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# Relative Performance Information Feedback and Just-Pass Behavior: Evidence from a Field Experiment\*

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## Abstract

This paper investigates the relationship between the feedback of performance information and effort input by students under a relative grading scheme. By conducting a randomized experiment in an economics course at a Japanese university, we demonstrate that relative performance information feedback improves the performance of students with only intermediate scores in the midterm examination, but worsens the performance of high-scoring students. A theoretical interpretation suggests that a decrease in uncertainty in the relative ability of students is responsible, which we refer to as “just-pass” behavior.

Keywords: education, experiment, relative performance information feedback, tournaments

JEL Classification: D03, D81, I21

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# 1 Introduction

Recently, researchers have become interested in information feedback as an efficient way of eliciting the incentives of students to study. This is because information feedback is associated with the reward scheme, and this is critically important in considering student incentives. As regards the reward scheme in an educational context, “relative grading” or “grading on a curve” is widely used, although it remains controversial.<sup>1</sup> In relative grading, student grades depend on their positions in the class score distribution. Such a reward scheme is then a type of rank-order tournament. Becker and Rosen (1992) extend the rank-order tournament model in Lazear and Rosen (1981) to understand better student incentives in a relative grading scheme. Becker and Rosen (1992) emphasize the importance of a student’s position in the distribution of academic attainment and show that competition between students indeed stimulates their learning effort. This indicates that information on a student’s position in the distribution of academic attainment affects their decision-making in providing effort. In actual schooling environments, multiple examinations, including midterm and final examinations, determine student grades. It is then worth considering the relationship between information on a student’s relative position in the distribution of past examination scores and the student’s incentive to provide study effort for future examinations.<sup>2</sup>

In this paper, we conduct a randomized field experiment using students undertaking a compulsory course in economics at a Japanese university, relatively graded using the results of midterm and final examinations. In our experiments, as in most academic coursework, the performance of students in the midterm and final examinations determines student grades. We divide the student into a control group and a treatment group immediately after the midterm examination. While students in the control group are informed only about their midterm examination score, those in the treatment group also receive their rank in the midterm examination. That is, we provide relative performance information feedback to students in the treatment group. We then explore the impact of this relative performance information feedback on student performance in the final

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<sup>1</sup>Volokh (2015) argues that relative grading is favorable for teachers as a means to control grade inflation and to ensure students have an opportunity to receive a higher grade, even if the examinations are too difficult to obtain high marks. Conversely, Grant (2016) points out the problematic aspects of relative grading that prevent students from collaborating owing to the overly competitive environment.

<sup>2</sup>Aoyagi (2010) and Ederer (2010) theoretically analyze information feedback in a dynamic tournament context.

examination. To our knowledge, this paper is the first attempt to investigate the impact of relative performance information feedback on student incentives to study when graded relatively.

Prior to investigating the experimental results, we construct a simple theoretical tournament model. We assume that students only care about whether they pass the course. That is, we assume that students are interested in passing the course with minimal provision of effort and do not consider getting a higher grade.<sup>3</sup> In our simple theoretical model, the information on relative performance in the midterm examination serves as a source of information for borderline passing as it depends on the distribution of the midterm examination scores. A student who knows her own relative performance can then more accurately calculate the effort provision they need to exert to pass the course than a student who does not. Our theoretical model demonstrates that for marginal students with intermediate marks in the midterm examination, relative performance information serves as a signal that they will need to work harder to pass the final examination. In contrast, for students with sufficiently high marks in the midterm examination, relative performance information is a signal that they can pass the final examination with only moderate effort. That is, students espouse just-pass behavior.

Using data from the field experiment, we then show that the impact of relative performance information feedback varies according to students midterm examination performance. This is because relative performance information feedback has a positive impact on the final scores of students whose midterm scores are intermediate, but a negative impact on the final scores of students whose midterm scores are high. These experimental findings are consistent with our theoretical results.

The remainder of the paper is organized as follows. Section 2 relates the study to the existing literature and Section 3 describes the experimental design. In Section 4, we construct the theoretical tournament model and provide the testable hypothesis. Section 5 presents the empirical framework and reports the estimation results. Section 6 concludes.

