Eliciting the Illicit: Choosing to Cheat

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Abstract

This paper reports the use of a choice experiment to investigate an illicit form of demand: student demand for essays from commercial providers. It investigates whether potential consumers will reveal a willingness to buy, and if so, how the value of the illicit good is affected by its price and quality and the risk of detection and the penalty associated with detection.

Analysing CE data from 3 UK universities we find potential consumers are prepared to reveal a willingness to buy: 50% ‘purchase’ on one or more choice occasion. Respondents’ choice behaviour conforms to economic theory with the essays’ value affected by their price, quality and the risk of being caught and the associated penalty.

Since we might expect the demand for an illicit good to be affected by the risk preferences of the potential buyer we use supplementary choice data from a paired gamble CE to derive individual estimates of risk aversion, via estimation of a mixed logit model. We find that responses to the risk & penalty attributes of essays are influenced by individuals’ level of risk aversion. Latent class analysis of the essay CE data suggests there are 2 segments within the sample, one of which is characterised by strong aversion to the purchase of essays, while members of the other segment are willing to enter the market if the conditions are right.

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The choice researcher typically uses the CE method to investigate preferences because the good for which demand information is sought is not observed in the market or, if the good is currently available, the revealed preference (RP) data available are unsuitable to address the research question at hand.

Unavailable goods include those which have not been licensed (eg GM or irradiated foods) and those which are technologically unavailable (eg new fuel vehicles). Where there is currently consumption the RP data may be unsuitable because, *inter alia*, the attributes for which values are sought are too correlated in the options currently consumed or because attributes of interest are absent.

This paper concerns research on a specific circumstance where the RP data are unavailable – when the demand is illicit. The demand for illicit and illegal goods is difficult to observe directly. For example consumption of recreational drugs has to be estimated indirectly from various sources such as customs seizures, medical data and surveys with potential users. However, the use of surveys to understand consumption levels and the nature of demand is problematic since the consumer may be reticent or unwilling to reveal their true behaviour and preferences because of a fear of self incrimination.

This paper reports the results of an investigation of illicit demand: the demand for commercially provided coursework among students at UK universities. It provides insights regarding the use of a CE to elicit illicit demand. There are very few examples of the use of the CE method to investigate illicit behaviour, an exception being the study Ibanez and Carlsson (2009) looking at Coca cropping in Colombia. The paper also provides insights regarding a market about which many are unaware, yet which is substantial, growing and which threatens academic integrity.

The fear of potential incrimination is an issue which survey researchers have engaged with for many years. As we discuss in the paper, the problem posed by fear among (potential) consumers in revealing their true preferences is particularly heightened in this study. The reason is that while a drugs researcher interviewing (potential) users is not charged with ‘policing’ illegal drug use, the academic researcher investigating the market for essays is likely to be seen as having that policing role. Hence the disincentive to truthfully reveal may be greater in the context where the researcher is seen as involved in the policing of the illicit behaviour investigated.

This paper reports results from the use of a CE to investigate the demand for essays purchased by students at UK universities. In the sections that follow we describe the nature of the market, the CE design process and analysis of the results from the CE itself. A first research question is simple but critical: will (significant numbers of) respondents reveal a willingness to buy essays? If they will, the research questions which follow include: what is the nature of the demand for essays – how are the essays valuations affected by their quality and the risk and penalty associated with their purchase, and how does this differ across individuals?

One facet of such variation in preferences across people when the good is illicit is variation in risk preferences. To investigate risk preferences, and their role in the demand for essays, we employed a 2nd CE comprising choices between pairs of gambles, played for real payoffs. Analysis of these gamble choice data via a mixed logit model allow estimation of individual-specific risk preferences. We find these risk preferences systematically affect the preferences for, and valuations of, the illicit essays.
1 Plagiarism and the rise of ‘contract cheating’

This paper is concerned with the demand for essays in Higher Education. This is an illicit, online and growing market. The demand for essays involves the interplay of risk, penalties and the payoffs associated with cheating and the ethics, norms and risk preferences of the individual facing the option to buy. Since the internet reduces the search costs for the potential buyer of illicit coursework to almost zero, the cheating market is constrained only by supply side capacity and consumers’ willingness to pay. It is the demand for essays which is the focus of this paper.

The market for essays is growing as the nature of plagiarism changes. One of the most significant developments in this regard has been the development of automated plagiarism detection software such as TurnItIn. While effective against ‘copy and paste’ plagiarism TurnItIn is ineffective against original material supplied by commercial contractors. We contend that the use of such anti-plagiarism systems has stimulated the market for commercially provided, original coursework; patterns of plagiarism and plagiarism detection are co-evolving.

There is a huge array of reports on the extent of the plagiarism problem in Universities. The Guardian newspaper reported that 25% of students admitted to some degree of plagiarism in a 2004 national survey. A 2008 survey of 1000 students at Cambridge University found that 49% of those surveyed had plagiarised, with the figure rising to 62% among Law students. In 2011 The Sunday Telegraph used FIO requests to UK universities as the basis for a claim that over 17 000 cases of cheating were recorded in 2009-10, an increase of 50% from four years previously.

Various factors have been identified as accelerating levels of plagiarism. These include the expansion of higher education meaning that students from more diverse backgrounds and with a wider range of skills are enrolled; a more instrumental or extrinsic view of the learning process with greater orientation on the final degree rather than the learning process per se; the introduction of fees and removal of grants which has increased financial and hence time pressures on many students; the increasing range of material available online to students and the associated increased difficulty for staff in recognising plagiarised material.

For the rest of this paper we limit ourselves to consideration of the rise, organisation and economics of the market in commercially provided coursework. This form of plagiarism was labelled ‘Contract Cheating’ (CC) by Clarke and Lancaster (2006, see also 2007, 2008) whose original interest was a particular form of Contract Cheating in which students post details of coding work required (using sites such as rentacoder1) and programmers bid for the work. Associated with each bidding programmer is feedback from previous buyers of their work (à la eBay). Once a bid is accepted, payment is escrowed and released by the intermediary (rentacoder) after delivery of the work. The understanding of Contract Cheating has since broadened to describe the now more typical situation in which students simply place an order for an assignment of a given level (eg 2nd year undergraduate), of given length at a given standard (eg First Class) to be delivered in a given period at a fixed price2.

A major driver of the development of the contract cheating market has been the widespread adoption of anti-plagiarism scanning systems, most notably TurnItIn. Used by over 90% of UK Universities and 9,500 institutions globally this system scans submitted work against a database of over 130 million student papers and 14 billion web pages. While this system may deter some potential plagiarisers, they also have the option of adaptation. Since work from ‘reputable’ CC companies is original it will not be detected by TurnItIn. Indeed many of the major commercial essay providers respond to being defrauded by a buyer (for example by the use of stolen credit cards) by posting the sold essays online in the expectation the essay will become incorporated within TurnItIn’s database and the plagiarising fraudster caught. The use of scanning systems creates incentives to move from a ‘copy and paste’ approach toward the CC market.

