On the optimality of escalating penalties for repeat offences against the academic honour code

Mohamad Khattar Awad, Bashar Zogheib & Hamed M.K. Alazemi

To cite this article: Mohamad Khattar Awad, Bashar Zogheib & Hamed M.K. Alazemi (2016) On the optimality of escalating penalties for repeat offences against the academic honour code, Applied Economics, 48:7, 553-562, DOI: 10.1080/00036846.2015.1078444

To link to this article: http://dx.doi.org/10.1080/00036846.2015.1078444

Published online: 27 Nov 2015.
On the optimality of escalating penalties for repeat offences against the academic honour code

Mohamad Khattar Awad\textsuperscript{a}, Bashar Zogheib\textsuperscript{b} and Hamed M.K. Alazemi\textsuperscript{a}

\textsuperscript{a}Computer Engineering Department, Kuwait University, Kuwait City, Kuwait; \textsuperscript{b}Department of Mathematics and Natural Sciences, American University of Kuwait, Salmiya, Kuwait

ABSTRACT

Although academic dishonesty has a long history in academia, its pervasiveness has recently reached an alarming level. Academic dishonesty not only undermines the purpose of education and the assessment process but also threatens the creditability of academic records. We propose a framework for analysing students’ behaviour with respect to academic policies and honour codes. We draw an analogy between law enforcement and academic integrity enforcement and highlight similarities and differences. The proposed framework captures major determinants of academic dishonesty reported in the literature, namely detection probability, punishment severity, class average and record of academic deviance. The framework models both students’ development of nonacademic skills to improve their grades and teaching assistants’ development of detection skills, which both affect the detection probability. Our analysis demonstrates that the optimality of escalating penalties is conditional on the offenders and academic policy enforcers learning. Use-case scenarios are presented to facilitate the implementation of our results in classrooms.

I. Introduction

Recent research indicates that the severity of academic dishonesty has reached alarming levels worldwide, and top-ranked universities are no exception. Cheating among university students is an international phenomenon in all disciplines, although higher rates are reported in business, engineering and humanities (Park 2003). According to one study (Bunn, Caudill, and Gropper 1992), up to 75% of students admit to cheating at least once. The situation is worse in some disciplines; up 96% of undergraduate engineering students admitted involvement in a cheating incident (Carpenter et al. 2006). Similar research conducted in engineering and economics reports a higher rate of cheating among students in these fields (McCabe and Trevino 1993; O’Leary and Pangemanan 2007; Sisson and Todd-Mancillas 1984). The authors of one study (McCabe and Trevino 1996) compared their research, which involved 6000 students at 31 different campuses in 1993, to a study conducted by Bowers (1964), who surveyed 5000 students at 99 campuses in 1963. The authors compared the results for tests and examinations with those for written work. For tests and examinations, the following rates were observed: 26% of students admitted copying from another student in 1963 compared with 52% in 1993; 23% helped another student cheat in 1963, and 37% admitted to this behaviour in 1993; utilizing crib notes was limited to 16% of students in 1963 but increased to 27% in 1993. For written work, only 11% of students admitted to collaborating on assignments requiring individual written work in 1963; 54% admitted this behaviour in 1993. The results for copying material without footnoting, falsifying bibliographies and submitting work completed by another were similar in 1963 and 1993. These results indicate that cheating has increased dramatically over the past 50 years.

The prevalence of dishonesty in academia has motivated researchers to investigate its driving factors and determinants. According to one study (Williams, Nathanson, and Paulhus 2010), students who cheat tend to be those with less academic ability...
or who believe that they are receiving inadequate instructions. Another study (Park 2003) attributes cheating to poor time management skills or insufficient background knowledge. It has also been proposed that students in competitive situations cheat to achieve success (Perry et al. 1990). One group found that cheating is related to age, ethnicity, participation in institutional clubs or sports teams, grades and maturity (Diekhoff et al. 1996). A student’s personality and attitude towards the instructor or the course have also been cited as factors (Park 2003). Additionally, the perceived benefit of grades improved by cheating relative to the perceived penalty of being caught is an important factor (McCabe and Trevino 1993). Several studies (Park 2003) also highlight the risks and consequences of detection.

