

Why Competition may Discourage Students from Learning? A Behavioral Economic Analysis

X. HENRY WANG & BILL Z. YANG

ABSTRACT *Combining the notion of self-worth in sociology and educational psychology with economic modeling, the present paper studies incentives on students' learning in a behavioral economic model. Allowing for 'conservativeness' to modify Bayes' rule in processing newly released information and employing the concepts of 'loss aversion' and 'endowment effect' in behavioral economics, we attempt to explain analytically why competition among students may discourage them from learning. Within an educational institution, competition as an incentive scheme evaluates students on their relative performance, which strengthens the connection between students' relative performance and their perceived ability. When the perception of ability becomes a major concern, competition may motivate students to make a low effort – a strategy to win by not losing.*

Keywords: competition, incentive, motivation, effort, ability, perception

Introduction

Education is always one of the major concerns of a modern society. One of the current hot issues in the USA, for example, is whether a voucher system should be employed as a competitive mechanism to enhance the quality of education.¹ From the perspective of economics, a basic question is whether 'competition among public schools benefits students and taxpayers' (Hoxby, 2000). A related topic within an educational institution is whether competition among students can help motivate them as an effective incentive scheme? Since competition has been intensively employed to enhance performance and economic efficiency among firms in the market system and among employees within an organization, a traditional wisdom is that competition among students should help motivate them and hence improve the quality of education.

Does competition among students motivate increased effort? Although competition is a well-accepted concept in Western societies, many educational experts and psychologists realize that competition among students for limited

X. H. Wang, Department of Economics, University of Missouri-Columbia, Columbia, MO 65211 USA.
B. Z. Yang, Department of Finance and Economics, Georgia Southern University, Statesboro, GA 30460-8151 USA. E-mail: billyyang@gasou.edu

rewards such as good grades leads to an 'ability game' (Covington, 1992, 1998). In this competitive learning game, students are ranked on their relative performance. Then one's rank within a group is interpreted as the perception of her/his ability. When students realize that higher ability will potentially increase career success, they would attach their self-worth² to their perceived ability. Increased scarcity of rewards under competition can strengthen the connection between one's self-worth and her/his perceived ability. Because effort is a substitute of ability in determining performance, hard work followed by failure can be indicative of low ability. Consequently, when self-worth becomes a major determinant of behavior, even capable students may lower effort, a winning-by-not-losing strategy. The present paper formalizes this self-worth effect in a behavioral-economic model and articulates how competition may change students' incentives to learn.

In the literature on economics of education, Hoenack (1994) classifies research in education economics into three main categories: (1) educational institutions and labor markets, (2) educational institutions as an industry, and (3) educational institutions as organizations. The topic studied in the present paper is in the third category. In the sub-area of behavior within an educational organization, such as students' incentive and motivation, Correa and Gruver (1987) have developed a game theoretic model to the grading policy and students' incentive to learn and performance. Based on data from upper secondary schools in Norway, Bonesronning (1999) further extends the Correa and Gruver model to examine the causes and consequences of teachers' grading policy, concluding that grading practice is determined by teachers' characteristics and that hard grading improves student achievement. However, as Hoenack noted, 'little attention has been given by academics to the question of incentives on students' (1994, p. 153).

Behavioral economics studies human fallibility by combining psychology and economics.³ It aims at providing more realistic description and analysis of human decision behaviors. Most research work focuses on financial decision such as saving and spending, while this paper attempts to apply the concepts and the principals from behavioral economics to study the incentive on students' learning. For example, self-worth is introduced into a student's objective in addition to grades to describe how students may actually make a choice in effort. Also, when deriving a 'posterior' belief we relax Bayes' rule to allow for 'conservativeness' in processing newly released information.⁴ Furthermore, principals in behavioral economics such as 'loss aversion' and 'endowment effect' (Kahneman *et al.*, 1991) are employed when we explain why students' concern over their self-worth tends to discourage them from learning under competition.