1http://www.rentacoder.com
2We note that in 2010 rentacoder rebranded itself as vworker, standing for ‘virtual worker’, as it sought to position itself in a broader market than that only for code.
The information available about this illicit industry is patchy and nearly all concerns the supply side of the market. The market in online plagiarism was estimated to be worth £200m in 2006 and is thought likely to have grown rapidly in the period since. One well known company (UKEssays) is reported to have 3,500 specialist writers with a turnover in 2005 of £1.6m. A JISC Plagiarism Advisory Service (JISCPAS) survey found that 11% of students thought that “buying an essay from a ghost writing service” was common.

This is a market with many particular and interesting features. It is an illicit market and one in which there is strong information asymmetry. In most cases it is very difficult for the novice purchaser to discern the quality of the product that will be delivered (if any is delivered at all). Many of the online companies serially reinvent and rebrand themselves. Observation of the relevant online forums reveals large numbers of students struggling to identify ‘reputable’ companies or complaining about having been defrauded by a particular site. There are also forums in which writers discuss the same issues, identifying problem companies who have not paid them for work they delivered. Informal assessment of the market indicates most sites are scam operations where the buyer receives nothing, or a piece of work of an unacceptably poor standard. This information asymmetry associated with purchasing essays (which are an experience good), saw the bizarre, (and now defunct) initiative to create a ‘quality assurance’ mark for commercial essay providers via the EssayFraud initiative with the stated aim of “protecting students from foreign essays and coursework fraud”.

While there is some evidence regarding the supply side of the market (for example turnover of some of companies, interviews with writers for, and managers of, such companies indicating the scale of the industry) there is very little information on the demand side. However the very limited scope for detection combined with the scale of turnover of the industry lead us to conclude that there is a significant volume of undetected CC material being submitted at UK universities.

We note that historically the detection of plagiarism was left to the individual marker. Detection often occurred because of contrasts in style and/or quality within a piece of submitted work, or across submissions by the same student. Further, we note that the growth in student numbers makes the formation of an expectation by a marker about particular students increasingly difficult and so this mode of detection becomes less feasible. Finally, even where such expectations are formed, the use of anonymised marking means that identifying a discrepancy between the expectation of quality or style and that found in the submitted work is increasingly infeasible. The same trends in Higher Education which are leading to greater levels of plagiarism are also undermining the classical means of detection.

The remainder of this paper concerns the demand side of the contract cheating market, beginning with a review of the literature concerning plagiarists’ motivations and behaviour, to which this paper contributes.

2 The economics and psychology of cheating

There is an extensive body of work within the education and psychology literature investigating the extent and drivers of student cheating. It is of sufficient concern that there have been two special issues of the journal Ethics and Behaviour on the topic in the last decade (2007, 17(3) and 2001, 11(3)). That literature has largely focused on psychological drivers of students’ academic malpractice, in terms of motivations and personal characteristics that lead to (usually) self-reported willingness to cheat, or past cheating, in some form. This research suggests that differences in the motivation for learning, social norms, attitudes and understanding of what represents cheating are all significant in explaining variations in the willingness to commit academic malpractice. Those with high intrinsic motivation regard study as being conducted for its own sake and are less likely to cheat than those exhibiting extrinsic motivation and regarding study as a means to an end (Davey et al 2007, Murdock and Anderman 2006). Perceptions of social norms regarding cheating, especially those of the person’s cohort or peer group, are found to affect the likelihood of cheating (McCabe and Trevino, 1997; O’Rourke et al 2010). The attitudes held by the individual towards cheating, and in particular the ability or inclination to construct neutralizing attitudes that justify the cheating behaviour also play a role. Such a neutralizing attitude might be the justification that a lecturer is incompetent and therefore cheating is justified to pass the unit (Murdock and Stephens, 2007). Finally, knowledge and understanding of what constitutes cheating behaviour affects the likelihood of cheating (Dec and Jacob, 2010).
Although the majority of previous work has been within the fields of education and psychology, an alternative, but related, perspective comes from the economics of crime and punishment, and rational choice (Becker, 1968). There have been few examples applying this approach to academic cheating. Collins et al (2007) and Quandt (2011) develop theoretical models of student behaviour, both within an expected utility framework. Collins et al (2007) develop two models, differentiated by the primary motivation of the student. In the ‘time saving model’ the student has an option to purchase plagiarized material which releases time for additional study, leisure or work. However, the purchase of an essay brings with it an additional (expected) cost associated with the probability of detection and the penalties associated. In the ‘mark enhancement model’ the cheater’s objective is to improve upon the quality of the mark that could be achieved through ‘honest work’. Again, there are direct costs associated with cheating and the maximisation of expected utility implies a tradeoff between the expected return and the costs (direct and the expected costs of being caught). Both models lead to intuitive results: one expects some level of cheating, but it can be reduced by increasing the probability of detection and severity of punishment.

Quandt (2011) also develops two models of plagiarism, the first of which is similar in intent to those of Collins et al. in that the act of plagiarism increases the individual’s utility (represented as a monetary benefit). Quandt incorporates heterogeneity across individuals via variation in the disutility associated with being caught. Quandt’s second model assumes that the cheating takes the form of bribery, that is, a student may pay to have the awarded mark increased. To some extent this is equivalent to plagiarism in that the student pays to increase marks (via the bribe) and trades off the expected costs of being caught, except now the price paid is determined endogenously, as it has to be sufficient to induce a risk averse ‘producer’ (staff member) to change the mark. As with Collins et al, Quandt’s model has increases in detection probability and penalty reducing the level of cheating, although the impact on the value of the equilibrium bribe is ambiguous (because of potential differential impacts on the supply and demand sides of the market).

These formal models generate anticipated outcomes, given their structure. However, whether cheating occurs, and the extent of it, will depend on both the institutional parameters and the individuals’ characteristics. If the utility costs associated with detection are large enough, then even opportunities for cheating which have zero direct costs and low detection rates will not be exploited. Further, the utility costs of detection depend upon the interaction of the penalties imposed and the individual’s characteristics: for some those costs may be so high that cheating would never be countenanced. This provides a point for integration of the formal economic models with the psychology literature outlined above - one can assume that different behavioural motivations will determine the parameterization of the utility function, such that differences in, inter alia, levels of intrinsic motivation result in differential utility being obtained from marks derived from ‘honest work’ as opposed to cheating, or that moral attitudes change the disutility associated with being caught. Another form of heterogeneity will be in risk attitudes, which influence the utility associated with the probability and consequences of being caught. The impact of risk preferences on the willingness to buy coursework is an issue investigated in the empirical work reported in this paper.

