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Of mice and pens: A discrete choice experiment on student preferences for assignment systems in economics

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ABSTRACT

With the development of online open courses, tailoring assignment systems to help students achieve their individual learning objectives will be possible. It is important therefore, from both an educational and business perspective, to understand more about how students value the different characteristics of assignment systems. The main contribution of this paper is the use of a discrete choice experiment to elicit students' preferences for various possible attributes of alternative assignment systems. Our results indicate that students have the strongest preference for assignment systems containing questions that have a high relevance for exam preparation. Our results also indicate that there is a high degree of heterogeneity within the student cohort in their preferences towards various attributes of assignment systems.

1. Introduction

Learning systems and universities are changing rapidly due to social, economic and technological changes. The diffusion of fast Internet access has made the use of online resources within the learning process more and more common and is particularly evident in the provision of course assignments. The main attraction of online assignments is that instructors can assign regular assignments to large

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classes knowing that the students will be able to receive timely feedback on the assignments they had submitted online. Disciplines such as economics has already experienced a large increase in the use of online assignment services and their use in economics and other disciplines is likely to increase significantly as more students take online courses. The increased use of online assignments prompts two issues that are worth investigating from an economics perspective. The first issue is whether online assignments are more or less effective in helping students learn economics (Lee et al., 2010; Trost and Salchi-Isfahani, 2012; Galizzi, 2010; Kennelly et al., 2011; Flannery et al., 2013). The second issue which is the focus of this paper concerns students' preferences for different kinds of assignments. Students are seldom involved in the choice of assignment systems and, therefore, there is little direct evidence on how students value online or paper assignments. In particular we don't know much about what attributes of online or paper assignments are especially useful and valuable to students. An assignment system is rarely, if ever, offered as an optional extra that the students could choose to purchase. With the development of massive online open courses (MOOCs) it is possible to imagine thousands of students who are taking an online course being offered a menu of assignment systems that they can choose from to help them succeed in realizing their individual learning objectives. Some students might choose assignment systems with a relatively large weight devoted to regular assignments while others might prefer that more of the assessment be based on examinations. The theoretical and empirical analysis in a study by Guest (2005) indicates that a shift to a more student-centred approach to teaching and learning that gives students greater choice over their learning environment or technology is likely to improve academic achievement for some students but not others. Our paper builds on this by examining in more detail how students think about the different characteristics of assignment systems. Our results are likely to be of interest from both educational and business perspectives.

Specifically, the main contribution of this paper is that we use a discrete choice experiment (DCE) to elicit students' preferences for assignment systems. The use of DCEs has increased significantly in recent years in areas such as environmental economics (Scarpa et al., 2007), health economics (Ryan et al., 2008), transport (Grisolía and Ortúzar, 2010) and cultural economics (Grisolía and Willis, 2011). Several comprehensive reviews of the basic technique and methodological developments in the analysis of DCEs have appeared in recent years (Louviere et al., 2011; De Bekker-Grob et al., 2010). As far as we are aware, DCEs have not yet been used to elicit students' preferences over different assessment systems and we think that our research will mark an interesting and innovative step in developing our understanding of what students think about different assignment systems.[1]

Our choice experiment was conducted with over 170 students in two intermediate economics classes at the National University of Ireland, Galway (NUI Galway). The students were a particularly suitable group for this experiment as many of them had experience in two different online assignment systems in economics courses that they had taken prior to the experiment. They had been required to purchase the Aplia online service for their principles of economics course and they also had used a free online service (Blackboard) for weekly assignments in a managerial economics course. They also had experience of traditional pen and paper assignments in courses in other disciplines.

The rest of the paper is organised as follows. We begin by outlining our methodological approach in detail including a brief introduction to DCEs and the econometric models that are used to analyse the data. The following section contains a detailed description of our experimental design and process as well as descriptive statistics of some of the key variables. Next we present results from the basic conditional logit model and from a series of latent class models which allow us to explore heterogeneity in students' preferences. This section also includes some simulations where we estimate what students would be willing to pay for certain hypothetical assignment systems. We conclude the paper with a discussion of the implications of our results.

[1] Flores and Savage (2007) do present choice experiment data to gauge student demand for streaming of lecture, however, the methodology employed here is not reflective of a robust DCE and their results may be biased given the modelling framework used.