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<sup>3</sup>As described in the following section, existing evidence on the Japanese higher education system and labor markets suggests that Japanese university students adopt “just-pass” behavior.

## 2 Background

Revealing the role of relative performance information feedback in providing agent incentives is often achieved through laboratory experiments. Existing research demonstrates that relative performance information feedback can have both a positive and a negative impact on the agent’s effort provision. Azmat and Iriberry (2016) conduct a laboratory experiment to compare piece-rate incentives, where the reward depends on the number of tasks the subjects solved, and a flat-rate incentive, where the reward is independent of the number of tasks the subjects solved. They find that the relative performance information feedback improves the subjects’ performance when rewards are absolute. In terms of relative performance information feedback in tournament schemes, Eriksson et al. (2009), Freeman and Gelber (2010), and Ludwig and Lünser (2012) explore the impact of relative performance information feedback on agent performance when subjects are rewarded relatively. Eriksson et al. (2009) and Freeman and Gelber (2010) conclude that relative performance information feedback lowers the performance of subjects whose interim performance is relatively low. However, those subjects whose midterm performance is relatively high do not slacken off. In contrast, Ludwig and Lünser (2012) examine the effects of effort information in a two-stage rank-order tournament in laboratory experiments. They demonstrate that the subjects who lead (“favorites”) tend to lower their effort, but those who lag (“underdogs”) increase it relative to the first stage, while favorites exert a greater effort than underdogs. These results suggest that the impact of relative performance information feedback should vary according to subjects’ initial level of attainment in our relative grading framework.

Information feedback is also the subject of investigation, in particular in actual educational decision-making.<sup>4</sup> Azmat and Iriberry (2010), using data from Spanish high schools, and Tran and Zeckhauser (2012), in a field experiment of Vietnamese university students, demonstrate that relative performance information feedback raises the performance of students when they are rewarded absolutely. Both these studies argue that if students have competitive preferences, which means that they inherently prefer getting a higher rank than do others, relative performance information has a positive impact on their incentives to study, even if the information is intangible in their reward scheme.

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<sup>4</sup>De Paola and Scoppa (2011) conduct a field experiment in an Italian university to prove that students taking midterm and final examinations obtain higher scores than students taking only final examinations, the difference being that the former receive information on the midterm performance.

Bandiera et al. (2015) employ a sample of students rewarded absolutely in a UK graduate school and demonstrate that absolute (but not relative) performance information feedback improves the performance of students whose midterm performance is high; the authors relate the results to knowledge of the educational production function. That is, absolute performance information, which provides students with precise information on their *absolute productivity*, makes students direct greater effort to study.

These findings imply that relative performance information feedback may have a positive impact on student performance, even in our relative grading setup. If absolute performance information feedback tends to improve student performance, because relative performance information provides students with precise information on their *relative productivity* and the distribution of examination scores, it will exert a significant impact on student behavior in a relative grading scheme. However, there has been no examination of the impact of relative performance information feedback on student incentives under relative grading or grading on a curve in an actual education environment.

Relative rewarding and grading on a curve are themselves issues worth considering because existing research demonstrates that relative grading has an empirically debatable impact on student performance.<sup>5</sup> For example, Ashraf et al. (2014) conduct a field experiment in Zambia's health assistant-training program. In their experiment, student rewards are absolute, with some students advised they will receive a rank-related reward. The authors conclude that the performance of students whose initial achievement level is relatively low is significantly lower when announced that they will receive a rank-related reward. In contrast, Jalava et al. (2015) conduct a field experiment in Swedish primary schools to compare schemes with different types of reward and find that student performance is higher when rewarded relatively. Czibor et al. (2014) conduct a field experiment in a Dutch university and compare relative and absolute grading. They find that motivated male students rewarded relatively tend to obtain higher performance than students rewarded absolutely. However, both female and male students as a whole are largely unaffected by the reward scheme. On this basis, Czibor et al. (2014) contend that rank incentives are weak if students adopt just-pass behavior. That is, if students only care about whether they can pass the course or not, they will not want to provide effort

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<sup>5</sup>From a theoretical viewpoint, Becker and Rosen (1992) employ a rank-order tournament model to analyze student incentives to study in an educational environment. Dubey and Geanakoplos (2010) compare absolute grading and relative grading, while Paredes (2016) and Brownback (2014) construct a theoretical model of relative grading employing an all-pay auction.

for any higher rank than that to which they aspired. Even if graded relatively, relative performance information feedback may exert different impacts on student incentives to study depending on their attitude toward getting higher grades.