The second section introduces a benchmark model in which students are only concerned about their grades. The following section develops a model of self-worth, wherein a typical student's objective includes both expected grade and perceived ability. Analysis and results are provided in the fourth section, followed by further discussion on the self-worth effect. The final section concludes the paper.

A Benchmark Model

In a classroom, grading policy specified in a syllabus serves as an extrinsic incentive scheme to motivate students' effort. It attaches rewards such as letter

grades to students' academic performance, evaluated in absolute or relative terms. Under a given grading policy, a student's performance is determined by her/his effort and ability, plus some random factors. Formally, in a given institution, a student's academic performance, measured in scores, S , is determined as follows:

$$S = S_0 + [(1 - g)t_A + g t_R] e + \varepsilon$$

where e is the student's choice in effort level, S_0 is a constant for a certain score that a student can earn with previous knowledge or common sense, and ε is a random variable with $E(\varepsilon) = 0$, reflecting the random effect on the examination outcome. The coefficient of effort is a convex combination of two parameters: 'absolute' ability t_A and relative ability t_R (see the next paragraph for more detailed discussion). It indicates two points: first, that ability and effort are substitutes; second, that ability determines the marginal productivity of effort. The value g features grading policy as an incentive scheme; a larger g value indicates a heavier weight on relative performance within a class. For example, in a polar case when $g = 0$, performance is determined by effort, 'absolute' ability of the student, and random factor, but is independent of the relative performance within the group. Both t_A and t_R are treated as unknown random variables. The absolute ability t_A follows a distribution with the mean being $E(t_A)$. And the relative ability t_R follows a two-point distribution on $\{t_H, t_L\}$, $t_H > E(t_A) > t_L$, with a *prior* probability of $P\{t = t_H\} = p_0$. We may interpret p_0 as a student's *ex ante* perceived relative ability, with a larger p_0 value representing a higher perceived relative ability.⁵

It is worth discussing the concepts between absolute and relative ability in a bit more detail. By nature, ability is a relative concept. It is measured against a standard. If the standard itself is preset independent of the relative performance of a specific group, it appears to measure in an absolute term. If the standard is based on the relative performance within the group, it measures a relative ability. For example, for a given examination the percentage mark measures a student's performance in an absolute term-how much percent of the problems she/he has done correctly. However, if a letter grade is determined by the rank within a class, then it only reveals relative performance. Note that the degree of difficulty in examination questions differs among different schools/classes/instructors. Hence, the so-called 'absolute' performance in percentage score is essentially measured relatively, because it is relative to the examination questions. From the students' perspective, however, it appears to be in an absolute term, because it seems to be independent of how others perform in the same group. Alternatively, the 'absolute' performance can also be interpreted as the relative position in a larger scope. In the USA, for example, in nationwide standard achievement tests such as the SAT or ACT, a student's score is actually her/his relative performance within the whole generation in that country. In the college admissions process, these scores are treated differently from the GPAs in the admission formula. The former may indicate how good the student is in verbal and mathematics compared with all applicants (a kind of absolute performance), whereas the latter may mainly reflect the student's performance in her/his class or school. Since in a given educational institution (in particular, university/college) students are statistically at a similar level, the 'absolute ability' can also be interpreted as the average ability of the group.⁶

A standard micro-economic approach models a typical student to solve the following benchmark problem:

$$\text{Max}_e E(S - c(e) = S_0 + [(1 - g) E(t_A) + g E(t_R)] e - c(e) \quad (1)$$

where $c(e)$ is the cost of effort with $c' > 0$ and $c'' > 0$. The optimal solution of e^* is obtained from the first-order condition: $(1 - g) E(t_A) + g E(t_R) = c'(e^*)$. Since $c'' > 0$, a greater e^* value will be resolved if the marginal productivity of effort [i.e., $(1 - g) E(t_A) + g E(t_R)$] increases. That is, the optimal e^* value depends on the parameters $E(t_A)$, $E(t_R)$ (i.e., the p_0 value) and g .