2. Methodology

Standard consumer theory is based on the premise that utility is a function of the quantities of a good that an individual consumes. Lancaster (1966) proposed an extension which forms the theoretical underpinning of DCEs. He argued that it is the attributes of a good that determine a good's utility and, as a result, utility can be expressed as a function of a good's attributes. In the current study, we define the good of interest as an assignment system and the attributes include the level of exam relevance, the nature and speed of feedback, the assignment form, the availability of practice assignments and price. The utility derived from each assignment system is determined by the preferences for the levels of the attributes provided by each assignment system alternative. The inclusion of a monetary attribute enables the students' willingness to pay (WTP) to be indirectly obtained for either an alternative assignment system in its entirety or for a non-monetary attribute, which is its marginal WTP or implicit price.

The standard econometric framework for the analysis of DCE data is the random utility model (RUM) as developed by McFadden (1974). The basic idea of the model is that, when presented with a number of choice alternatives, individuals will choose the alternative that provides them with the highest utility level in any choice occasion. Under this assumption, utility for individual n is made up of an observable component V_{ni} and a random component ε_{ni}. Therefore, the total utility U_{ni} associated with individual n's chosen alternative i is represented by:

$$U_{ni} = V_{ni} + \varepsilon_{ni} \tag{1}$$

where $V_{ni} = \beta' x_{ni}$ with β' representing a vector of parameter coefficients used to describe preferences for the x attributes. Different discrete choice models can be estimated depending upon the assumptions made about the random component of utility. The conditional logit (CL) model is underpinned by the assumption that error terms are independently and identically distributed, which implies that the associated variances of the unobserved components of a random utility expression describing each alternative in a choice set are identical.

Under the CL model, the probability of individual n choosing alternative i from the set of j alternatives can be written as:

$$Prob_{ni} = \frac{\exp(\beta' x_{ni})}{\sum_j \exp(\beta' x_{nj})} \tag{2}$$

The CL model is associated with a number of convenient properties but does have a number of limitations (Train, 2003). For instance, the independence of irrelevant alternatives (IIA) assumption implies that the probability of choosing one alternative over another is unaffected by the addition or removal of other alternatives in the choice set (Train, 2003). Another important limitation with the CL model is that the model does not capture variations in taste adequately. Within the models it is possible to interact socio-demographic information with the coefficients so that their value varies with demographics. However, if two people have the same demographic information (e.g. education and income), then the CL model assumes they have the same tastes up to an idiosyncratic error component. Finally, the CL model does not account for the panel nature of most DCEs and, therefore, it cannot capture correlation between unobserved factors for any one respondent over a series of choice situations. This is important for panel data, as correlations are expected to exist between the choice situations presented to an individual (Train, 2003).

As a result of these limitations, we use a further model specification, the latent class (LC) model which falls under the mixed logit (ML) umbrella. In the LC model specification the vector β' takes on a finite set of distinct values. In LC models taste heterogeneity is statistically accounted for by simultaneously probabilistically assigning individuals into latent classes (similar to clusters) and estimating the choice model. A primary benefit of this approach is being able to explain the preference variation across individuals conditional on the probability of membership to a latent class.[2] Therefore, in our analysis this allows us to investigate the possibility that certain factors such as gender, aptitude

[2] Hensher and Greene (2005) provide an in-depth analysis of latent class models.

to economics, etc. help explain variations in student preferences for different assignment systems. This type of analysis has been utilised previously within discrete choice experiments in agricultural economics (Hynes et al., 2011) and transportation economics (Greene and Hensher, 2003).

The LC model used in this paper is estimated using a panel specification which provides a more realistic representation of the data by accounting for observations drawn from the same respondent. Therefore we define a sequence of choices y_n which is observed for a particular respondent as $y_n = \langle y_{nt=1}, \ldots, y_{nt=T} \rangle$ for T choice occasions. In the case of the LC model we assume that β takes c possible values labelled $\beta_1, \ldots, \beta_c$ with probability $Prob_c$ so that the LC choice probability becomes:

$$Prob_{y_n} = \sum_{c=1}^{C} Prob_c \prod_{t=1}^{T} \left(\frac{\exp(\beta_c' x_{nit})}{\sum_j \exp(\beta_c' x_{njt})} \right) \tag{3}$$

For the panel model the probability is estimated as the product of logit formulas, one for each choice occasion. 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 LC model, respondent n is probabilistically assigned into a particular class c based on their preferences for the good under consideration. The assumption is that respondents probabilistically assigned to one class have the same preferences but differ in their preferences from respondents assigned to another class (Swait and Adamowicz, 2001).