Various approaches have been proposed to address cheating. For example, cheating can be reduced through verbal warnings of the consequences of cheating and giving open-ended questions (Kerkvliet and Sigmund 1999). Others (Moffatt 1990) believe that cheating can be reduced by using essay questions. It has also been suggested that schools adopt an honour code and make its significance clear to students (McCabe, Trevino, and Butterfield 1999). Some researchers (McCabe, Trevino, and Butterfield 2001) recommend that universities encourage faculty members to report cheating. Implementing technology in the classroom has been found to have positive impact on students’ attitudes towards cheating (Carpenter et al. 2004). Some authors (Bisping, Patron, and Roskelley 2008) note that students should be made aware of the high probability of detection of cheating. Negative correlation has commonly been reported between the propensity to cheating, and the probability of detection and the severity of penalties (Buckley, Wiese, and Harvey 1998; Bunn, Caudill, and Gropper 1992; McCabe and Trevino 1993). Research demonstrated that unethical behaviour during the student’s education has a long-term impact on behaviour (Carpenter et al. 2006). It has been suggested that such students are potential shoplifters (Beck and Ajzen 1991) and may behave unethically at work (Lawson 2004; Nonis and Swift 2001). It may be that students who cheat once find it easier to cheat again; in one study, 42% of college students who were caught cheating admitted that they cheated multiple times (Davis 1993). Engineering students tend to cheat more in college if they cheated in high school and are more likely to cheat again in the future (Carpenter et al. 2006). Students are more inclined to repeat an academic offence if previous attempts were rewarding or did not have negative consequences. Universities have begun adopting academic policies and honours codes that impose escalating penalties for repeat academic offences. For example, the University of Waterloo’s academic policy outlines common academic offences and the corresponding penalties (University of Waterloo 2010). The university’s penalty for plagiarism or cheating in courses graded numerically is a grade of zero on the course element and 5 points off the final course grade. For a subsequent offence, a more severe penalty is imposed, including suspension. An even more severe penalty, including a three-term suspension, is imposed for the third subsequent offence. A fourth offence results in expulsion. Similarly, the academic integrity policies of McMaster University, the University of Victoria and the University of Western Ontario call for more severe penalties (McMaster University 2013; University of Victoria 2014; University of Western Ontario 2013). Under Stanford University’s honour code and Oklahoma University’s academic integrity code, more severe penalties are imposed for repeat or egregious offences (Stanford University 1921; University of Oklahoma 2010). These are selected examples from the US and Canada; many other universities around the world have implemented similar policies. Such academic policies and honour codes hinge on two major assumptions. First, the achievable deterrence is proportional to the perceived severity of the penalty; more severe penalties are applied for repeat offences. This assumption is well established in the field of crime control, in which an offender is considered a rational agent who will refrain from committing an offence if the perceived severity of punishment and the detection probability are high enough to outweigh the benefit of committing the offence. Second, students analysing the benefits and cost of an academic misconduct apply the same decision-making process applied by law offenders in an academic system that is assumed to map onto the judicial system (Michaels and Miethe 1989). We revisit these assumptions to evaluate the effectiveness of escalating penalties in
deterring cheating in academia, where students and invigilators (e.g. teaching assistants (TAs)) improve their cheating skills and invigilation skills, respectively.

Since Becker published his pioneering work on the economic analysis of crime and punishment (Becker 1974), many studies have adopted his approach to analysing individuals’ violation of the law. One report, noting that individuals decide to violate a law based on their analysis of the costs and benefits, provided a theoretical description of unlawful actions undertaken by individuals to maximize their utility (Becker 1974). Several studies of student cheating behaviour have employed this utility maximization model to develop empirical regression models. These studies model students’ decisions to cheat as a function of cheating determinants, that is, regressors, that are either costs or benefits. In a survey of 264 students’ perception towards 31 types of academic misconduct, the authors conclude that educating students on what constitutes academic misconduct and increasing the detection probability of detection are important deterrents (Bisping, Patron, and Roskelley 2008). Data from 573 students in one study (Dee and Jacob 2010) confirm previous results (Bisping, Patron, and Roskelley 2008) and highlight the importance of punishment severity. In one study (Bunn, Caudill, and Gropper 1992), the authors modelled cheating behaviour based on data collected from 476 students and found that the propensity to cheat decreases with the increasing grade point average. A student’s class (e.g. freshman, senior) is also an important determinant of the propensity to cheat (Kerkvliet 1994).