Based on anecdotal and other evidence concerning the university advancement rate and labor markets in Japan, the just-pass behavior observed by Czibor et al. (2014) is a key feature of Japanese university students. The School Basic Survey, which is conducted by the Ministry of Education, Culture, Sports, Science and Technology, shows that the university advancement rate was about 50% in 2014, whereas it was less than 20% in 1990. Increasing the university advancement rate in Japan could reflect demand-side forces that lead to greater incentives to pursue university education. Most Japanese firms distinguish new college graduates from other job seekers, in the sense that many vacancies for regular full-time jobs explicitly target new college graduates (Genda et al. 2010). Moreover, Lise et al. (2014) show that the wage premium for education, measured by the ratio of mean wages for college-educated full-time workers to less-than-college-educated full-time workers, has tended to increase since 2000 in Japan. Interestingly, while the admission process to prestigious Japanese universities is competitive, credit standards in college courses are low (Abe 2002). That is, hard work is not generally needed for graduation.<sup>6</sup>

The hiring policy of many Japanese firms also discourages students from studying hard. For example, before 2013, most Japanese firms did not consider a student's grade point average (GPA) when seeking recruits in labor markets for new graduates.<sup>7</sup> Taken together, the high college wage premium, low credit standards in college courses, and recruitment policies in labor markets for new graduates that ignore student GPAs may result in students adopting just-pass behavior.

This background contextualizes our research question: Does relative performance information feedback improve student examination scores under a relative grading scheme? We shed light on how students with high midterm scores slacken off when given this information. To examine this issue, we construct a simple theoretical model where students exhibit just-pass behavior in a relative grading scheme, and conduct a field experiment

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<sup>6</sup>Kaji (2015) notes that a nontrivial proportion of students in Japanese universities eschew classes that demand serious reading and homework, instead preferring classes in which they will easily earn a credit (*raku-tan*) and seeking off-campus experiences.

<sup>7</sup>According to the *Nihon Keizai Shinbun* (in Japanese), the reason for this was that most firms considered the GPA an unreliable indicator of student attainment. Because each university has its own grading guidelines, firms cannot account for the difference in GPA between one university and another (*Nihon Keizai Shinbun*, December 8, 2013).

to investigate relative performance information feedback in a relative grading setting.

### 3 Experimental Design

We performed an experiment using first-year students enrolled in an introductory economics course during the second semester of 2012 (Economics II) offered by a faculty of economics at a Japanese private university.<sup>8</sup> Prior to taking Economics II, these students had already taken an earlier introductory economics course during the first semester of 2012 (Economics I). Credits for both Economics I and II are required for graduation. Therefore, successfully completing the Economics II course is a primary concern for students. If a student fails the course, she has to repeat the course the following year. There is a separate class for those students who have previously failed the course (the *Sai-rishu* class). Students were obliged to attend one of four classes in one of four classrooms available for Economics I and II. We placed all students with a top-40 score obtained in a mathematical test conducted immediately following university entrance (Pretest of Mathematics) in one class in one small classroom. We then randomly allocated the remaining students to the other three classes and classrooms, with all class enrolments fixed across the first and second semesters.

A weighted average of the midterm and final examination scores and the number of homework submissions determine student grades in this course.<sup>9</sup> All students take the

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<sup>8</sup>The university where the experiment was conducted is not very selective. Most Japanese universities hold entrance examinations and universities are ranked by their selectivity, as measured by *hensachi*. *Hensachi* is a standardized score published by major cram schools, which offer specialized training for students to pass university entrance examinations. The median *hensachi* for students seeking admission to university is 50. Most high school students who wish to enter university sit simulation examinations offered by these cram schools. The schools collect information on student scores in these simulation examinations and the universities whose entrance examinations they successfully passed. Although the manner of calculating *hensachi* varies according to the school, we consider that it reflects the approximate relationship between student scores in the simulation examinations and the university entrance examinations they are expected to pass. According to Kawai-juku (2016), one of the most prominent cram schools, the borderline *hensachi* for the economics department where the experiment was conducted indicates that the *hensachi* score (giving a student a 50% chance of gaining admission to the faculty) is relatively low (40.0–42.5 in 2017).