While the formal theoretical models discussed above have not been systematically empirically tested, some studies share the intuitions from them in their study design. For example, Teixeira and Rocha (2010) use regression analysis to explain self reported cheating behaviour on the basis of self-reported expected benefits and expected sanction if caught, with significant results with the anticipated signs reported. Ogilvie and Stewart, (2010) conduct a ‘scenario’ analysis in which students were presented with a vignette describing a situation in which a student has the opportunity to cheat, and are asked if they would cheat in that same situation. The probability of detection, and the severity of punishment if caught, were systematically manipulated, to give 4 scenarios. They find that certainty and severity of punishment did not affect likelihood of plagiarism, while perceived sanctions and benefits did have the expected effects. Furthermore, increased academic self-efficacy reduced likelihood of plagiarism. Koh et al, (2010) take a similar approach, but vary the importance of the assignment in terms of its credit load and the time remaining before submission. They found that increased credit load and reduced time to submission both increase the probability of plagiarism occurring.

The approach of the current study is now outlined before the results are presented and discussed.
3 Study Approach & Design

The research reported here uses a discrete choice experiment (DCE) to address students' willingness to buy essays. More specifically it investigates how students' willingness to buy an essay is affected by the essay's price, grade, the risk of being caught and the associated penalties. Similarly we seek to identify the proportion of students who are unwilling to buy an essay no matter how the price, risk etc vary.

We conduct two choice experiments. The first concerns essay choices under a number of different conditions. The second is over a series of consequential gambles. The objective of the second is to identify individuals' risk preferences as we believe a priori that risk attitudes will be important in explaining willingness to buy the illicit essays. The structure of these two experiments is now outlined.

3.1 Choice experiment over essays

Students were asked to consider essays which differed in terms of 4 attributes: price, grade\(^3\), risk and penalty, as shown in Table 1.

### Table 1. Essays' Attributes And Levels

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Levels</th>
</tr>
</thead>
<tbody>
<tr>
<td>Essay grade</td>
<td>1st class, 2(i), 2(ii), 3rd class</td>
</tr>
<tr>
<td>Risk of being caught</td>
<td>None, 1/1000, 1/100</td>
</tr>
<tr>
<td>Penalty</td>
<td>None, 0% for module, Repeat the year</td>
</tr>
<tr>
<td>Price</td>
<td>£100, £50, £75, £25</td>
</tr>
</tbody>
</table>

An experimental design maximising D-Efficiency (Ferrini & Scarpa, 2007; Scarpa and Rose, 2008) was generated to combine the attributes and levels into options and sets. The design comprised 2 blocks of 8 choice sets with each set comprising 4 alternatives. Respondents were randomly allocated to either block of 8 choice sets. The 4th alternative in each set was a “buy none” option. This 'none' option raises an important issue regarding the recruitment of students into a study of this nature. Some students are expected to always choose the None option, whether that be for ethical reasons or because of a fear of choosing to buy. However, for those who consider purchase, then a critical issue is what the “buy none” alternative means for them. That is, the student will consider what will be involved if they decide not to buy and instead write the essay themselves. Consequently it is necessary to ask the participating students for a prediction of the grade they would receive if they completed the work alone. This then defines the None option for each individual: an essay of their own predicted grade with zero penalty, risk and price. The predicted grade will vary across students and across courses/modules. A student might be prepared to buy an essay for one course unit in which they struggle, but not in a unit in which they excel. This means that the research into the willingness to purchase needs to be conducted regarding specific course units, it can not be meaningfully done in a generic setting. This makes the collection of data considerably more burdensome.

\(^3\)The UK undergraduate grading system classifies marks using the categories: 70%+ [1st class], 60-69% [2(i)], 50-59% [2(ii)] and 40-49% [3rd class]. Marks below 40% are classified as fails.
An example essay choice set is shown in Figure 1

**Figure 1. An Example Choice Set.**

<table>
<thead>
<tr>
<th></th>
<th>Buy Essay 1</th>
<th>Buy Essay 2</th>
<th>Buy Essay 3</th>
<th>Buy None</th>
</tr>
</thead>
<tbody>
<tr>
<td>Price of Essay</td>
<td>£50</td>
<td>£100</td>
<td>£75</td>
<td></td>
</tr>
<tr>
<td>Risk of Being Caught</td>
<td>1/1000</td>
<td>1/1000</td>
<td>1/100</td>
<td></td>
</tr>
<tr>
<td>Penalty if Caught</td>
<td>0% for Module</td>
<td>Repeat the Year</td>
<td>0% for Module</td>
<td></td>
</tr>
<tr>
<td>Essay Grade</td>
<td>2(ii) Mark</td>
<td>2(i) Mark</td>
<td>1st Class Mark</td>
<td></td>
</tr>
<tr>
<td>Which would you choose?</td>
<td>✗</td>
<td>✗</td>
<td>✗</td>
<td>✗</td>
</tr>
</tbody>
</table>

3.2 *Choice experiment over consequential gambles.*

We wanted to explore whether individuals' risk preferences affected the impacts of changes in risk and penalty on willingness to buy and pay within the essay experiment. To this end, we implemented a consequential gamble experiment comprising 8 paired gambles of the form shown in Figure 2. Students chose in each case which gamble they preferred to play (A or B). To ensure all gamble choices were consequential, it was explained that one of the gambles would be selected at random and played at the end of the session, with the associated rewards paid in cash. We explain in Section 5 how the gamble choice data allow the estimation of respondent-specific measures of risk aversion which are used to augment the statistical analysis of essay choice. The gambles were presented in this intuitive form but in the analysis were reformulated in terms of their expected payoff and the associated variance.

**Figure 2. An Example Gamble Choice Set.**

### Game 1

- **Game A**
  - 10% chance of £4

- **Game B**
  - 10% chance of £8

**OR**

- 90% chance of £3
- 90% chance of £0.20

**Enter your choice (A or B) here:** I want to play Game ____
4 Recruitment & Sample

To make the choice situations as realistic as possible they had to be presented in the context of a specific piece of work that was due to be submitted not long after the survey was conducted. The process conducted at the 3 universities\(^4\) was to identify a 2\(^{nd}\)/3\(^{rd}\) year module which had a piece of coursework due which accounted for a significant proportion of the unit’s final mark. Then, with the approval of the unit lecturer, students were invited to attend the survey/experiment which was held 2-3 weeks before the submission date. At the session the precise purpose and format of the survey was explained and students given the opportunity to leave. It was made clear that the research was unequivocally based on confidentiality, and had been approved by a University Research Ethics Committee on that basis.