Let us first examine the determination of e^* when $g = 0$. That is, when a grading policy puts no weight on relative performance. In this case, the first-order condition becomes $E(t_A) = c'(e^*)$. For illustrative purpose, we further specify that t_A follows a two-point distribution on $\{t_{AL}, t_{AH}\}$, where $t_{AL} < t_{AH}$, and $\text{Prob}\{t_A = t_{AH}\} = \alpha$. Then, $E(t_A) = (1 - \alpha) t_{AL} + \alpha t_{AH}$. We can see that as α and/or t_{AH} increases, $E(t_A)$ increases. Hence, it results in a greater e^* value in the equilibrium. Note that the effort choice in this case is independent of the perceived relative ability. We put it in the following proposition.

Proposition 1. Assume that students maximize $E(S) - c(e)$, and that the grading policy puts no weight on relative performance (i.e., $g = 0$). Then a student would make a greater effort if she/he perceives a higher the probability of doing well, or if her/his good mark is absolutely higher. But the student's choice in effort is independent of the perceived relative ability.

When a grading policy introduces competition among students and evaluates performance in terms of relative position within a class, a student's choice in effort is also influenced by perceived relative ability. In this case, $g > 0$, and the first-order condition is: $(1 - g) E(t_A) + g E(t_R) = c'(e^*)$. We can see that both g and $E(t_R)$ will affect the optimal choice in effort.

Proposition 2. Assume that students maximize $E(S) - c(e)$, and that a student's grade is determined by relative performance within a class (i.e., $g > 0$). Then,

- (a) those perceived better students (i.e., those with larger p_0 and hence larger $E(t_R)$ values) will make greater efforts than other students with smaller p_0 and $E(t_R)$ values;
- (b) the more competitive an incentive scheme is (i.e., the larger the value of g), the more effort those perceived above-average students [i.e., those with $E(t_R) > E(t_A)$] may make, and the less effort those perceived below-average students [i.e., those with $E(t_R) < E(t_A)$] may make.

The results in this proposition are consistent with our casual observations on campus. Many students study harder in the beginning of a semester than they do later in the semester, and those better students seem to work consistently harder than others. Also, increasing the extent of competition increases the effort of students with higher relative ability. Note that a competitive atmosphere more or less exists on campus. In the beginning of a semester, thanks to overconfidence, most students may extend effort.⁷ However, as students learn more about their relative position in a class, those perceived better students continue to exert effort while below-average students decrease effort. In this benchmark model, competition among students as an incentive scheme can motivate above-average students at

a cost of discouraging below-average students. We will shortly demonstrate that competition may even discourage many ‘better’ students from making a greater effort when they are concerned about their self-worth.

A Model of Self-Worth

According to the self-worth theory in educational psychology, grades are not the only concern of many students. They also care, if not more, about the perception of their ability, which is determined by their relative performance.⁸ When students get old enough, they start to realize the importance of ability in determining their grades and, more importantly, their career path. In a tournament-like competitive learning game, evaluation of performance is based on rank. It naturally leads students to interpret one’s relative performance as her/his ability. To be seen as intelligent or capable in a class becomes as important as a good grade *per se* (Covington, 1992, 1998).

We now incorporate the concept of self-worth into a student’s effort-choice problem. A typical student is assumed to solve the following reduced form of a ‘pseudo-dynamic’ program:⁹

$$\begin{aligned} \text{Max}_e ES - c(e) \text{ } v \text{ } E_e[p_1(S, e)] = S_0 + [(1 - g)t_A + g E(t_R)] e - c(e) \\ + \text{ } v \text{ } E_{ge}[p_1(S, e)] \end{aligned} \quad (2)$$

In the second term, $p_1(\dots)$ is the student’s updated perception of her/his ability, inferred by the realized performance together with the effort level chosen. For simplicity, we assume the value of self-worth to be linear in expected p_1 with a constant coefficient v , which evaluates the importance of the perceived ability.