3. Experimental design and data descriptives

The project began with a focus group discussion with the relevant population of interest, which in this case consisted of second year business and finance majors at NUI Galway. The purpose of the focus group was to discuss the relevant attributes of assignment systems that students felt were important. One point we emphasised to both the focus group and the students who took part in the actual experiment was that we wanted them to think of a hypothetical course in a subject such as accounting or economics where regular assignments would be generally a feature of the assessment process. Of course, as with all methods of stated preference techniques, it is very likely that students based their responses in part on their actual experience with assignments in difference courses that they had taken. Based on this discussion and on our knowledge of educational research, we established six relevant attributes. Four of the attributes had three possible levels, one had two, while the other, cost, had seven possible levels. Table 1 summarises the attributes and the different levels of each attribute. The first attribute listed in Table 1 is the nature of feedback. Given the importance of feedback in the education literature it was deemed crucial to establish student experience and expectations with regard to feedback (see Boud and Falchikov, 2007 for a discussion of these issues). Students remarked during the focus group discussion that they had experienced considerable variation in the quality of feedback they had received and the three levels of the attribute – high, moderate and low – were used to depict a range of different possibilities associated with the level of potential feedback. Another attribute deemed important by students was how relevant the questions on an assignment were for their exam preparation. This is in keeping with the literature on strategic learners (Biggs, 2003). This attribute was presented at three levels in the DCE – high, moderate and low – to capture differences in how many questions in a hypothetical assignment system helped in preparing for an exam. A high level of exam relevance was defined as an assignment system where most of the questions on the exam help in exam preparation. Our third attribute was assignment form which also had three levels – paper, online with graphic interface, and online without graphic interface. We were particularly interested to see how students rated the traditional paper based assignment systems against the newer online methods of conducting assignments. Additionally, we wanted to establish what student preferences were between online systems that provided a detailed graphical interface which allowed students to manipulate graphs online and more basic online systems that did not enable graphic manipulation (see Dermo, 2009 for a summary of recent educational literature on electronic assessment).

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 h of the deadline for the assignment
	Moderate	The student gets her/his mark within 1 week of the deadline
	Slow	The student gets her/his mark more than 1 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

The fourth attribute was the availability of practice assignments which students could complete prior to answering similar questions on their formal graded assignment. The availability of practice assignments is one of the key features of services such as Aplia but some instructors worry that students simply deduce the answers on the graded assignment by looking at the answers to the practice assignments without learning the underlying concepts. This attribute was presented at two levels; practice assignments were either provided or not provided. The fifth attribute was the speed of getting assignment results. This ranged from receiving results within 24 h (fast level) to receiving results more than 1 week after submitting the assignment (slow level). Online assignment systems are able to give results instantly and this possibility is captured by the fast level of this attribute.

The final attribute in the DCE is a cost attribute. The inclusion of a cost attribute enables us to determine how much students are willing to pay for the different levels of each attribute as well as how much they are willing to pay for different combinations of the non-cost attributes. This was presented as an additional once-off payment that students would be required to make for the assignment system in a particular course. This attribute was presented at six levels to reflect realistic payment amounts that students could be asked to pay for assignment services. We found that six levels were sufficient to enable students to make meaningful trade-offs while providing enough variation in the levels to establish the range in students' WTP amounts. We felt that providing more than six levels would have increased the burden in answering the DCE. Studies that employ DCEs in

Table 2
Sample choice card.

	Assignment system A	Assignment system B	Assignment system C
Nature of feedback	Moderate (brief answers to all of the questions are provided)	High (complete answers to all of the questions are provided; explanation of each student's mistakes is also provided)	Moderate (brief answers to all of the questions are provided)
Exam relevance	Low (few of the questions on the assignment help in exam preparation)	High (most of the questions on the assignment help in exam preparation)	Low (few of the questions on the assignment help in exam preparation)
Assignment form	Paper assignments	Online with graphic interface	Paper assignments
Practice assignments provided	No	Yes	No
Speed of getting back result of assignment	Fast (the student gets mark within 24 h of the deadline for the assignment)	Slow (the student gets mark more than 1 week after the deadline has passed)	Slow (the student gets mark more than 1 week after the deadline has passed)
Additional cost of assignment System.	€5.00	€35.00	€0
Please tick the one option you prefer	☐	☐	☐

Note: Assignment system C is the status quo option in the choice experiment.

other areas also present a similar number of levels for the cost attribute. We did consider a number of other possible attributes such as the time required to complete assignments and the ease of cheating on assignments but decided not to include them in the experiment based on our discussions with the focus group.

We adopted a Bayesian efficient design, based on the minimisation of the Db-error criterion to develop the choice cards and choice alternatives (for a general overview of efficient experimental design literature, see Scarpa and Rose, 2008). The choice cards were generated using the Ngene software. An example of a choice card used is presented in Table 2. In each choice card, respondents were asked to choose between two experimentally designed alternatives and a status quo option. The status quo option, whose cost was zero, did not vary over the choice cards. Two blocks of choice sets were created and in each block the students were asked to complete 12 choice cards.