Given the need to identify a suitable unit, obtain the permission of the relevant lecturer, circulate the recruitment letters and then run the session this was a difficult and time consuming recruitment process. In total we recruited 90 students who were a mix of Humanities and Science students. The questionnaire comprised sections concerning demographics and educational past, views and experiences of plagiarism, and the choice experiments over essays and gambles.

5 Modelling Choices

The analysis of the choice experiment data for both essays and gambles is based on Random Utility Theory, and extensions of conditional logit model (McFadden, 1974). The formulation of the random utility choice models employed differs for the gamble and essay data, and these are now outlined.

Assume that individual \(i\) is faced with a choice situation \(t\) with \(M\) alternatives given the attributes in the \(m\)th choice set is the vector \(z_{itm}\. We denote \(Z_{it} = \{z_{itm}\}_{m=1}^{M}\) as the set of attributes defining choice situation \(t\) for individual \(i\) and \(\beta_i\) as the parameters defining the \(ith\) individual’s utility function. The probability that they select alternative \(m\) is given by:

\[
P(y_{it} = m \mid Z_{it}, \beta_i)\]

The conditional logit model of this probability is given by:

\[
P(y_{it} = m \mid Z_{it}, \beta_i) = \frac{\exp(V_{m|z_{itm}, \beta_i})}{\sum_{m'=1}^{M} \exp(V_{m'|z_{itm'}, \beta_i})}
\]

where \(V_{m|z_{itm}, \beta_i}\) is the systematic component of utility derived from the attributes’ levels, which differ across alternatives, and the additive random component of utility is drawn from a Gumbel distribution.

In the case of the consequential gambles it is assumed that the deterministic element of the utility function for alternative \(m\) is a standard mean-variance function defined as:

\[
V_{m|\mu_{itm}, \sigma^2_{itm}, \beta_i} = \exp(\alpha_i) \left( \mu_{itm} + \frac{\tau_i}{2} \sigma^2_{itm} \right)
\]

where \(\beta_i = (\alpha_i, \tau_i)\) and \(\mu_{itm}\) is the expected payoff faced by individual \(i\) in alternative \(t\) in gamble \(m\), and \(\sigma^2_{itm}\) is the variance of that expected payoff. As is well known, the coefficient \(\tau\) can be interpreted as the

\(^4\)Identified here only as Universities A, B and C
Arrow-Pratt Risk Aversion Coefficient (Meyer, 1987). Individual heterogeneity is introduced by making the coefficients of the utility function in (3) individual specific (hence \( \alpha_i \) and \( \tau_i \)). This is done by employing a mixed or random parameter logit model (Revett and Train, 1998), estimated using Bayesian methods (Train and Sonnier 2004; Train 2005; Balcombe et al 2009). \( \beta_i = (\alpha_i, \tau_i) \) is assumed to be a normally distributed random vector with mean \( \bar{\beta} \) conditioned on the student’s gender and university, and a covariance matrix \( \Omega \). Mixed logit estimation involves estimation of the parameters (mean and variance) which define the distribution from which the preferences of those in the sample are drawn.

Estimation also permits inferences to be drawn regarding the preferences of each respondent conditional on that distribution and their individual choices. Bayesian Monte Carlo Markov Chain estimation make this trivial since it requires that latent parameters for each individual are drawn from their posterior distribution. Using \( \{ \beta_i \} | \bar{\beta}, \Omega, D \) to denote a draw of \( \beta \) from its conditional distribution given \( \Omega \) and \( D \), with \( D \) denoting the data (choices made by all individuals), estimation proceeds by taking some arbitrary starting values of \( \bar{\beta} \) and \( \Omega \) and proceeding to draw \( \{ \beta_i \} | \bar{\beta}, \Omega, D \) then \( \bar{\beta} | \Omega, D, \{ \beta_i \} \) and then \( \Omega | \bar{\beta}, D, \{ \beta_i \} \), and repeating this sequence for \( g = 1, \ldots, G \). The first \( g^* \) draws are disregarded so that the draws are approximately independent of their starting values. Accordingly, the draws for \( \{ \beta_i \}^g \) from each iteration \( g \) of the chain can be recorded. The mean values for \( \tau_i \) for each individual can then be calculated as:

\[
\tau_i = (G - g^*)^{-1} \sum_{g=g^*+1}^{G} \tau_i^g
\]  

(4)

For the model estimated on gamble choices the sampler was run for an initial 100,000 iterations, without recording the parameters (the ‘burn in’) followed by another 1,000,000 iterations in which every 100th point was recorded leaving 100,000 values with which to summarise the posterior. Convergence was monitored both visually and using modified t-tests.

In the case of the essay choices, a different approach to individual heterogeneity is taken. There is no reason to believe that risk aversion is discrete in nature, hence the use of a mixed logit model which locates risk preferences on a continuous scale. In the essay choice analysis the expectation was that attitudes towards cheating are polarised. Some individuals have strong ethical objections to cheating while others do not, and hence a discontinuity in preferences was anticipated (we note that 50% of respondents never ‘purchased’ an essay in any of the 8 choice situations). Consequently a latent class model was deemed a more appropriate formulation in the analysis of the essay choice data (Clark et al, 2005) rather than constraining individuals to lie within a given (normal) distribution of preferences.

We model the utility associated with an essay as a linear-in-parameters function of \( P \) attributes, the levels of which vary across the \( m \) alternatives. Additionally, we assume that there are a number of discrete latent classes \( (x = 1, \ldots, K) \) within the sample, which differ with respect to the parameters of the utility function. We define the class specific vector of parameters as \( \beta_{x}^{\text{att}} = (\beta_{x1}^{\text{att}}, \ldots, \beta_{xP}^{\text{att}})' \) and the set of all parameters as \( \beta^{\text{att}} = \{ \beta_{x}^{\text{att}} \}_{x=1}^{K} \). The vector of essay attributes faced by the \( ith \) individual in set \( t \) is \( z_{itm} = (z_{itm1}, \ldots, z_{itmP})' \) and, as above, we denote \( Z_{it} = \{ z_{itm} \}_{m=1}^{M} \). The systematic component of utility for a member of class \( x \), is modelled as:

\[
V_{m|z_{itm}, \beta^{\text{att}}}^{\text{Essay}} = \sum_{p=1}^{P} \beta_{zp}^{\text{att}} z_{itmp}
\]  

(5)

Under the assumption that the errors in the utility function are gumbel distributed we can restate (2) as:

\[
P(y_{it} = m \mid x, Z_{it}, \beta^{\text{att}}) = \frac{\exp \left( V_{m|x,z_{itm}, \beta^{\text{att}}}^{\text{Essay}} \right)}{\sum_{m'=1}^{M} \exp \left( V_{m'|x,z_{itm'}, \beta^{\text{att}}}^{\text{Essay}} \right)}
\]  

(6)
We explicitly model class membership using a multinomial logit functional form, based on a $J \times 1$ vector of characteristics $C_i$ and a set of parameters $\phi = \{\phi_x\}_{x=1}^K$ where $\phi_x = (\phi_{x_0}, \phi_{x_1}, \ldots, \phi_{x_J})$ such that:

$$P(x \mid C_i, \phi) = \frac{\exp(S_{x[C_i, \phi_x]})}{\sum_{x' = 1}^K \exp(S_{x'[C_i, \phi_x']})}$$

where:

$$S_{x[C_i, \phi_x]} = \phi_{x_0} + \sum_{j=1}^J \phi_{x_j} C_{ij}$$

and the restriction $\sum_{x=1}^K \phi_{x_J} = 0$ is imposed for purposes of identification.