Note that the information structure in this model is similar to those of learning through experimentation and signal jamming.¹⁰ Unlike most studies on incentives and motivation, we do not assume that a student knows her/his true ability level. Also, we do not consider how to measure or monitor a student’s effort. Instead, we assume that a student does not possess perfect information about her/his own ability. This results in a problem of learning under uncertainty, rather than a problem of signaling or screening under asymmetric information. Moreover, it concerns one’s incentive to discover her/his ability (a problem of learning via experimentation) and under what condition she/he might want to conceal it (a problem of signal jamming).

We show in the next section that when self-worth is added into a student’s objective, her/his effort will be different than what she/he would pick in the benchmark problem, in particular, in a very competitive learning environment. A positive self-worth effect may induce optimistic students to work hard so as to affirm their ego, whereas a negative self-worth effect leads some perceived better students to take an information-reducing strategy by lowering their effort level in order to keep a favorable image.

Why Competition may Discourage Students from Learning?

When speaking of students’ lack of motivation, economists are apt to think of more competition as a solution. Our analysis in the present section argues that elevating competition among students in learning may discourage students from learning.

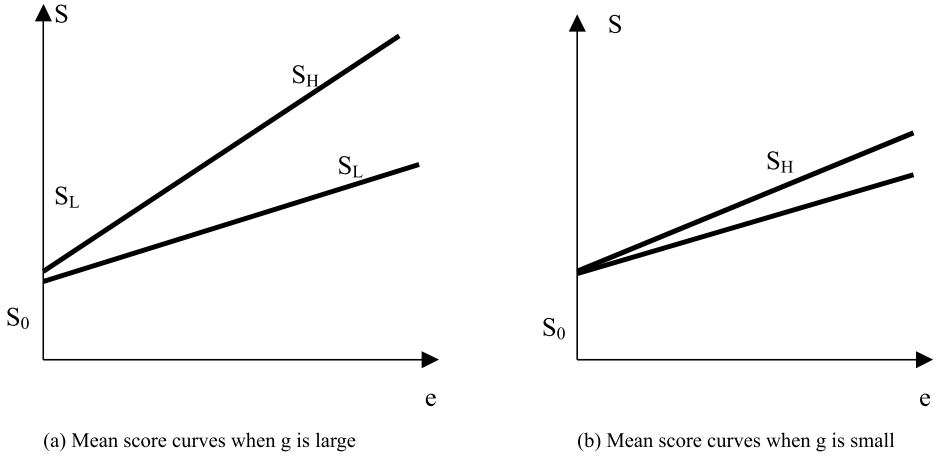


Fig. 1. The mean score curves. (a) Mean score curves when g is large. (b) Mean score curves when g is small.

Because of uncertainty, success is not always guaranteed even when a good student has extended maximum effort. If a student did try very hard, but still failed, it is indicative of a low ability. When this happens, an intention to learn a subject may lead to an undesirable discovery – a low ability. However, ‘low effort in success enhances a reputation for brilliance and low effort also obscures the causes of failure’ (Covington, 1992, p. 83). If students are concerned about their perceived ability, they may be motivated to lower effort—a strategy to win by not losing. We now provide a formal analysis for this argument.

Let S_H and S_L be the mean score curves with high ability t_H and low ability t_L , respectively. That is, $S_H = E_e((S | t_H) = S_0 + [(1 - g) E(t_A) + g t_H] e$, and $S_L = E_e(S | t_L) = S_0 + [(1 - g) E(t_A) + g t_L] e$. In e - S space, these two curves have different slopes, as long as $g > 0$. Figure 1(a) is for a larger g value and Figure 1(b) for a smaller g value. Note that the gap between the two mean score curves widens as effort level e increases. Also, the two curves move further away from each other at any level of effort at a larger g .