Research on the topic is limited to exploratory, descriptive and regression-based studies that focus on identifying the determinants of unethical behaviour in academia. If controllable determinants can be designed, educators and university policymakers can optimize them to discourage unethical behaviour. Here, using a framework that captures students’ behaviour over two periods and a decision process in reaction to perceived penalties and benefits, we provide insights into how penalties can be optimized in order to deter students from engaging in such behaviour. The proposed framework captures various determinants of the decision to commit academic offences. The examined determinants – detection probability, punishment severity, class average and record of academic deviance – have been examined in previous exploratory studies on this topic. Moreover, the framework encompasses students’ development of cheating skills to obtain higher grades and TA’s development of their detection skills, and how both types of learning affect the probability of detection. The framework also provides guidelines for course instructors to develop their cheating-deterrence policies.

The remainder of the article is organized as follows. The following section describes the student behaviour model. The decision-making process is presented in Section III. In Section IV, the optimal deterrence strategy is derived. Finally, we provide concluding remarks in Section V.

II. Modelling student behaviour

The proposed framework corresponds to a setting common to most academic institutions. Many academic institutions around the world published their academic discipline policies and honour codes on websites and in their course catalogues. Policies include academic principles, various academic and nonacademic offences, and the corresponding penalties (McMaster University 2013; Stanford University 1921; University of Oklahoma 2010; University of Victoria 2014; University of Waterloo 2010; University of Western Ontario 2013). Thus, students are aware of the potential penalties before making a decision to commit an offence. Various factors affect students’ attitudes towards cheating; however, the common objective is improving their grades. The gain in grades, \( g \), derived by committing an offence varies from one student to another; this variation is captured by a grades distribution function \( Z(g) \) where \( g \in [0, \tilde{g}] \). \( \tilde{g} \) represents the maximum grade improvement that can be obtained by committing an academic offence, e.g. turning in work completed by others, cheating on an exam, and using crib notes. Previous work (Bisping, Patron, and Roskelley 2008) lists 31 possible academic offences. The instructor or TA detects academic offences with probability \( p(r) \) where \( r \) is the reward gained by detecting an academic offence. The reward here refers to reduction in time and effort assessing a student’s work and providing feedback. Given a large number of assignments they have to evaluate, TAs might find it easier to check for cheating and, if indicated, give a grade
of zero for the whole assignment than to read the work closely and provide feedback. This is particularly true in science and engineering courses in which detecting cheating is as simple as comparing lines of code or comparing chosen mathematical variables. TAs can easily skim through students’ submitted solutions and compare students’ approaches to solve the assignment to detect cheating and reduce their workload. One engineering TA said, ‘Grading homework is so fast when they [students] all cheat and use the illegal solutions manual’ (Young 2010). The recent development of software to detect plagiarism and assess originality, e.g. Turnitin and ithenticate, facilitates recognition of academic dishonesty in written assignments. Therefore, the reduction in a TA’s workload can be considered a reward, \( r \), that is equivalent to grades of the reported assignments, that is, the student work that the TA avoids grading. This implies that the detection probability is an increasing function of \( r \).

