90% level. ** indicates significant at 95% level, *** indicates significant at 99% level. Note: Within the random parameters of the model, both assignment form attributes are assumed to have a normal distribution while the rest of the random parameters are assumed to follow a log normal distribution. The estimates presented here are the transformed log normal means, following Train (2003).

TABLE 6: Willingness to Pay Estimates for Attributes from Random Parameters Model

	Mean WTP (€)	Stand Dev of WTP(€)
High feedback	22.61	16.35
Moderate feedback	18.91	46.58
High exam relevance	53.50	42.20
Moderate exam relevance	32.02	16.44
Assignment form online with graphical aids	11.16	23.95
Assignment form online with no graphical aids	11.14	27.74
Practice assignments available	5.76	0.83
Speed of getting back assignment result is fast	16.87	25.65
Speed of getting back assignment result is moderate	9.75	14.98

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