<sup>9</sup>In the second semester of 2012, the score calculation was as follows: “40% of the midterm examination score” + “60% of the final examination score” + “the number of homework submissions” (there were 10 homework assignments each worth one point). Perfect scores for both examinations were 110 points. From the total score of 110 points, 100 points were for the economics component, and the remaining 10 points for basic mathematics.

same examinations at the same time regardless of their classroom. According to the university’s guidelines, the standard pass score for the course is 60 out of 100. If students were to be strictly graded using this guideline, the number of students who fail the course and then have to attend the *Sai-rishu* class in the following year would be inordinately high. This is because the capacity of the *Sai-rishu* class is limited and there is only one classroom. Consequently, in many cases, relative not absolute scores decide if students pass or fail the course, with instructors adjusting the final scores to obtain a reasonable pass rate. For example, in Economics I, because the perfect score was 100, the official pass score was 60 but the instructors set the pass score at 51. In other words, instructors determine the borderline score between success and failure. Students are aware of this particular evaluation system as the course instructors announce it at the beginning of the semester. However, students do not know the exact borderline score in advance of taking their examinations.

The details of the experiment are as follows. We randomly assigned all students to a treatment or a control group regardless of classroom. Following the midterm examination, we sent students letters revealing their total score for the midterm examination and their score for the mathematics problems, delivered to them in person during class time. In addition, the letters sent to students in the treatment group also reported their ranks in the midterm examination (i.e., the rank of each student in relation to other students in the course and the total number of students in the course). We did not include this information in the letters to the students in the control group.<sup>10</sup> Therefore, while students in the treatment group know their precise rank, students in the control group will only have a vague awareness of their rank. Thus, our experiment can reveal whether the difference in the precision of their relative performance information accounts for the difference in final examination scores under a relative grading setup.<sup>11</sup>

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<sup>10</sup>The student letter content is similar to that in Ashraf et al. (2014). Appendix Figure 1 reproduces the information provided to the students in the treatment and control groups. One point to note is that the sample used in the estimation model in Section 5.1 is excluded to individuals who could not receive the letters (e.g., those who were absent from classes) regardless of whether they took the final examination (28 individuals). Comparing their mean scores in the midterm examination for the control and treatment groups, the means (standard deviations) for the control and treatment groups are 40.62 (16.75) and 38.27 (18.89), respectively. However, the null hypothesis that “the mean values of the two groups are not different” is not rejected.

<sup>11</sup>We note that because our experimental design is similar to Tran and Zeckhauser (2012), except for the grading scheme, we share the same problem that students could always exchange rank information to determine their own rank. Moreover, we excluded from our sample the 5% of students who took the

## 4 A Theoretical Model

In this section, we construct a simple model in which students choose effort input under uncertainty at the borderline of the final examination score to pass the course. The borderline is the score of a representative imaginary rival, which is uncertain because students cannot observe the potential ability of the rival. Student just-pass behavior is then one of the following equilibrium actions.

### 4.1 Setup and Equilibrium

**Setup** Consider a course where the assessment comprises a midterm examination and a final examination. The course grade awarded for each student depends on a total score, which is the sum of the scores in the midterm and final examinations:  $s_0 + s$ , where  $s_0$  and  $s$  are the scores in the midterm and the final examinations, respectively.<sup>12</sup> The midterm examination results are available and each student knows her own score in that examination. Consider a student with midterm examination score  $s_0$ . She chooses a level of effort input for the final examination to pass the course, incorporating the effort cost. The student imagines that she competes with a rival student representing the borderline for passing. Because the number of participants is sufficiently large, she thinks of this as an approximately nonstrategic situation. Given this, she regards the rival's features, such as the score in the midterm examination, ability, and effort inputs, as exogenously given. The student assumes that to achieve a pass, it suffices to beat her imaginary rival in terms of the total score, that is, to control her own score in the final examination to satisfy

$$s_0 + s \geq S_0 + S, \quad (1)$$

where  $S_0$  and  $S$  are the rival's score in the midterm and final examinations, respectively. The inequality (1) is the condition for the student winning.