One of the problems with some DCEs in environmental and health economics is that a significant number of respondents refuse to consider the possibility of paying for whatever good or service is being considered in the experiment. Most of the students in our experiment had been required to pay for an online assignment system for their principles of economics course and we felt it was likely that the students would not have a problem about considering the cost of an assignment system as one of the attributes in the experiment. We found very little evidence of students always choosing the status quo option on different choice cards which suggests that the students did not have an issue with the idea of paying for an assignment system.[3] The exact attributes of the status quo option can be seen in the sample choice set in Table 2 with assignment system 3 presenting the non-varying status quo choice.

Following the focus group, a pilot survey was conducted with 55 students taking a course in financial economics at NUI Galway. The purpose of the pilot study was to test the choice cards and to see whether 12 choice cards could be completed in the time available. Additionally we wanted to ensure that we had not left out any important attributes. The pilot study revealed that students had no difficulties in completing the 12 choice cards in the time available. We also ran some basic models after the pilot study to check whether the estimated coefficients associated with the attributes conformed to a priori expectations. We were reassured by the results of the pilot study. For example, we found that price was negative and significant and that students showed a stronger preference for

[3] Only 5.6% of the full sample always picked the status quo option.

Table 3
Summary statistics.

	Mean	SD
Proportion of students that are male	0.38	0.48
Proportion of students that are non-mature (i.e. aged under 23)	0.77	0.52
Proportion of students that feel the cost of higher education is a great burden	0.51	0.49
Proportion of students that received a grade equivalent to a B+ or higher in a previous economics course	0.17	0.37

high exam relevance level compared to moderate and low exam relevance levels. The results indicated that the attributes and their levels that we had chosen adequately captured the salient features of the assignment systems from the students' point of view. Therefore, we did not make any substantial changes to the design of our main survey and conducted the main DCE with a group of 122 second year business majors. This was conducted in class. We began by outlining what we meant by an assignment system and what the experiment required the students to do. The students were asked to think of assignment systems for a course in a subject such as economics or statistics where frequent assignments were required of the students and where the assignments counted for approximately 25% of the overall course grade. A sample choice card was presented to the students along with a note that explained in detail what each attribute and their respective levels were meant to convey. The students were assured that their responses would be treated confidentially and were not asked to identify themselves either by name or ID number. If the students had any difficulties they could speak to a member of the research team that was present during the experiment. We did not observe students having any major difficulties completing the questionnaire.

Since we did not make any changes to the attributes and levels used in the experiment between the pilot and actual experiment, we combined the pilot and the main sample in our analysis. This resulted in a sample size of 177 students resulting in over 2000 observations for our analysis. Table 3 presents summary statistics on the characteristics of the students in our sample. The majority of students were female and mostly younger than 23 years. Approximately half of the students indicated that they found the cost of higher education of great burden (either to themselves or their family). About one sixth of the students said they had received the equivalent of a B+ or higher in their principles of economics course.

4. Empirical results

The indirect utility for any particular assignment system is assumed to depend on the levels of the attributes of that system. The level of attributes on the third option on each card is held constant across all choice sets presented to each respondent[4] and represents the *status quo* situation. The attribute levels (apart from price) are treated as dummies in the model specification with the *lowest* level of each attribute being always taken as the base case. The final chosen model assumes that *U* = *f*(*Nature of Feedback, Exam Relevance, Assignment Form, Availability of Practice Assignments, Speed of getting back the Assignment Mark, Assignment System Cost*). An alternative specific constant for option 3 (the *status quo* option) was also included in the model specification.

The results of the conditional logit model of student preferences for assignment attributes are presented in Table 4. The model is well specified with regard to the sign and significance of the coefficients. As expected, the coefficient on price is significant and negative. The results indicate that students prefer assignment systems that provide better feedback, have higher exam relevance, faster turnaround time for results, have practice assignments available, and are completed online (as opposed to on paper). The alternative specific constant variable is insignificant, suggesting that we have not omitted any attribute that would have led students to choose the status quo option over the other alternatives.

[4] While the levels of each attribute in option 3 stayed constant in all the cards presented to any particular respondent, the level of the exam relevance attribute was set at low for one half of the students and moderate for the other half.

Table 4
Conditional logit model estimates of preferences for assignment attributes.