The likelihood of individual $i$ making their sequence of choices over the $T$ choice sets faced is:

$$P(y_i \mid \{Z_{it}\}_{t=1}^T, C_i, \beta^{\text{att}}, \phi) = \prod_{t=1}^T P(x \mid C_i, \phi) \prod_{t=1}^T P(y_{it} \mid x, Z_{it}, \beta^{\text{att}})$$

where $y_i$ is the vector of all responses by the $i$th individual. The likelihood function is therefore the product of (9) over all individuals in the sample. Estimation proceeds by maximising this likelihood with respect to $\beta^{\text{att}}$ and $\phi$.

The latent class formulation requires ex ante specification of the number of the classes. We discuss in Section 6 the criteria for identification of, $K$, the number of classes within the sample.

6 Results

6.1 Estimation of Risk Aversion Coefficients

Results from the mixed logit model estimated on the gamble choice data are reported in Table 2. The non-stochastic utility obtained by individual $i$ from alternative $m$ in choice set $t$ is:

$$V_{m|\mu_{itm}, \sigma_{itm}^2, \sigma_i^2}^{\phi} = \exp(\alpha_0 + \alpha_B B_t + \alpha_C C_t + \alpha_{\text{gen}} \text{gen}_i) \left( \mu_{itm} + \frac{\tau_{0i} + \tau_B B_t + \tau_C C_t + \tau_{\text{gen}} \text{gen}_i}{2} \sigma_{itm}^2 \right)$$

where $B$ and $C$ are dummy variables indicating enrollment at universities B and C, and $\text{gen}=1$ if male.

The upper panel of Table 2 reports the mean and standard deviations of the estimates of the mean of the distributions of $\alpha$ and $\tau$, which have been conditioned by university attendance and gender. The lower panel shows the mean and standard deviations of the estimates of the variance of the distributions of $\alpha$ and $\tau$.

Our focus is the degree of risk aversion and hence we focus on the estimated distribution of $\tau$. The estimates of the mean of $\tau$ indicate significant risk aversion at University A, at the mean. The terms $\tau_B$, $\tau_C$, and $\tau_{\text{gen}}$ capture any differences in the mean of the distribution of risk preferences for those groups, with reduced mean risk aversion evident among respondents from universities B and C relative to those from University A. The estimate of $\text{var}(\tau)$ indicate significant heterogeneity around the mean value of risk aversion, in addition to the heterogeneity captured by the dummies for university and gender.
Table 2. Parameter Estimates: Mixed Logit Model on Gamble Choices.

<table>
<thead>
<tr>
<th></th>
<th>mean</th>
<th>st.dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\alpha_0$</td>
<td>2.655</td>
<td>0.482</td>
</tr>
<tr>
<td>$\alpha_B$</td>
<td>-0.857</td>
<td>0.571</td>
</tr>
<tr>
<td>$\alpha_C$</td>
<td>0.118</td>
<td>0.809</td>
</tr>
<tr>
<td>$\alpha_{gen}$</td>
<td>0.295</td>
<td>0.451</td>
</tr>
<tr>
<td>$\tau_0$</td>
<td>-0.297</td>
<td>0.107</td>
</tr>
<tr>
<td>$\tau_B$</td>
<td>0.324</td>
<td>0.115</td>
</tr>
<tr>
<td>$\tau_C$</td>
<td>0.348</td>
<td>0.127</td>
</tr>
<tr>
<td>$\tau_{gen}$</td>
<td>-0.104</td>
<td>0.086</td>
</tr>
</tbody>
</table>

$\text{var} (\alpha_{0i})$ 0.675 0.542
$\text{var} (\tau_{0i})$ 0.076 0.022
$cov (\tau_{0i}, \alpha_{0i})$ -0.039 0.061

N=720; simulated LL = -275.08

Since estimation requires latent parameters for each individual to be drawn from their posterior distribution (see (4)) individual-specific measures of risk aversion ($\tau_i$) are obtained. The motivation is to assess whether these risk preferences play a significant role in the model of essay choice and hence we consider these estimates of risk aversion further when discussing the models estimated on essay choice data, which now follow.

6.2 Estimation of Models of Essay Choice

The choice set attributes in (5) are defined as the price and grade of the essay being purchased (defined as dummy variables) and the risk-penalty regime in which it is available. We specify the risk and penalty attributes as a combined term (Table 3) since the risk attribute has little intuitive meaning if there is no penalty, and vice versa.

Table 3. A Combined Risk-Penalty Measure

<table>
<thead>
<tr>
<th>Probability of Detection</th>
<th>Penalty</th>
<th>risk/penalty dummy</th>
<th>label</th>
</tr>
</thead>
<tbody>
<tr>
<td>1/1000</td>
<td>0% for the module</td>
<td>RP$_0$ : rLpL</td>
<td></td>
</tr>
<tr>
<td>1/1000</td>
<td>repeat the year</td>
<td>RP$_1$ : rLpH</td>
<td></td>
</tr>
<tr>
<td>1/1000</td>
<td>0% for the module</td>
<td>RP$_2$ : rHpL</td>
<td></td>
</tr>
<tr>
<td>1/1000</td>
<td>repeat the year</td>
<td>RP$_3$ : rHpH</td>
<td></td>
</tr>
</tbody>
</table>
Defining $\beta^{att} = \{\beta_{x0}, \beta_{x1}, ..., \beta_{x3}, \delta_{x1}, ..., \delta_{x4}, \varphi_{x1}, ..., \varphi_{x4}\}_{x=1}^K$, we specify the systematic component of utility that person $i$ derives from essay $m$ in choice set $t$ as:

$$V^{Essay}_{m|x, \beta^{att}, z_{i,t}} = \beta_{x0} price_{tm} + \sum_{g=1}^3 \beta_{xg} grade_{tmg} + \sum_{r=1}^4 (\delta_{xr} + \varphi_{xr} \cdot \tau_{i}) RP_{tmr}$$ (11) 

where:

- $grade_{tmg}$ is the grade of the essay in alternative $m$ in choice set $t$.
  For essays offered for purchase this is the level of the grade attribute (specified as $g$ dummies for a 1st through to 3rd class essay, the latter used as the baseline: see Table 1).
  For the ‘none’ option this will be the respondent’s self-predicted grade.