The student has a production function of final examination scores such that

$$s = b + as_0e, \quad (2)$$

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midterm examination and received a letter, but who did not subsequently sit the final examination. As for the average midterm score, we cannot readily observe a distinct difference between the two groups. We discuss these in Section 5.3.

<sup>12</sup>We consider the case of the weighted average, such as  $\phi s_0 + (1 - \phi)s$ , where  $\phi \in [0, 1]$  is the relative weight of the two examinations. However, because the basic results do not depend on the relative weight, we adopt the case of a simple sum.

where  $b$  is the expected minimal score that students can obtain without making effort,  $a$  is her potential ability, which is observable to herself, and  $e$  is the level of effort input.<sup>13</sup> The productivity of the student is  $as_0$ . Note that this consists of not only ability  $a$  but also  $s_0$ . This is because the accumulation of knowledge by the midterm examination positively affects the result of the final examination as effective preparation. The imaginary rival has a similar production function, such that

$$S = B + AS_0E, \quad (3)$$

where  $B$  is the expected minimal score of the rival, and  $A$  and  $E$  are the rival's potential ability and the level of effort input, respectively. The productivity of the imaginary rival is  $AS_0$ . Suppose that the student can read the level of  $B$ ,  $S_0$ , and  $E$  but not observe  $A$ .<sup>14</sup> While the student knows the difference in potential ability among all students is not generally large, whether the rival's potential ability  $A$  is higher or lower than her own is uncertain given the lack of firm belief. The student has a confidence interval of  $A$  that depends on the volume of information on the rival's potential. Suppose that her subjective distribution of  $A$  is a uniform distribution along the interval  $[a - \varepsilon, a + \varepsilon]$ , where  $0 < \varepsilon < a$ . Parameter  $\varepsilon$  measures the degree of uncertainty for students and captures the degree of her confidence. Note that the distribution is centered at  $a$ . By this setting, we interpret  $A$  as relative potential ability, although from (3) it appears only like absolute potential ability. Hereafter, we consider  $A$  as the level of relative potential ability. Therefore, we believe that  $\varepsilon$  decreases when the student is given some information that contributes to the estimation of her relative position in ability among other students. For example, when the student is informed of her ranking in the midterm examination score, which provides a proxy for relative performance, she also obtains information about the relative ability of her rivals. The confidence interval of the rival's ability,  $[a - \varepsilon, a + \varepsilon]$ , then becomes narrower, that is,  $\varepsilon$  decreases.

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<sup>13</sup>We adopt the multiplicative form of the production function, as in the theoretical analysis of tournaments, such as Hammond and Zheng (2013).

<sup>14</sup>We may choose a setting in which the structure of  $S$  is unknown to each individual. It suffices to assume that the students have a subjective distribution of  $S$  in such a case.

In reality, students appear able to conceive the average competitor's achievement and learning attitude from the state of affairs in the various classrooms. However, potential ability seems more difficult to estimate precisely and hence is one of the most natural sources of uncertainty. In addition, it helps us obtain a simple analytical expression and concrete interpretation. Therefore, for simplicity, we assume that  $B$ ,  $S_0$ , and  $E$  are deterministically given parameters and  $A$  is a random variable for the student.