Variable	Coefficient
Assignment price	−0.028 (0.002)***
Nature of feedback is high	0.651 (0.079)***
Nature of feedback is moderate	0.458 (0.078)***
Exam relevance is high	1.418 (0.089)***
Exam relevance is moderate	0.972 (0.077)***
Assignment form – online with graphical aids	0.183 (0.074)**
Assignment form – online with no graphical aids	0.173 (0.075)**
Practice assignment is available	0.293 (0.055)***
Speed of getting back assignment result is fast	0.293 (0.076)***
Speed of getting back assignment result is moderate	0.224 (0.073)***
Alternative specific constant	−0.076 (0.1)
Log likelihood	−2099.86
Pseudo R^2	0.08
AIC	4221.78
BIC	4283.85
Obs	2124

Standard errors in parentheses.
*Significant at 90% level.
** Significant at 95% level.
*** Significant at 99% level.

Table 5 presents the willingness to pay (WTP) estimates derived from the conditional logit model. The exam relevance attribute of an assignment system is of most value to the students in our sample. On average students are willing to pay €51 to have an assignment system with questions that are highly relevant for the final exam, compared to one where only a few of the questions are relevant for the exam. They are willing to pay €35 for assignments that are moderately exam relevant, again compared to an assignment system where only a few of the questions are relevant to the exam. The second most valuable attribute for the students was the nature of feedback that they would receive on their assignments. Students were willing to pay €24 for an assignment system with a high level of feedback compared to one with a low level of feedback. The WTP estimates for the other three attributes – speed of results, availability of practice assignments, and the format of assignments – were all lower indicating that these attributes are not as important to students as exam relevance and nature of feedback. For instance, the WTP in moving from a paper based assignment to one online with graphical aids is €6.63 while the WTP for practice assignments is €10.60.

Table 5
Conditional logit willingness to pay estimates for attributes of assignments.

	WTP (€)
Nature of feedback is high	23.62 (2.9)***
Nature of feedback is moderate	16.59 (2.88)***
Exam relevance is high	51.41 (3.7)***
Exam relevance is moderate	35.22 (3.13)***
Assignment form – online with graphical aids	6.63 (2.69)**
Assignment form – online with no graphical aids	6.2 (2.68)***
Practice assignments available	10.6 (2.05)***
Speed of getting back assignment result is fast	10.6 (2.78)***
Speed of getting back assignment result is moderate	8.1 (2.67)**

Standard errors in parentheses.
*Significant at 90% level.
** Significant at 95% level.
*** Significant at 99% level.

Table 6
Latent class model estimates of preferences for assignment attributes.

	Class I	Class II	Class III
Assignment price	−0.01 (0.004)***	−0.07 (0.006)***	−0.03 (0.006)***
High feedback	0.16 (0.156)***	1.25 (0.177)***	0.38 (0.27)
Moderate feedback	0.71 (0.136)***	0.73 (0.17)***	0.262 (0.25)
High exam relevance	2.06 (0.198)***	2.36 (0.24)***	0.23 (0.295)
Moderate exam relevance	1.42 (0.162)***	1.76 (0.20)***	0.04 (0.29)
Assignment form – online with graphical aids	0.32 (0.145)**	0.46 (0.18)**	−0.55 (0.25)**
Assignment form – online with no graphical aids	0.31 (0.139)**	0.39 (0.176)**	−0.63 (0.248)**
Practice assignments available	0.44 (0.095)***	0.34 (0.12)***	0.17 (0.22)
Speed of getting back assignment result is fast	0.33 (0.143)**	0.32 (0.163)*	0.14 (0.24)
Speed of getting back assignment result is moderate	0.50 (0.127)***	0.4 (0.142)***	−.58 (0.26)**
Alternative specific constant	−0.98 (0.23)***	−0.99 (0.23)***	0.44 (0.283)
Estimated class probabilities	0.39	0.36	0.25
Log likelihood	−1626.29		
Pseudo R^2	0.29		
AIC	3322.58		
BIC	3520.27		

Standard errors in parentheses.
* Significant at 90% level.
** Significant at 95% level.
*** Significant at 99% level.

As noted in the previous section, the conditional logit choice model suffers from limitations related to variations in taste and the IIA assumption. To account for these limitations and enable a more robust estimation of the relationship between assignment system characteristics and student preferences we next estimated a LC model. In this model taste heterogeneity is statistically accounted for by simultaneously assigning students into behavioural groups and estimating the choice model. A primary benefit of this approach in the current context is being able to explain the preference variation across students conditional on the probability of membership in a latent class. In order to decide the number of classes with different preferences, we used a number of 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 minimise each of these statistics suggests the preferred model although the number of latent classes chosen also involves the discretion of the researcher (Scarpa and Thiene, 2005). We report the latent class model estimates for three classes (Table 6), even though the AIC were lowest for the four-class model. We rejected the four-class model as one of its classes had a positive price attribute parameter and one of the classes also displayed mostly insignificant attribute coefficients. In addition, the BIC statistic indicated that the three-class model was the preferred model.