- $price_{tm}$ is the price of the essay in alternative $m$ in choice set $t$;

- $RP_{tmr}$ is the risk/penalty regime (specified as dummies, see Table 3) operational in alternative $m$ within choice set $t$.

- $\tau_{i}$ is the absolute risk aversion score of individual $i$.

- $\delta_{xr}$ is the utility associated with risk/penalty level $r$, for members of class $x$, with $\tau_{i} = 0$.

- $\varphi_{xr}$ is the additional utility associated with risk/penalty level $r$, for a member of class $x$, given a unit increase in individual $i$’s level of risk aversion, $\tau_{i}$.

We now consider the results of the model estimated on essay choice data. Each respondent was presented with 8 choice sets, leading to 720 choice occasions in total. We find that 50% of the sample indicated they would have bought at least one of the essays offered. This 50% proportion of “buyers” was stable across the 3 universities. The frequency of ‘purchase’ was variable across the sample, with 7 people indicating they would buy on each occasion while ten people were persuaded to ‘buy’ on only one of the 8 choice occasions.

Latent class models, using the utility function specification shown in (11), are estimated, with the number of classes specified ex ante. In the absence of a test regarding the appropriate number of classes we follow the established procedure (Clark et al., 2005) of using information criteria (IC) to compare the competing model specifications. The Bayesian Information Criterion (BIC, Schwarz 1978) and the Consistent Akaike Information Criterion (CAIC) suggested a 2 class specification and it is this specification which we proceed to report results from.

While it is possible to segment the sample into classes on the basis only of choices, individual characteristics may be used additionally to explain class membership (see 7, 8). A range of demographic and attitudinal characteristics were tested but only one was found to be consistently significant: English not being the student’s first language ($EAL = 1$, 0 otherwise). The results presented in Table 4 for the preferred 2 class model include this variable.

---

5 We note that, given the illicit nature of the choices examined, an obvious question is whether respondents report their choice behaviour truthfully. In other model specifications we tested for significant misreporting using the Bayesian misreporting framework of Balcombe et al., (2007) and found little or no evidence of a tendency to misreport by over-selecting the “buy none” option. Brevity precludes their inclusion here, but results available upon request.
Table 4. A 2 Class Model Of Essay Choice.

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Class 1</th>
<th></th>
<th></th>
<th>Class 2</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff</td>
<td>s.e.</td>
<td>z-value</td>
<td>Coeff</td>
<td>s.e.</td>
<td>z-value</td>
</tr>
<tr>
<td>price</td>
<td>-0.0196</td>
<td>0.0077</td>
<td>-2.5522</td>
<td>-0.0136</td>
<td>0.0057</td>
<td>-2.3845</td>
</tr>
<tr>
<td>rLpL</td>
<td>-1.5780</td>
<td>0.7588</td>
<td>-2.0795</td>
<td>2.2978</td>
<td>0.5939</td>
<td>3.8688</td>
</tr>
<tr>
<td>rLpH</td>
<td>-2.4843</td>
<td>0.5944</td>
<td>-4.1792</td>
<td>1.7607</td>
<td>0.5716</td>
<td>3.0805</td>
</tr>
<tr>
<td>rHpL</td>
<td>-2.7854</td>
<td>0.6168</td>
<td>-4.5157</td>
<td>1.8133</td>
<td>0.5361</td>
<td>3.3825</td>
</tr>
<tr>
<td>rHpH</td>
<td>-4.2847</td>
<td>0.8402</td>
<td>-5.0998</td>
<td>-0.3405</td>
<td>0.6645</td>
<td>-0.5124</td>
</tr>
<tr>
<td>rLpH * τ</td>
<td>-5.5093</td>
<td>1.2615</td>
<td>4.3672</td>
<td>-1.2434</td>
<td>1.0501</td>
<td>1.1840</td>
</tr>
<tr>
<td>rLpH * τ</td>
<td>-2.8417</td>
<td>1.1540</td>
<td>2.4624</td>
<td>-3.6854</td>
<td>1.2418</td>
<td>2.9678</td>
</tr>
<tr>
<td>rHpL * τ</td>
<td>-2.3375</td>
<td>1.2369</td>
<td>1.8898</td>
<td>-3.8517</td>
<td>1.515</td>
<td>2.5423</td>
</tr>
<tr>
<td>rHpH * τ</td>
<td>-3.5526</td>
<td>2.4867</td>
<td>1.4286</td>
<td>-3.0826</td>
<td>1.993</td>
<td>1.5467</td>
</tr>
<tr>
<td>grade_2(ii)</td>
<td>0.3462</td>
<td>0.0823</td>
<td>0.5074</td>
<td>1.2360</td>
<td>0.422</td>
<td>2.9290</td>
</tr>
<tr>
<td>grade_2(i)</td>
<td>1.9240</td>
<td>0.5985</td>
<td>3.2145</td>
<td>2.0961</td>
<td>0.4048</td>
<td>5.1778</td>
</tr>
<tr>
<td>grade_1st</td>
<td>3.3805</td>
<td>0.6262</td>
<td>5.3985</td>
<td>2.2675</td>
<td>0.4151</td>
<td>5.462</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Class membership:</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Coeff</td>
<td>s.e.</td>
<td>z-value</td>
<td>Coeff</td>
<td>s.e.</td>
</tr>
<tr>
<td>Intercept</td>
<td>0.8861</td>
<td>0.1908</td>
<td>4.645</td>
<td>-0.8861</td>
<td>0.1908</td>
</tr>
<tr>
<td>EAL</td>
<td>-0.9704</td>
<td>0.3005</td>
<td>-3.229</td>
<td>0.9704</td>
<td>0.3005</td>
</tr>
</tbody>
</table>

N=720; LL = -361.3138

We note that this model correctly predicts 83% of the observed choices. For both classes the price term is negative and there is the expected progression of increased utility from essays of higher grade. A striking difference between the two classes occurs in the impact of changes in the risk/penalty regimes. For Class 1 the marginal utilities for risk/penalty are all negative from $rLpH$ through to $rHpH$ and show progressive aversion to the increased severity of the regime. They imply a loss in utility if the purchased essay was of 3rd class quality (the baseline) and the student was risk neutral. The interaction effects between risk/penalty regime and are of the expected sign: increased risk aversion leads to a greater negative utility associated with a more stringent risk/penalty regime. All these interaction terms are significant apart from that associated with the most stringent regime ($rHpH$). This suggests that this regime is so punitive that the disutility associated with it is equal, irrespective of the respondents’ risk aversion level.