Research indicates that students’ previous experience with violating academic integrity policies influences students’ future behaviour. The results of one survey (Bunn, Caudill, and Gropper 1992) indicated that 28% of the respondents knew students who routinely cheated on exams. In the same study, only 7% of those who answered ‘Yes’ to ‘Have you ever cheated on a test or a written assignment?’ were caught. To capture variation in students’ behaviours over time, three types of students are considered: students of integrity who never violated the code of academic conduct (type \( I \)); students who committed an at least one offence but were never caught (type \( NC \)) and students who were caught at least once (type \( C \)). The general approach adopted for modelling student behaviour is based on previous work (Mungan 2010) that models law-breaking behaviour and decision-making. A high correlation among students’ previous, current and future unethical behaviours has been reported (Beck and Ajzen 1991; Carpenter et al. 2004; Lawson 2004; Nonis and Swift 2001). Figure 1 shows the alternative scenarios students have over two periods.\(^1\) During the first period, all students are assumed to start as type \( I \) students. The probability of detecting an offence committed by a type \( I \), \( NC \) or \( C \) student is denoted by \( p^I(r) \), \( p^{NC}(r) \) and \( p^C(r) \), respectively. The TA is indifferent between type \( I \) and type \( NC \) students because no offence was detected. These students are referred to as clean-record \( CR \) students. The above description is illustrated in Fig. 1. A student’s future type depends on his or her actions and detection outcomes. For example, a type \( I \) student faces three choices: the student does not commit an offence and remains the same type; the student commits the offence but is not caught with probability \( 1 - p^C(r) \) and becomes type \( NC \); alternatively, the student commits the offence and is caught with probability \( p^C(r) \) and becomes type \( C \); during the second period, the probability of detection depends on the student type at the end of period 1. A penalty \( f^{CR} \) is imposed when a type \( CR \) student commits an academic offence; \( f^C \) is imposed for type \( C \) students. This work focuses on finding the optimal \( f^{CR} \) and \( f^C \)

\(^1\)A period refers to a time period of an arbitrary duration over which a student makes a decision about committing an academic offence.
in a penalty scheme that aims to maximize the level of academic integrity among students.

Students develop their cheating skills with each academic violation they commit. They learn how to subvert the TA’s techniques for spotting cheating and plagiarism (Davis 1993). This assertion is supported by a type $C$ student’s assessment of education ‘It’s like you [are] not really there to learn anything. You [are] just learning to run the system’ (Vojak 2006). Students learn to modify their submissions, mathematical variables, assumptions and wording to make the plagiarized work distinct enough to avoid detection. Compared with type $I$ students, type $NC$ learn that their approach to avoiding detection is successful. Similarly, students who are caught cheating might acquire additional details of the detection mechanisms and utilize this knowledge to avoid future detection. To illustrate these changes in probabilities, consider the following scenario. A student with accesses to the textbook solutions manual decides to submit copies of the ideal solutions. If the transgression is not detected, the student learns that it is a safe offence and develops his or her cheating skills by modifying the approach while subsequently submitting the same final answer. This reduces the probability of detection for type $NC$ students to be less than or equal to the probability of detection for type $I$ students. In cases of mistakes in the solutions manual, the TA detects the offence because that solution is not possible, and the student learns that solutions must not only be presented differently but also be checked to ensure that it is a possible solution. Based on this information, the probability of detecting cheating by type $C$ student declines relative to probability of detecting cheating by a type $NC$ student. If the student does not learn, or know how, to check the answers, the probabilities remain the same; this situation is represented by the possible equality of all three probabilities. Therefore, the three detection probabilities can be represented as follows: $p^C(r) \leq p^{NC}(r) \leq p^I(r)$. The decrease in detection probability from $p^I(r)$ to $p^{NC}(r)$ is proportional to the knowledge gained by a student $K^I_{NC}$. Similarly, the knowledge gained from being caught cheating, denoted by $K^C_{NC}$, is proportional to the reduction in the detection probability from $p^{NC}(r)$ to $p^C(r)$. On the other hand, the TA learns students’ approaches to violating the honour code and academic policies. In addition, the TA blacklists students who have been caught and carefully reviews their subsequent submissions; this process increases the probability of detection $p^C(r)$ to $p^{C+}(r)$. This increase is proportional to the knowledge, $K^{TA}$, gained by the TA about misbehaving students. The changes in the detection probabilities are illustrated in Fig. 2. The knowledge gained by the TA relative to the knowledge gained by the student plays a vital role in determining the optimal penalties. On Fig. 2, we show two possible values of $K^{TA}$.