A couple of points are worth noting before we proceed to our discussion of the LC model results. First, the latent classes do not necessarily represent any individual in the sample as each respondent has a differing probability of belonging to each of the latent classes. Second, the classes are chosen so as to maximise the statistical goodness of fit criteria. This may result in LC locations that are often more extreme than individuals in the sample, given that individuals have a mixture of probabilities of belonging to each of the latent classes.

The class probabilities suggest that 39% of respondents are probabilistically assigned to Class I, 36% to Class II and 25% to Class III. The coefficients on all of the non-cost attribute coefficients in Classes I and II are positive and significant suggesting that these classes differ as regards the strength of preferences for different attributes. While it may not be entirely meaningful to compare coefficients across latent classes we observe that Class II is associated with a much larger coefficient for an assignment system that provides a high level of feedback. Class III is different from the other classes in a number of respects. The coefficients on several attribute levels have the same sign as in the other classes but are not statistically significant. More importantly, in the case of assignment form, the coefficients associated with the online forms are negative and significant suggesting that there is a

Table 7
Willingness to pay estimates for attributes from latent class model.

	Class I	Class II	Class III	Weighted average WTP
	WTP (€)	WTP (€)	WTP (€)	WTP (€)
High feedback	68.06 (23.12)***	16.9 (2.13)***	10.9 (7.74)	35.35
Moderate feedback	65.44 (24.69)***	9.87 (2.2)***	7.5 (7.35)	30.95
High exam relevance	185.57 (63.95)***	32.02 (2.49)***	6.62 (8.22)	85.55
Moderate exam relevance	130.92 (45.48)***	23.87 (2.06)***	1.1 (8.31)	59.93
Assignment form online with graphical aids	29.26 (15.7)*	6.19 (2.34)***	−15.8 (8.18)*	9.69
Assignment form online with no graphical aids	28.74 (15.2)*	5.33 (2.27)**	−18.1 (8.31)*	8.59
Practice assignments available	40.21 (16.4)**	4.5 (1.58)***	4.87 (6.32)	18.52
Speed of getting back assignment result is fast	30.73 (14.68)**	4.34 (2.2)*	4.1 (6.85)	14.52
Speed of getting back assignment result is moderate	45.75 (19.3)**	5.36 (1.89)***	−16.9 (8.3)**	15.55

Standard errors in parentheses.
* Significant at 90% level.
** Significant at 95% level.
*** Significant at 99% level.

significant portion (25%) of students in our dataset who have a preference for paper-based assignment methods. There is no surprise that a sizeable number of respondents would prefer paper assignments to online assignments. But what is puzzling is the significant coefficient on the speed of getting one's result which suggests that these respondents prefer to wait a long time to get their results. One possible explanation is that these respondents feel very strongly about having paper assignments even though they accept that this means that they may have to wait longer to get their marks. In addition, a student who prefers paper assignments might think that there will be better quality feedback on an assignment if the instructor takes a long time to grade it instead of a short or moderate length of time to do so.

The alternative specific constant for the status quo option in Classes I and II is negative and significant indicating that there are unspecified attributes leading students in these classes to prefer the experimentally designed alternatives over the status quo option. Again this heterogeneity in preferences was not picked up in the conditional logit model where the alternative specific constant for the whole group was not significant. Finally, and importantly for WTP estimation, the price coefficients in all three classes are negative and significant at the 1% level.[5]

To help understand if and how some factors may help explain the variation in preferences for assignment systems we see across the three classes in Table 6, these estimations were also carried out using a range of socioeconomic variables as covariates explaining class membership. These socioeconomic variables included the 4 variables outlined in the summary statistics in Table 3-gender dummy, mature student dummy, a dummy for finance burden, and a dummy indicating whether or not a student received a B+ grade in a previous economics course. However, they all proved not to be significant when estimated and so cannot help explain the heterogeneity that we see in our 3 class models.

Table 7 reports the mean marginal WTP estimates (which are equivalent to implicit prices) for the assignment attributes for each of the classes. The marginal WTPs are all statistically significant for Classes I and II but only the implicit prices for the alternative levels of assignment form and receiving assignment marks in a moderate time are statistically significant in Class III. We can see that the marginal WTP for high exam relevance and high levels of feedback is €185 and €68, respectively, in Class I. Meanwhile the weighted average marginal WTP across classes for these attributes is lower, but still sizeable at €84 and €35, respectively.[6]

[5] We checked whether membership of the sub classes was correlated in any way with the data we have on student characteristics but we did not find any evidence that student performance in other economics courses or students' financial situation was associated with membership of different sub classes.