For Class 2, the risk/penalty coefficients show the same progression, but here start positive, implying that for risk neutral members the purchase of essays is more attractive than for those in Class 1. These results are suggestive of the possibility that Class 1 represents those who have a strong aversion to the purchase of essays, while Class 2 represents those who are willing to enter into the market if they consider the conditions right.

Not having English as a first language was found to be a significant explanator of class membership: those without English as a first language ($EAL=1$) are significantly more likely to be a member of Class 2. The sample mean class membership probabilities are 0.8 and 0.2 for Classes 1 and 2 respectively. However, the Class 2 membership probability is 0.55 for those without English as a first language, compared to 0.15 for those for whom it is their first language.

A fuller assessment of the interpretation of the behaviours represented by the 2-class model of essay choice requires a formal consideration of willingness to pay (WTP) for essays, and predicted probabilities of purchase, conditional upon class membership. This analysis requires consideration of an additional piece of information: the individuals’ expectation of the grade they would receive for their own work.
7 Essay valuations and probabilities of purchase

Choice experiment data permit estimation of both the value associated with a marginal change in an attribute level and the value associated with switching from one alternative to another. The DCE design was such that the ‘purchased essay’ options always featured a non-zero level of risk and penalty, while the ‘buy none’ option always featured zero risk and penalty. Hence the risk/penalty variables collectively represent both the risk penalty characteristics of a purchased essay and other, unstated, elements associated with purchasing an essay. These include both positive aspects of purchase (savings in time and effort) and negative aspects (ethical or moral qualms associated with the illicit act). The derivation of the WTP associated with an essay needs to take account of the essay’s quality, cost, the risk/penalty regime under which it is bought, and the risk preferences and grade expectation of the potential buyer.

The WTP for an essay will be individual and class specific and can be identified as that price \( \text{price}_{igr} \) at which student \( i \) becomes indifferent between buying an essay of grade \( g \) under risk/penalty regime \( r \) and submitting their own work. We define self predicted grade as \( P \) and hence \( \beta_{xP} \) represents the utility from submitting one’s own essay in the expectation of that grade. Student \( i \) is therefore indifferent between purchase and submission of own work when:

\[
\beta_{xP} = \beta_{x0} \text{price}_{igr} + \beta_{xg} + (\delta_{xr} + \varphi_{xr} \ast \tau_i) \tag{12}
\]

Rearranging (12) yields the maximum price at which the student will purchase:

\[
\text{price}_{igr}^* = \frac{\beta_{xP} - \beta_{xg} - (\delta_{xr} + \varphi_{xr} \ast \tau_i)}{\beta_{x0}} \tag{13}
\]

The parameters in (13) will be class \((x)\) specific and hence one can generate conditional WTP values for each class, or an unconditional value based on the expected probability of class membership. WTP for specific essay conditions are obtained through simulation. Taking 1000 random draws of the parameters, based on a multivariate normal distribution and utilizing the estimated variance covariance matrix of the parameters, a distribution of simulated WTP values is generated (Krinsky and Robb, 1986). This distribution yields median WTP and associated 95% confidence intervals\(^6\) for each essay type.

Figure 3 shows how the valuations of the essays varies with class membership, essay grade, risk/penalty regime and the risk preferences of the buyer, conditional on the buyer predicting a 3\(^{rd}\) class mark if they submit their own work. Table 5 reports these values.

Each of the four panels in Figure 3 show how WTP varies for a different level of risk aversion \((\tau)\). These \( \tau \) values are the 5\(^{th}\) and 95\(^{th}\) centiles of the \( \tau \) distribution (-0.135, 0.64) and the risk neutral (0) and median (0.205) \( \tau \) values. For each of these \( \tau \) values the WTP is shown, for both Class 1 and Class 2, for essays of differing quality and for each of the risk/penalty regimes. It is clear from Figure 3 that, for members of Class 1, there are very few occasions where there is a significant positive WTP value for an essay.

We turn now to the essay valuations of members of Class 2. Considering a risk liker \((\tau=-0.135)\) the WTP for a 1\(^{st}\) and 2\((i)\) class are similar (£348 and £335 respectively). These valuations are fairly stable across the lower three risk/penalty regimes (a 1\(^{st}\) class essay under \(rHpl\) is valued at £317). It is only under the \(rHpH\) risk/penalty regime that the WTP for essays of this quality fall sharply, by approximately half, to £172 and £160 respectively. Thus, even the Class 2 risk lovers’ valuation of the illicit essays are markedly reduced by this high level of risk/penalty. The lower quality essays (2(ii) and 3\(^{rd}\) class essays) have no value under this most stringent regime.

\(^6\)The confidence interval is based on a 1-tail test since our concern is identifying statistically significant positive WTP values.
The remaining 3 panels in Figure 3 report the WTP values for students with increasing levels of risk aversion, from risk neutrality ($\tau=0$) through to strong risk aversion. The valuations fall across all quality and risk/penalty categories, as one would expect. The most risk averse members of Class 2 ($\tau=0.640$) are prepared to purchase all grades of essays under the lowest risk/penalty regime, and the two higher grade essays under the next most lax regime, albeit with values far below those of students who exhibit less extreme risk aversion.

**Fig.3 Variation In WTP for Essays, by Level of Risk Aversion, Class Membership, Essay Grade and Risk/Penalty Regime**

The shaded bars represent the WTP under the 4 risk/penalty regimes (rLpL, rLpH, rHpL, rHpH)
Table 5. Class 2 WTP (£) For Essays Of Differing Quality, By Level Of Risk Aversion And Risk/Penalty Regime.