We further specify the distribution of ε . Let $f(x)$ be its probability density function. Given effort level e and realized score s , by Bayes’ rule, the updated p_1 value is given by:

$$p_1(s, e) = \frac{p_0 f\{s - S_0 - [(1 - g) E(t_A) + g t_{H\#}]e\}}{p_0 f\{s - S_0 - [(1 - g) E(t_A) + g t_{H\#}]e\} + (1 - p_0) f\{s - S_0 - [(1 - g) E(t_A) + g t_L]e\}}$$

If ε is focused around its mean (e.g., its density function is around its mean), a high level of e together with a low s value would imply an unfavorable updated perception of p_1 . To obtain a compact form of $E_e[p_1(S, e)]$, we assume that ε follows a uniform distribution on interval $[-\eta, \eta]$.

By Bayes’ rule, posterior p_1 is inferred as follows. In Figure 2, if (s, e) lies in area I, then $p_1 = 1$; if it lies in area II, $p_1 = p_0$; and if it lies in area III, $p_1 =$

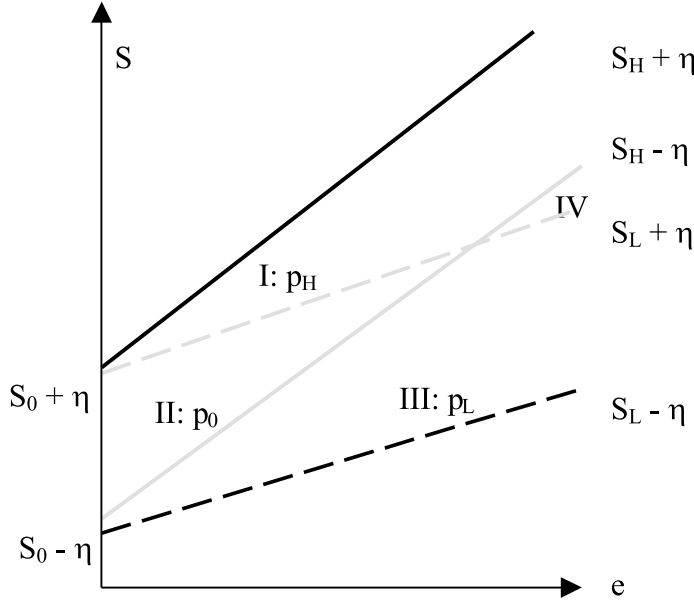


Fig. 2. Area for different inference on p_1 .

0. From a behavioral economics perspective, however, we introduce an imperfect Bayesian inference, which includes the Bayes' rule as its special case. In Figure 2, if (s, e) lies in area I, then $p_1 = p_H$; if it lies in area II, $p_1 = p_0$, and if it lies in area III, $p_1 = p_L$, where $0 \leq p_L < p_0 < p_H \leq 1$. Area IV is impossible under the uniform distribution. Clearly, the Bayes' rule is a special case when $p_L = 0$ and $p_H = 1$. This imperfect Bayesian inference with $0 < p_L < p_0 < p_H < 1$ can be justified by the concept of 'conservativeness' in behavioral economics. That is, real people usually update their beliefs regarding a variable in the same direction as Bayes' rule predicts when new information is released. However, they do not react as much as Bayesian statistics warrant (Shleifer, 2000, p. 113).¹¹

Under the assumption for the distribution of ε and the imperfect Bayesian inference, we derive the expected posterior p_1 value as follows.

$$E_e[p_1(S, e)] = (1-p_0) p_L \frac{(t_H - t_L)ge}{2 \eta} + p_0 \frac{2\eta - (t_H - t_L)ge}{2 \eta} + p_0 p_H$$

$$\frac{(t_H - t_L)ge}{2 \eta} = p_0 - [p_0 - (1 - p_0) p_L - p_0 p_H] \frac{(t_H - t_L)ge}{2 \eta} e$$

Hence,

$$\frac{\partial E_{ge}[p_1(S, e)]}{\partial e} = - [p_0 - (1 - p_0) p_L - p_0 p_H] \frac{(t_H - t_L)g}{2 \eta} \quad (3)$$