The student obtains utility depending on the result of the tournament with the imaginary rival. We assume that the student is concerned only whether she passes the course, which is the source of just-pass behavior:<sup>15</sup>

$$u = \begin{cases} 1 & \text{if she wins,} \\ 0 & \text{otherwise.} \end{cases}$$

Effort inputs generate effort cost, denoted by  $c$ . The cost function is of the form

$$c = \frac{e^2}{2}. \quad (4)$$

The student selects a level of effort input,  $e$ , to maximize her expected net payoff conditioned on her own information set. In a mathematical formulation, the optimization problem for the student is

$$\begin{aligned} &\text{Maximize} && U(e) \equiv \mathbb{E}[u - c], \\ &\text{subject to} && (2), (4), e \geq 0. \end{aligned}$$

For simple expressions, we set  $B = b$  and normalize  $S_0 E = 1$  and  $a = 1$ .<sup>16</sup>

**Equilibrium** Substituting (2) and (3) into (1) and rearranging it, we reduce the condition for winning to

$$A \leq \hat{A}(e),$$

where  $\hat{A}(e) = s_0 e + (s_0 - S_0)$ . Given her own effort level  $e$ ,  $\hat{A}(e)$  represents the maximal productivity of the rival with which the student can win the tournament. Given the rival's productivity  $A$  is uncertain, the student has to control  $\hat{A}(e)$  by incorporating the degree of uncertainty,  $\varepsilon$ , and effort cost.

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<sup>15</sup>This zero–one payoff is a variant of the ordinal tournament structure in Hammond and Zheng (2013). The reward system in our experiment is a tournament because of the relative evaluation of students. Of course, in reality, some students will attempt to obtain the best grade possible. However, in general, the reward is discretized into a set of some values in relative grading. Thus, we can locally approximate the reward system using the zero–one payoff structure. To keep the model simple and to understand better the role of a borderline as clearly as possible, we assume this preference relation.

<sup>16</sup>Although we obtain the same theoretical results without these parameter constraints, it requires some complicated algebra.

Through simple calculations, we obtain the functional form of  $U$ :

$$U(e) = \begin{cases} -\frac{e^2}{2} & \text{if } 0 \leq e < \underline{e}, \\ \frac{(s_0 - S_0) - (1 - \varepsilon)}{2\varepsilon} + \frac{s_0}{2\varepsilon}e - \frac{e^2}{2} & \text{if } \underline{e} \leq e < \bar{e}, \\ 1 - \frac{e^2}{2} & \text{if } e \geq \bar{e}, \end{cases}$$

where  $\underline{e} \equiv \frac{1 - \varepsilon - (s_0 - S_0)}{s_0}$  and  $\bar{e} \equiv \frac{1 + \varepsilon - (s_0 - S_0)}{s_0}$ .<sup>17</sup> For  $e < \underline{e}$ , the student deterministically loses and only incurs the effort cost. For  $\underline{e} \leq e < \bar{e}$ , it is probabilistic whether the student wins. Therefore, she weighs the expected gain of winning and the effort cost. For  $e \geq \bar{e}$ , she necessarily wins. Note that the thresholds decrease in the midterm examination score:  $\frac{\partial \underline{e}}{\partial s_0} < 0$ ,  $\frac{\partial \bar{e}}{\partial s_0} < 0$ . Because the midterm examination score is her own initial condition for preparing for the final examination, the reduced payoff function depends on it, as does the student's optimal choice.

We adopt the following assumption to focus on the solution most relevant for the empirical analysis.

**Assumption.** *Uncertainty for students is sufficiently strong:*

$$\varepsilon \geq \underline{\varepsilon},$$

where  $\underline{\varepsilon} = \frac{1 + S_0}{4}$ .<sup>18</sup>

If  $\varepsilon$  is small, then each student selects either a zero or minimal input for passing the examination regardless of  $s_0$ . This is because students can deterministically control their grades because of weak uncertainty and hence weigh the certain benefits of qualification and the required effort costs. In contrast, if  $\varepsilon$  is sufficiently large, then students cannot do this when their scores in the midterm examination are of an intermediate value. Because the latter case is relevant for the experimental results, we adopt this assumption to rule out the former irrelevant case.<sup>19</sup>

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<sup>17</sup>See Appendix A for the derivation.

<sup>18</sup>We also assume  $S_0 < 3$  to ensure  $\underline{\varepsilon} < 1$ .

<sup>19</sup>Strictly speaking, we need assume only  $\varepsilon > (\sqrt{2} - 1)^2(1 + S_0)$ , which is implied by the assumption, to ensure that the following proposition holds, as explained in the proof. However, we adopt the assumption to obtain one of the main results for the comparative statics, Result 1, in Section 4.2.