### III. Academic offence decision-making

A student’s decision to commit an offence in either period depends on the expected payoff gained in terms of grades and expected cost in terms of penalties. A student will cheat in a given period if and only if the grade gain is greater than the expected penalty. Specifically, a student of type $I$ commits an academic offence iff $g > p^I(r) \times f^{CR} + (1 - p^I(r)) \times 0$. Similarly, $NC$ and $C$ students commit an offence iff $g > p^{NC}(r)f^{CR}$ and $g > p^C(r)f^{C}$, respectively. Table 1 tabulates the students’ decisions during period 1 and period 2, the possible consequences and the corresponding penalties. An offence committed by a student in period 1 would be detected by the TA with probability $p^I(r)$, or not detected with probability $1 - p^I(r)$. Because all students begin period 1 as type $I$, the penalty is $f^{CR}$. Thus, the resulting expected payoff is

![Figure 2](image)

**Figure 2.** The probability of detecting academic offences based on the student type, knowledge gained by the student about the detection mechanisms, $K_{NC}^{I}$ and $K_{NC}^{C}$, and knowledge gained by the TA about the cheating approaches, $K^{TA}$. Note that $K^{TA}$ can be smaller or larger than $K_{NC}^{C}$. The diagram illustrates both possible values.
where $[.]^+ = \max(\cdot, 0)$. Table 1 shows that all students have two possible decisions in the second period regardless of whether they were caught: commit an offence or refrain. The expected payoffs during second period depend on the students’ previous behaviour, which determines the detection probability and penalty. The different expected payoffs are tabulated in the second to last row of Table 1.

The decision variables described above model students’ decisions during a specific period for a given penalty and history. The model is limited to independent incidents during which a student decides to cheat in a particular scenario. For instance, a student who lacks the time management skills tends to cheat when being under pressure to meet multiple deadlines (Park 2003). Modelling the behaviour and decision-making process of students who adopt cheating as an approach to improve their grades can be achieved by considering students’ possible type changes, penalties and payoffs over both periods. For a student committing an academic offence during the first period and making either decision during the second period, the expected payoff over both periods is

$$P_O = [g - p^I(r)f^{CR}]^+ + p^I(r)[g - p^{C^+}(r)f^C]^+ + (1 - p^I(r))[g - p^{NC}(r)f^{CR}]^+$$

However, students who decide not to commit an offence during the first period face an expected payoff equivalent to

$$P_{NO} = [g - p^I(r)f^{CR}]^+$$

over both periods. Students are aware of their university’s penalty policies and compare the expected payoffs in Equations 2 and 3 to decide whether to adopt a cheating approach in the first period, if $P_O > P_{NO}$. Knowing students’ decision-making process and behaviour, university policymakers and instructors can determine $f^{CR}$ and $f^{C^+}$ to deter cheating and promote academic integrity.

**IV. Optimal deterrence strategy**

Although academic dishonesty creates intangible negative consequences, in this work we are interested in measurable, tangible consequences. In academic settings where instructors curve-fit students’ grades to a particular distribution or scale grades to meet a predefined grade average, students’ grades are correlated. In such competitive environments, an increase in one or more grades inflates class average and decreases the remaining grades. In addition, type $I$ students might be discouraged from studying when cheating students obtain higher grades, which negatively impacts performance and grades. We refer to the reduction of students grades due to the academic offences committed by others as the harm, $h$. TA’s strong temptation to reduce their workload by detecting academic offences increases the probability of detection. The detection probability is an increasing function of the reward $r$ which is equivalent to the summation of all reported assessments methods (i.e. the assignments that the TA avoid grading) grades; therefore, students’ grades are reduced by an amount, $r$. 

<table>
<thead>
<tr>
<th>Decision</th>
<th>Offence</th>
<th>Penalty</th>
<th>Payoff</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period 1</td>
<td>Detection</td>
<td>C with probability $p^I(r)$</td>
<td>NC with probability $1 - p^I(r)$</td>
</tr>
<tr>
<td>Penalty</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Decision</th>
<th>Offence</th>
<th>Penalty</th>
<th>Payoff</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period 2</td>
<td>Detection</td>
<td>C, $p^{I+}(r)$</td>
<td>NC, $1 - p^{I+}(r)$</td>
</tr>
<tr>
<td>Penalty</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Payoff</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** NO, no offence; C, caught; NC, not caught.