This implies that

$$\frac{\partial E_{ge}[p_1(S, e)]}{\partial e} \begin{matrix} < \\ = \\ < \end{matrix} 0$$

if and only if

$$p_0 - (1 - p_0) p_L - p_0 p_H \begin{matrix} < \\ = \\ < \end{matrix} 0 \quad (4)$$

Note that in equation (4), if $p_L = 0$ and $p_H = 1$, then the equality holds. However, as long as $p_H < 1$, then equation (4) is equivalent to

$$p_0 \begin{matrix} < \\ = \\ < \end{matrix} \frac{p_L}{1 - p_H + p_L} \quad (5)$$

Recall that the first-order conditions for problems (1) and (2) are, respectively,

$$(1 - g) E(t_A) + E(t_R) = c'(e^*)$$

$$(1 - g) E(t_A) + E(t_R) + v \frac{\delta E_{ge}[p_1(S, e)]}{\delta e} = c'(e^{**})$$

From expression (3) and inequalities (4) and (5), we obtain the following proposition.

Proposition 3. Assume that students are concerned about their self-worth and that ε is uniformly distributed. Let e^* and e^{**} be the optimal solutions for program (1) and (2), respectively.

- For confident students who see $p_H \sim 1$ and $p_L \sim (p_0)$, self-worth has a positive effect on effort choice (i.e., $e^{**} > e^*$;
- For students with a lack of confidence who interpret $p_H \sim (p_0)$ and $p_L \sim 0$, the self-worth effect can be negative in effort choice (i.e., $e^{**} < e^*$;
- Given any imperfect Bayesian inference on p_H and p_L with $0 < p_L < p_H < 1$, self-worth effect tends to be negative (i.e., $e^{**} < e^*$) for *ex ante* perceived better students—those with a *prior* $p_0 > p_L/(1 - p_H + p_L)$;
- The self-worth effect, positive or negative, becomes stronger in a group where difference in ability among students is larger (i.e., a larger $t_H - t_L$);
- The more tournament-like an incentive scheme is (i.e., the larger g), the stronger the self-worth effect is.

We interpret the propositions based on student's rationality, personality, the quality difference within the group, and the nature of the incentive scheme. First, if a student remains confident, or simply optimistic *ex post*,¹² she/he will not lower p_L much from p_0 even when S turns out to be low, but will take p_H pretty close to 1 when S is high. From inequality (4) again, we see the self-worth effect to be positive in effort choice. That is, concern over the value of self-worth can further motivate

those students to study harder than if they merely study for a good grade. This is consistent with behaviors of those top students in many classes. They often behave confidently, which may result in or from their success.

On the other hand, however, if a student is failure prone, or loses confidence when failing to earn a good grade, she/he tends to interpret p_L as close to 0 when S is low, and does not see p_H much higher than p_0 . In this case, there is a negative self-worth effect on effort choice. Theoretically, whether self-worth effect tends to be positive or negative is both possible. We will come back to discuss this point from a behavioral economic perspective in the next section.

Second, as long as p_H is not perfectly inferred by Bayes' rule, inequality (5) implies that currently perceived better students may have an incentive to make a low effort. For those students, lowering effort is a strategy to win by not losing. Because success is not always guaranteed, a bad performance following great effort reveals a lower ability. It can damage the perception of ability very badly. This may capture how many people might usually think: If someone does not try, she/he might be smart; however, if she/he tried hard and failed, then she/he cannot be smart, viewed by others, perhaps even by her/himself.

Third, the self-worth effect, positive or negative, becomes stronger in a group with larger difference in students' ability. This can be seen from equation (3) when the difference between t_H and t_L is larger. This is because the perceived ability is usually inferred by relative performance within a group. If all students in the same group were very much equally capable, the perceived ability would become less important.