**Proposition.** Let  $\underline{s}_0 = 2 \left[ -\varepsilon + \sqrt{(1 + S_0)\varepsilon} \right]$  and  $\bar{s}_0 = -\varepsilon + \sqrt{\varepsilon^2 + 2\varepsilon(1 + \varepsilon + S_0)}$ . In equilibrium, the optimum  $e^*$  is characterized by

$$e^* = \begin{cases} 0 & \text{if } s_0 < \underline{s}_0, \\ \frac{\underline{s}_0}{2\varepsilon} & \text{if } \underline{s}_0 \leq s_0 < \bar{s}_0, \\ \frac{1+\varepsilon-(s_0-S_0)}{s_0} & \text{if } s_0 \geq \bar{s}_0, \end{cases}$$

and continuous with respect to  $s_0$  at  $\bar{s}_0$ .

**Proof** See Appendix B.

The intuition underlying the proposition is as follows. If the student obtains a low score in the midterm examination (that is,  $s_0 < \underline{s}_0$ ), she will make no effort because an unacceptably large effort is required in the final examination to pass the course. In the intermediate case (that is,  $\underline{s}_0 \leq s_0 < \bar{s}_0$ ), the student selects the inner solution as a means of balancing the uncertain benefit and certain cost. In this case, the student cannot predict with certainty the result of the final examination. Finally, if her score in the midterm examination is sufficiently high (that is,  $s_0 \geq \bar{s}_0$ ), the student will minimize her effort under the constraint of a passing score because this can be at a small effort cost. This case captures the just-pass behavior. In this case, the higher the midterm scores the student receives, the less effort she puts into the final examination.

## 4.2 Empirical Implication

We focus on the relationship between uncertainty and the final examination score,  $s^* \equiv b + s_0 e^*$ . For clarity, we divide the distribution of the students into three classes according to the forms of equilibrium behavior,  $e^*$ : A student with midterm score  $s_0$  belongs to class  $L$  if  $s_0 < \underline{s}_0$ , class  $M$  if  $\underline{s}_0 \leq s_0 < \bar{s}_0$ , or class  $H$  if  $s_0 \geq \bar{s}_0$ . Decreasing uncertainty has two distinct effects. One is to prompt some students to transfer to other classes, and the other is to make a difference in the equilibrium effort input of the students remaining in the same class.

**Transferring Effect** Let us first examine the effect of decreasing uncertainty on the thresholds of the classes,  $\underline{s}_0$  and  $\bar{s}_0$ , defined in the proposition. The student with  $s_0$  can

move from one class to another after  $\varepsilon$  changes. Given the assumption, we obtain the following:<sup>20</sup>

$$-\frac{\partial s_0}{\partial \varepsilon} \geq 0, \quad (5)$$

$$-\frac{\partial \bar{s}_0}{\partial \varepsilon} < 0. \quad (6)$$

By (5), decreasing uncertainty raises the threshold between class  $L$  and  $M$ , which implies that the region of class  $L$  spreads. This is because class  $M$  students near the lower threshold  $s_0$  recognize the small possibility of passing by information provision and cease the input of effort. In addition, a decrease in uncertainty enlarges class  $H$  by (6). Intuitively, class  $M$  students around the upper threshold  $\bar{s}_0$  find that they can pass the course with certainty with an acceptable degree of effort input.

As an implication for practice, we can state the following result.

**Result 1** *Decreasing uncertainty expands the class of students who abandon the course and who exhibit just-pass behavior. In particular, the former implies that the observed final score of students with relatively lower midterm score is lower because some students' scores jump into the minimal level by giving up the final examination.*

**Stimulating and Dampening Effect** Next, we consider the second effect of a decrease in uncertainty. Suppose that the student with  $s_0$  remains in the same class after  $\varepsilon$  changes. Then, given the equilibrium marginal effect of an increase in uncertainty,

$$\text{sign} \left\{ \frac{\partial s^*}{\partial \varepsilon} \right\} = \text{sign} \left\{ \frac{\partial e^*}{\partial \varepsilon} \right\}$$

holds according to the student's production function. Immediately from the proposition, we obtain the relationship between the degree of uncertainty and the final examination score.