*Arrow points to subsequent event in the process.

© 2013 IEEE. Reprinted with permission from TALE 2013.
In this section, we propose a law enforcement approach (Polinsky and Shavell 2007) to maximize students’ academic welfare. We introduce the term academic welfare to refer to the grades increase that students gain from their academic decisions and behaviour, less the harm caused to the rest of the class, less the reward gained by the TA. The students’ gain is reduced by the harm caused by their academic offences and the TA’s rewards. Students are assumed to be rational and risk-neutral in the sense that they commit the academic offence if and only if the gain exceeds the expected penalty. In other words, academic offences are committed if \( g > p^{T}(r)f^{CR} \) for type I, \( g > p^{NC}(r)f^{CR} \) for type NC, and \( g > p^{C+}(r)f^{C} \) for type C students. As a result, over both periods, students adopt the cheating approach if \( p_{O} > P_{NO} \). Based on the above description, the academic welfare function can be captured by

\[
\begin{align*}
\frac{\bar{g}}{p^{T}(r)f^{CR}} (g - h)Z(g)dg \\
+ \frac{\bar{g}}{p^{NC}(r)f^{CR}, p^{NC}(r)f^{C}, p^{C+}(r)f^{C}} (g - h)Z(g)dg - r
\end{align*}
\]

In the proposed framework, \( r \) and \( p(r) \) are variables; therefore, an expected fine, that is, \( p^{NC}(r)f^{CR} \) and \( p^{C+}(r)f^{C} \), can be achieved by raising/lowering the penalty and lowering/raising the reward (Polinsky and Shavell 2007). Although TAs face the temptation to increase their reward, \( r \), which is inversely proportional to their work load, the reward is limited to the total grades of assignments in which the TA detected cheating, \( \max(r) \). The optimal TA rewards are not determined by the college or department but rather by students’ behaviour. The more students cheat, the higher the potential reward \( r \) and the smaller the TA’s workload. Lowering \( r \) corresponds to turning a blind eye to academic offences and is considered unethical. Conversely, increasing \( r \) to the maximum possible value is educationally desirable and increases the level of integrity. The optimal \( r \) is therefore \( r^* = \max(r) \), that is, grades of all incidents of cheating that are reported. This implies optimal detection probabilities of \( p^{T}(r^*) \), \( p^{NC}(r^*) \) and \( p^{C+}(r^*) \). Practically, TAs should be motivated to do their best to detect academic offences in order to improve academic integrity in the course and reduce their workload.

A student’s wealth of grades, \( w \), is considered the cumulative sum of assessments’ grades in a course; \( w \) is larger than the possible harm caused to others and any penalties imposed. In the economics of crime literature, incorporating the benefits of crime into the social welfare function has been controversial (Curry and Doyle 2012; Dharmapala and Garoupa 2004). For example, including money stolen from a bank in the social welfare seems unethical and socially undesirable. From an academic perspective, counting all students’ grades towards the class average is a common practice. Thus, including grades obtained via academic offences in the academic welfare function (4) is completely uncontroversial. Another unique quality of the academic settings is that the harm-relative excess gain does not compensate for the harm caused to others; even efficient offences\(^2\) are not desirable. In other words, although the extra grades derived from an academic offence could be higher than the loss in other students’ grades, the difference is not redistributed to other students to compensate for the harm caused. Unlike judicial system in which reducing the high cost of enforcement is desirable, in academia, enforcement has no financial value and maximizing it is desirable.

On the basis of these conditions, complete deterrence is optimal especially when a high enforcement cost, \( r \), is educationally desirable. University makers of policy and professors maximize academic welfare in Equation 4 while aiming for complete deterrence through optimized penalties denoted by \( f^{CR} \) and \( f^{C} \).