[6] The weighted implicit price for an attribute is calculated by multiplying each of the individual class WTP estimates by their respective class probabilities from Table 6 and summing the three values obtained. For example, the weighted implicit price for a high level of exam relevance is calculated as follows: (€185.57 × 0.39)+(€32.02 × 0.36)+(€6.62 × 0.25)=€85.

Table 8
Attribute levels and compensating surplus value estimates for the three policy scenario assignment systems relative to the base case (€ per student).

	Scenario 1	Scenario 2	Scenario 3	Base case
Nature of feedback	High	Moderate	High	Moderate
Exam relevance	High	Moderate	Low	Moderate
Assignment form	Paper assignments	Online without graphic interface	Online with graphic interface	Paper assignments
Practice assignments provided	No	No	Yes	No
Speed of getting back result of assignment	Moderate	Fast	Fast	Slow
Compensating surplus (€ per student)				
Latent Class I	103.088 (14.7)***	59.48 (29.44)**	−28.03 (33.97)	
Latent Class II	20.67 (3.31)***	9.68 (3.05)***	−1.61 (4.2)*	
Latent Class III	−16.98 (8.33)***	−18.16 (8.31)**	−15.79 (8.18)*	
Weighted average across LC model	42.93 (14.75)**	22.88 (9.91)**	−15.34 (13.05)	

Standard errors in parentheses.
* Significant at 90% level.
** Significant at 95% level.
*** Significant at 99% level.

We can use the coefficients from the LC model in Table 6 to run some simulations estimating the welfare gain or loss that would be experienced by students if there was a change from one kind of assignment system to another. To begin, we specified a base case as an assignment system that was paper based without practice assignments and where marks were returned to students more than a week after the assignments were submitted. In addition, in the base case, the questions on the assignments were assumed moderately relevant for the exam and the feedback they received was moderate. We think that this base case might be a reasonable approximation to the actual situation in many universities but it is obviously not universally so as many universities use online assignments in some economics courses.

The results of the simulation exercises are reported in Table 8. We begin with Scenario 1 which is a hypothetical assignment system that is the same as the base case on two attributes – both are paper based and practice assignments are not available. The difference between them is that Scenario 1 is an assignment system with a high level of feedback and the questions on it are highly relevant to the exam. In addition, students get their marks back within a week of submitting their assignment rather than after a week. Thus Scenario 1 might be of interest to an institution that is wondering whether it should increase the number of tutors or teaching assistants in order to provide quicker and more comprehensive feedback to the students taking the course. The results in Table 8 indicate that a move from the base case to Scenario 1 would provide a very large welfare gain of over €100 to students most probabilistically assigned to Class I, a much lower benefit to students most probabilistically assigned to Class II, and would actually represent a loss to students most probabilistically assigned to Class III. Note that the latter result is due to the fact that in calculating welfare gains for a particular class we exclude any coefficients that are not statistically significant in Table 6. Thus for Class III, the welfare effects of a move from the base case to Scenario 1 is in effect a move to an assignment system with a moderate speed of getting results back instead of a slow speed and the students in that class prefer getting their marks slowly (the other attribute levels that are significant for Class III are the same in the base case and Scenario 1).

The second scenario is an assignment system that is the same as the base case except that the assignments are done online without graphic interface and the results are received by the students within 24 h rather than after a week. In developing this scenario we had in mind a situation where an instructor might use a system such as Blackboard for delivering assignments. Such a move would be welcomed by students who have a higher probability of belonging to either Classes I and II who would appreciate the assignments being done online as opposed to being done on paper and who prefer getting their results faster. The welfare gain for Class I is particularly high. But a move from the base case to Scenario 2 would reduce the welfare of those students who have a high probability of belonging to Class III.

The third scenario is an assignment system that is different in all of the attributes from the base case. Scenario 3 is an online assignment system with graphic interface, the nature of feedback is high, practice questions are provided and results are received quickly. Lastly, the exam relevance of the questions is low. We specified this attribute level as low because some of our students that have used online assignment systems in economics courses have voiced some concerns about how good the systems are for preparing them for traditional paper-based examinations. The results in Table 8 indicate that the welfare gain for students with a high probability of belonging to Class I is negative but not significantly different from zero. This result is due to the very strong preference for exam relevance denoted by the large coefficient and clearly a move to an assignment system that has low exam relevance from a base of moderate is going to negatively impact on students who have a high probability of belonging to Class I. This negative effect is offset somewhat by other changes. Students who have a high probability of being in Class II experience a small but significant welfare loss from the move to Scenario 3. In their case the benefits from moving to attribute levels that they prefer such as a high level of feedback, a practice assignment provided and doing the assignments online are not enough to offset the loss from moving to an assignment system with low exam relevance. Finally, students probabilistically assigned to Class III prefer paper-based assignments to online ones and this means they experience a welfare loss in the move from the base case to Scenario 3 as the coefficients on the other attribute levels are not statistically significant for this class in Table 6.