<table>
<thead>
<tr>
<th>τ</th>
<th>Grade of Essay Purchased</th>
<th>1st</th>
<th>2(i)</th>
<th>2(ii)</th>
<th>3rd</th>
</tr>
</thead>
<tbody>
<tr>
<td>-0.135</td>
<td>r_{LpL}</td>
<td>348</td>
<td>335</td>
<td>271</td>
<td>182</td>
</tr>
<tr>
<td></td>
<td>r_{LpH}</td>
<td>327</td>
<td>320</td>
<td>256</td>
<td>166</td>
</tr>
<tr>
<td></td>
<td>r_{HpL}</td>
<td>336</td>
<td>326</td>
<td>261</td>
<td>170</td>
</tr>
<tr>
<td></td>
<td>r_{HpH}</td>
<td>172</td>
<td>160</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0</td>
<td>r_{LpL}</td>
<td>333</td>
<td>321</td>
<td>260</td>
<td>167</td>
</tr>
<tr>
<td></td>
<td>r_{LpH}</td>
<td>292</td>
<td>287</td>
<td>220</td>
<td>129</td>
</tr>
<tr>
<td></td>
<td>r_{HpL}</td>
<td>295</td>
<td>288</td>
<td>220</td>
<td>131</td>
</tr>
<tr>
<td></td>
<td>r_{HpH}</td>
<td>142</td>
<td>127</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.205</td>
<td>r_{LpL}</td>
<td>317</td>
<td>304</td>
<td>244</td>
<td>150</td>
</tr>
<tr>
<td></td>
<td>r_{LpH}</td>
<td>239</td>
<td>228</td>
<td>165</td>
<td>75</td>
</tr>
<tr>
<td></td>
<td>r_{HpL}</td>
<td>242</td>
<td>230</td>
<td>162</td>
<td>75</td>
</tr>
<tr>
<td></td>
<td>r_{HpH}</td>
<td>95</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.64</td>
<td>r_{LpL}</td>
<td>277</td>
<td>264</td>
<td>199</td>
<td>111</td>
</tr>
<tr>
<td></td>
<td>r_{LpH}</td>
<td>123</td>
<td>111</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>r_{HpL}</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>r_{HpH}</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The WTP estimates in Figure 3 and Table 5 are for a student expecting a 3rd class mark for their own work. These are likely therefore to be the highest values, since it seems unlikely that a student who expects to get a First class mark for the assignment would be WTP as much as someone expecting a Third (although differing marginal valuations of time saved would play a role also). Figure 4 shows the variation in the WTP as the predicted grade varies, holding τ at the sample median value (0.205). Class 2 members who expect to gain a First have much lower WTPs, and these values are positive only under relatively lenient risk/penalty regimes. Reduced own grade expectations increase WTP but the major increase occurs only when the expected grade is a Third. No Class 1 members have a positive valuation of essays at this level of τ.
We consider the probability that a student will purchase an essay. Figure 5 displays the probability of a member of Class 2 purchasing a 1st class essay priced at £300. It shows how this probability of purchase varies with the student’s degree of risk aversion and under each of the 4 risk/penalty regimes. These probabilities are conditional on membership of Class 2. For those with very low levels or risk aversion the probability of purchase are very similar for the 3 least harsh risk/penalty regimes. However as the value of $\tau$ increases the purchase probabilities under $r_{LPH}$ and $r_{HPL}$ regimes fall away markedly. Under the toughest regime the probability of purchase never exceeds 0.2 for Class 2 members, even for the risk preferrers among them. We note that under all but the most stringent risk/penalty regime the predicted probability of purchase exceeds 50% at risk neutrality ($\tau=0$). Under the least stringent regime the probability of purchasing is greater than 50% at the median value of risk aversion (0.205).
Figure 5. Conditional probability of Class 2 member purchasing a 1\textsuperscript{st} Class essay for £300 as $\tau$ and risk/penalty regime vary.

![Figure 5](image)

Figure 6 shows these purchase probabilities but relaxes the Class 2 membership condition. The purchase probabilities are unconditional, derived as the expected probability of purchase over the two classes, using sample mean class membership probabilities.

Figure 6. Unconditional probability of purchasing a 1\textsuperscript{st} Class essay for £300 as $\tau$ and risk/penalty regime vary.

![Figure 6](image)
8 Conclusions

This paper has used the CE method to investigate demand for an illicit good. We regard it as surprising that there has been little or no past use of the method to explore demand for such goods. We investigate the willingness to buy, and willingness to pay for, bespoke, original essays from external commercial providers. It has done so using choice experiments and is the first study of its kind. To investigate these issues meaningfully it is necessary to pose the choices with respect to a realistic scenario for the potential buyer. Given that an individual’s willingness to buy may differ across course units, it is necessary to frame the choices with respect to a specific piece of work on a specific course unit. This approach was employed with a total of 90 students at 3 UK universities. This sample is small (because of the difficult sampling process described above) and while the results are indicative, they are statistically robust and rather disturbing.

Half of the sample, in each of the universities, indicated a willingness to buy one or more essays. Statistical analysis of the choice data reveal that respondents typically considered all of the essay’s attributes, with changes in the levels of all attributes having significant impacts on the probability of an essay being chosen. The WTP value for some in the sample exceeds £350 for a 1st class piece of work. The valuations decline with the quality of the essay, with increases in the risk and penalty associated its purchase and with the individual’s level of risk aversion.

A degree of caution is required when considering results from such stated preference studies as one needs to consider how reliable and realistic the choices, and implicit valuations they reflect, are. When considering such hypothetical bias one is wary of systematic misreporting of preferences. For example, economists often conduct such choice experiments regarding choices where there may be a ‘warm glow’ associated with certain choices, for example choosing to buy a ‘green’ product. This leads to over-valuation of that green product. In this case it might be the case that students might not treat the choices sufficiently seriously and over-report their willingness to buy. However, in this study there may be an opposite effect: the fear of self incrimination may have caused respondents to under-report their willingness to buy. The warm glow of giving might have been replaced by the cold fear of self-incrimination. Given the illicit nature of the choices we tested for significant misreporting using the Bayesian misreporting framework of Balcombe et al., (2007). We found little or no evidence of a tendency to misreport and over-select the “buy none” option.

Although a relatively large number of students revealed a willingness to enter the market, it should be noted that we provided very good conditions for this to occur: some essays presented will have been high quality, cheap, and with relatively low risk and penalty profiles. We also removed one of the main characteristics of the real market: uncertainty about the quality of the good being purchased. Buyers were assured that the essay would be delivered and that it would be of the stated grade. Asymmetric information and the fear of buying a lemon may well prevent many students from participating in the real market. Research extending the approach should address the additional element of risk associated with the unknown quality of the essay delivered.

In conclusion, it is (to us) quite remarkable how many university students indicated a willingness to buy. Their apparent lack of concern at revealing this in a survey run by university academics is startling. The assurances of confidentiality were genuine but the level of purchasing indicated was still contrary to our expectations. Why is there such an apparent lack of stigma in revealing a willingness to purchase coursework? It may be that the ethical line that most lecturers perceive as being crossed when such purchases are made is not that significant to many students. One could argue that in the modern University the student is treated as, and increasingly identifies and mobilises as, a consumer demanding ‘value for money’. Further one could argue that an increasing amount of University teaching is being subcontracted away from tenured academics to PhD students and teaching-only staff on short term contracts. It would appear that the subcontracting of the learning experience extends to increasing numbers of students also, and that buying in the work required to achieve a good degree is seen as just another rational choice by many consumers on campus.
9 References