Last but not least, it is worth noting that the self-worth effect on effort choice, positive or negative, becomes stronger if parameter g is larger. Recall that a larger g represents a grading policy that puts heavier weight on relative performance when evaluating students. In the extreme case when relative performance is not used at all to evaluate students, the self-worth effect can be minimized, if not completely eliminated. Although whether the self-worth effect is positive or negative is independent of the value of g , a larger g value can exaggerate the self-worth effect whenever it exists, positively and negatively.

Therefore, to introduce sharp competition among students as a 'high-powered' incentive scheme (i.e., a large g value) can indeed motivate students on effort, either positively or negatively. In the benchmark problem without self-worth, we see that a larger g value may induce a greater effort from above-average students at a cost that below-average students may make less effort. In the model with self-worth, however, even *ex ante* perceived better students prone to a negative self-worth effect have an incentive not to try hard. Under a very competitive incentive scheme, those better students do not try hard not because they lack motivation to learn a subject, but because they may be over-motivated to maintain their current favorable perception in ability.

Self-Worth Effect: Positive or Negative?

In the previous section, we examined the self-worth effect and found that a more tournament-like (and hence ability-oriented) incentive scheme, modeled in a larger g value, would further exaggerate the self-worth effect, positively and negatively. The question remains: Is the self-worth effect positive or negative? In the following, we discuss this issue using concepts and principles from behavioral economics.

One concept in behavioral economics is ‘loss aversion’. That is, people hate to lose: they hate to lose money financially, and they hate to lose in games, competitive or recreational, sport or academic. Losing \$200 causes more pain than the joy from earning \$200. In particular, people hate most to lose anything they possess. Research indicates that people put more value on their own possessions than the same goods of others. This is called the ‘endowment effect’ in behavioral economics (Kahneman *et al.*, 1991).

Applying the notions of ‘loss aversion’ and ‘endowment effect’ to effort choice problem, we believe that many currently perceived better students could suffer a negative self-worth effect. For those students, a favorable prior p_0 value is something important that they currently possess. They may have much more pain when an unexpected low score is obtained than joy from an expected high score. Hence, the attitude of ‘loss aversion’ and ‘endowment effect’ lead them to view p_L very low, *ex post*, but p_H not much higher than p_0 . As we showed earlier in Proposition 3, part (c), they may make less effort because in this case $p_0 > p_L L / (1 - p_H + p_L)$.

Finally, we acknowledge that quite a few top students do work very hard in many classes no matter how grades are determined. In our model, they could be so confident that they always see things positively, or simply optimistic in their ego, and want to prove and keep proving it. From an incentive perspective, most confident students with positive attitude happen to be those who need the least extrinsic motivation, because they are usually well self-motivated. For students living on an optimistic ego, competition can provide them with an opportunity to prove their ego as long as they continue to make it. Hence, it may well motivate them on effort. However, things can change dramatically once they are unexpectedly beaten. For example, when a used-to-be top student (say, in high school or college) is toppled in a new environment (say, in college or graduate school), she/he might try less hard or quit once she/he fails to stay top.

Concluding Remarks

The present paper studies students’ motivation and incentives in a behavioral-economic model. By incorporating the notion of self-worth in educational psychology into a traditional micro-economic analysis, it argues that a competitive learning environment may provide a negative incentive on students. Under a rank-based incentive scheme, students compete for limited rewards such as good grades, evaluated by their relative performance within a group. It links a student’s relative performance to her/his perceived ability, indicating her/his potential self-worth. The fewer the rewards are available for winner(s) in a learning game, the more closely one’s self-worth is attached to the perception of ability. Consequently, a sharp competition among students can cause so much concern over their perceived ability that it is as important to maintain a favorable perception of being able as to earn a good grade. When success is not guaranteed due to uncertainty, failure, in particular, following a high effort, is indicative of a low ability. As a result, those students prone to negative self-worth effect can be motivated not to study hard-a strategy to win by not losing.