It is worth noting the advantages of using a weighted class model as the welfare gains and losses from a particular change vary a great deal across the three classes. These simulation exercises are not meant to be exhaustive; they simply illustrate what the gains and losses might be in some moves. One could just as easily specify a different kind of assignment system as the base case and analyse gains and losses in various moves from that.

5. Discussion

The whole nature of education provision and learning opportunities is undergoing a period of rapid technological change, one that is likely to accelerate in the near future as more possibilities for alternatives to the traditional university model of delivering higher education are explored. While we cannot predict the outcome of this transformation in detail, it seems reasonable that whatever system or systems that will emerge will have a number of features. There will be more online education and greater use of technology to deliver assignment systems. There will be more emphasis on students choosing features of the learning system that suit them best. In an ideal world students might be able to select from a menu of assessment choices. This may happen with the passage of time as technology and ideas about assessment evolve. In the meantime DCEs such as ours can be used to elicit student preference for the design of programmes, courses, and assessment (as Cunningham et al., 2006 have done with conjoint analysis). This type of analysis also provides a better understanding of students' tastes which could be exploited for marketing purposes. For instance, the model shows which assignment systems would command a higher price on the basis of their attributes. We also see that the willingness to pay for certain attributes is subject to heterogeneity, with some individuals willing to pay more than the average and some individuals willing to pay much less than the average for attributes such as feedback. In a world where assignment systems may be tailored to student desires this type of model has the potential to detect differences among students, which might justify greater differential pricing strategies.

The size of some of the willingness-to-pay estimates may seem surprising at first glance especially the estimates for Class I in Table 7 which suggest that the marginal WTP for high exam relevance and high levels of feedback is €185 and €68, respectively, in this class. Note though that this is just an estimate of the willingness to pay for a move from an assignment system with low exam relevance to one with high exam relevance. A better estimate of what a student might be willing to pay overall for an assignment system is contained in the compensating surplus figures in Table 8. The estimates of an overall welfare gain of over €100 for Class I seem reasonable in a context where many students purchase privately provide grinds to help them prepare for examinations. Also, most of the students in the experiment had been required to purchase an online assignment system in their principles of economics course that they had taken in their first year at university and the cost of that was about

€35. It is interesting that students are only willing to pay for a move to an online assignment system if there is a moderate or high level of exam relevance associated with such a system. Some instructors have found that online assignment systems were of little benefit for helping students prepare for written examinations although this may change as smarter online assignment systems are developed.

From a pedagogical viewpoint, the results of the DCE give us the opportunity to establish how students see the purpose of assignments. To no great surprise our results show that student regard examination relevance as the most valuable attribute of an assignment system. However, what is surprising is that the results of Latent Class III suggest that some students value getting feedback more slowly. One possible explanation is that students want the instructor to take more time considering their work. Price et al. (2011, pp. 484–485) argue that students' assessment performance can easily be improved by supporting their understanding of assessment tasks and criteria. They claim that good assessment practice requires student engagement with feedback, student engagement with standards, and crucially, student engagement with staff. If this is the case then it is not only important to engage with students on the design of their assessment; it may also be important to engage with their work.

Eliciting student preferences is likely to become more important as higher education adopts a more service orientated approach to instruction and assessment (Birenbaum, 2007). In this environment, student feedback is likely to play a greater role than previously. A consistent finding in student surveys is a high level of dissatisfaction with assessment (Price et al., 2011). The DCE method has the potential to go well beyond the typical end-of-semester course evaluation in eliciting students' preferences about different aspects of the learning experience.

There are some caveats to our DCE that need be acknowledged, mainly relating to the issue of student experience and timing. The experiment was conducted in the second half of the semester and perhaps we might have got different responses from the students at another stage in the semester. The possible difference between a student's preference starting out on a course as opposed to in the middle is an interesting research question, but beyond the scope of this study. Finally, the experiment was conducted in class and so there is an issue of sample selection within our estimates. In particular it is likely that our sample includes a disproportionate number of students who performed well in their courses.

In terms of potential future research within this area, a larger sample of students in a variety of faculties would make it possible to model further heterogeneity across universities/higher education institution types and programmes of study in relation to assignment system preferences. This may help provide even further information as regards potential tailoring assignments systems to specific student needs and developing non uniform pricing strategies. Future research might also consider some attributes that we did not include such as the ease of cheating on assignments.

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