Given the academic welfare function in Equation 4, complete deterrence can be achieved by imposing expected penalties equivalent to, or higher than, the maximum possible gain. Mathematically, complete deterrence can be achieved when

\[
\begin{align*}
\frac{p^{T}(r^*)f^{CR}}{g}, \\
\frac{p^{NC}(r^*)f^{CR}}{g} \geq \bar{g} \quad \text{and} \\
\frac{p^{C+}(r^*)f^{C}}{g} \geq \bar{g}
\end{align*}
\]

Since \( p^{NC}(r^*) \leq p^{T}(r^*) \), the optimal penalties are as follows:

\(^2\text{In the economics of crime literature, efficient offences refer to offences that result in a gain greater than the harm caused.}\)
\[
f^{CR} \geq \frac{\bar{g}}{p^{NC}(r^*)} \quad (5)
\]
\[
f^{C} \geq \frac{\bar{g}}{p^{C+}(r)} \quad (6)
\]

With respect to payoffs in Equations 2 and 3, it is clear that with penalties (5) and (6), students’ expected payoff is zero which is insufficient incentive to commit an academic offence. The ultimate objective of academic policies is to discourage students from committing academic offences rather than to lower their average grade. Therefore, an adequate set of expected penalties would be the lowest possible, that is,

\[
p^{NC}(r^*)f^{CR} = \bar{g} \quad (7)
\]
\[
p^{C+}(r^*)f^{C} = \bar{g} \quad (8)
\]

Section II establishes that \(p^{NC}(r^*)\) decreases to \(p^{C}(r^*)\) by a magnitude proportional to \(K^{NC}\). The latter increases to \(p^{C+}(r^*)\) by an amount proportional to \(K^{TA}\) (see Fig. 2). On the basis of these observations, the severity of the punishment can be related to a student’s record of academic offences and the amount of knowledge gained with respect to cheating and detection by the student and TA, respectively. Based on Equations 7 and 8, both expected fines are equal to the maximum possible gain, \(\bar{g}\); thus, a decrease in the detection probability enforces an increase in the penalty and vice versa. At the same time, a decrease in the detection probability is controlled by knowledge gained. If the knowledge gained by the TA is less than the knowledge gained by the student, \(K^{TA} < K^{NC}\), then \(p^{C+}(r^*) < p^{NC}(r^*)\) and the penalty increases from \(f^{C}\) to \(f^{C}\). Based on Equations 7 and 8, the penalty for a first offence is \(f^{C} = \frac{10\%}{0.5} = 20\%\). This translates to a zero on assignment 1 (loss of 10%) and additional 25% off the final examination grade (an additional loss of 10%). For a second offence, the penalty is \(f^{C} = \frac{10\%}{0.4} = 25\%\). The student receives zero on assignment 2 (a loss of 10%) and an additional 37.5% off the final examination grade (a loss of an additional 15%). A student who commits two offences loses 45% of the total course grades. The same logic is applied to any subsequent offences until the student fails the course. If the probabilities of detection for the first and the second offences are the same, then a fixed fine of 20% would be optimal for each offence. However, if the detection probability for the second offence was greater than the first offence because the TA has identified a student as a cheater and therefore detects offences committed by the same student with a higher probability, then fixed penalties would be optimal too.

V. Conclusions

This article provides a model of students’ behaviour and decision-making process with respect to violation of academic policies. The framework represents a common academic setting that would apply to most academic institutions. Detection probability, penalties, grades improvement, grader incentive and cheating record are among the considered determinants of cheating. We assume that students are rational and risk-neutral actors who commit academic offences if the benefit in terms of grades is higher than the perceived cost. Two major results are presented. First, complete deterrence is achieved...
when the expected penalty is higher than the maximum possible gain. Second, increasing penalties are not always optimal to punish repeat offences when learning by both offender and TA is considered.

This study is primarily concerned with rational and risk-neutral students. Our future research will focus on irrational students who commit offences irrespective of the severity of the penalty or the increase in grade.

Acknowledgement

The authors thank Murat Mungan for very informative discussions on the topic.

Disclosure statement

No potential conflict of interest was reported by the authors.

Funding

This work was supported by Kuwait University [research grant number EO03/13].

References


TALE. 2013. “A Penalty Scheme for Academic Dishonesty.” In IEEE International Conference on Teaching, Assessment and Learning for Engineering (TALE), Kuta, August 26–29, 580–584. IEEE.