The policy implication from our study is self-evident. Although competition among firms in a market system can help allocate economic resources efficiently, it can be harmful to introduce it into schools as an incentive scheme. In a sound education system, learning and intellectual development should be a human capital investment process rather than a means to beat each other. Indeed, the labor market

may use grades and other measures of performance for screening purposes when recruiting employees, in particular, new graduates from schools. Within an educational institution, however, the incentive on students should mainly tie rewards to learning processes and outcomes. Whenever possible, performance should be measured against a (seemingly, at least) objective standard, instead of relative performance. As a campus culture, students' performance should be separated from their perceived ability as much as we can.¹³

Acknowledgements

The authors thank Chris Paul and an anonymous referee for very helpful suggestions and comments.

Notes

1. 'Since Milton Friedman's early proposal to convert public school financing to a voucher system, a few economists have addressed questions of how to design this type of system' (Hoenack, 1994, p. 152). Among others, for example, see Chen and West (2000) for the current state of the art in this regard and the references therein.
2. Self-worth theory in social psychology holds that in a modern society, when other basic needs are met, people are concerned with their value or acceptance. See Covington (1992), for example.
3. The seminal work in behavioral economics was Kahneman and Tversky (1979). For a recent survey of the literature, see Rabin (1998). Shleifer (2000) is a well-written text for behavioral finance at graduate level. Frank (2000, pp. 252–278) devotes a chapter to behavioral economics in his intermediate micro-economics text. While Belsky and Gilovich (1999) provide excellent non-technical readings that introduce the principles of behavioral economics, for academic researchers Kahneman and Tversky (2000) contains most major contributions to behavioral economics made by themselves as well as many others in the past two decades.
4. 'Conservativeness' here has nothing to do with the political attitude as what it is usually referred to. Rather, in behavioral economics, it means that people usually do not react to the newly released information as the Bayesian statistics suggest (Shleifer, 2000, p. 113).
5. The value of g can be interpreted more generally as campus culture and general practice in evaluation of performance, instead of an individual instructor's grading policy only. Recently, in a class of one of the authors, who does not curve to give grades, two students came to ask about their rank within the class. When asked why they were interested in it even though their grades are not determined by their relative performance, they explained that some of their other classes (current and previous, even in high schools) use curves to determine letter grades and they were just curious about how good they are 'exactly'. This case also reveals that students tend to interpret their relative, but not absolute, performance as their ability.
6. We thank a referee of this journal for addressing and clarifying this point on the absolute ability, which also influences a student's choice in effort, as shown in Proposition 1.
7. Abundant evidence indicates that people are, in general, over-confident; in particular, *ex ante*. For example, according to Belsky and Gilovich (1999, p. 153), 'a 1981 survey of automobile drivers in Sweden shows that 90 percent of them described themselves as above-average drivers'.
8. A student may want to brag more about the highest mark of 89 in a class than a 100 together with the 50% of class.
9. Note that though there are two stages in this program, no action will be taken in the second stage. Only the perception will be updated, contingent on the realized performance and the effort made.
10. According to Mirman *et al.* (1993), a firm is said to 'experiment' if it adjusts its first-period behavior away from the myopically optimal action in order to increase the informativeness of its outcome in this period and then uses this information to increase the later-period profit. According to Tirole (1988, p. 443), when a player takes an unobservable action to garble the payoff-relevant information received by another player, it involves signal jamming. See also Fudenberg and Tirole (1986) and Riordan (1985) for examples of signal jamming games.

11. Individuals systematically violate Bayes' rule and other maxims of probability theory in their predictions of uncertainty outcomes (Kahneman and Tversky, 1973).
12. Confident and optimistic are different; the former means one knows what to do, how to do it, in particular, when she/he realizes that she/he has made a mistake, how to correct it and learn the lesson from it, whereas the latter means one simply believes what she/he is doing must be right. When it turns out to be wrong, an optimistic person can become pessimistic, losing confidence completely.
13. In practice, many university administrations have realized this point and have obviously done good job in this regard. As many school handbooks for instructors suggest, for example, it is better to say to a student that 'you did not do very well in question 3 this time' than 'many other students did better than you in exam'.

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