**Result 2** *A marginal decrease in the degree of uncertainty improves the final examination scores of students with intermediate scores in the midterm examination. However, this exerts a detrimental effect on the final examination scores for students with high scores in the midterm examination.*

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<sup>20</sup>A derivation is provided in Appendix C.

Result 2 demonstrates that the effects of information feedback on the final examination scores vary according to the range of midterm examination scores. In particular, the information feedback has positive (negative) effects for students with intermediate (high) midterm scores. Greater transparency thus encourages students with intermediate scores in the midterm examination. This is because it reduces the risk of a fail in the final examination and therefore induces them to increase their required effort to achieve a passing score. However, decreasing uncertainty through information provision also expands the opportunity for students with high scores to economize on the required level of effort to pass the final examination. This possibly amplifies student just-pass behavior.

For information, we visualize a decomposition of the two above effects using a numerical example. Figure 1 illustrates the case where  $b = S_0 = 1$  and  $\varepsilon$  changes from 0.8 to 0.6. This illustrates a hump-shaped relationship between the midterm and equilibrium final scores. Classes  $L$  and  $H$  expand with the decrease in uncertainty, which corresponds with the transferring effect. For a sufficiently high and genuinely intermediate  $s_0$ , decreasing uncertainty has only the dampening and stimulating effect, respectively. These are the assertions of Result 2. For every student who remains in the same class, the total effect simply coincides with the stimulating or dampening effect. However, it is more complicated for students who transfer from class  $M$  to  $H$ . In the right neighborhood of the latter threshold (the dotted line  $W$  in Figure 1), the total effect is positive because the positive transferring effect accompanied by the stimulating effect for class  $M$  dominates the saving of effort input by the just-pass behavior. We interpret this as a stimulation of just-pass behavior with certain success. Conversely, the total effect is negative in the left neighborhood of the former threshold (the dotted line  $Z$  in Figure 1) because of the strong reduction in effort input. In contrast, for students who transfer from class  $M$  to  $L$ , the total effect is necessarily negative. This is because there is neither a stimulating nor dampening effect within class  $L$  and the transferring effect is negative. Intuitively, information provision discourages marginal students and encourages them to give up.

[Insert Figure 1 here]

**Testable Hypotheses** If a student does not have information on the potential ability of her rival, she has to consider the possibility that her rival's potential ability is much higher or lower than her own. That is, the variance of her subjective distribution of the

rival's ability is high. On the other hand, if she has some information on the potential ability of her rival as in our experiment, she can narrow the distribution of the potential ability of the rival. Therefore, we argue that students in the control group have a smaller  $\varepsilon$  than students in the treatment group.

According to Results 1, 2, and Figure 1, the predicted relationships between the midterm and final scores are as follows. For students whose midterm scores are sufficiently low or high, the more precise the information on relative ability, the lower the final scores students achieve. Conversely, for students whose midterm scores are intermediate, the more precise the information on relative ability, the higher the final scores the students achieve. In interpreting the experimental results, we draw on these theoretical predictions.

## 5 Estimation Model and Results

### 5.1 Estimation Model

Students in the treatment group have information about both their own midterm scores and rank, whereas students in the control group have information only on their own midterm scores. That is, the students in the treatment group have more precise information on relative ability than do students in the control group. Thus, from a theoretical point of view, the  $\varepsilon$  of students in the treatment group is lower than the  $\varepsilon$  of students in the control group. According to Results 1, 2, and Figure 1, for students whose midterm scores are sufficiently low or high, the students in the control group tend to achieve higher scores than those in the treatment group. In contrast, for students whose midterm scores are intermediate, the students in the control group tend to achieve lower scores than those in the treatment group. To confirm this theoretical prediction, we use a quadratic specification.

We employ the following empirical framework:

$$Y_{Fi} = \alpha (Y_{Mi}^2/100 \times D_i) + \beta (Y_{Mi} \times D_i) + \gamma D_i + \theta Y_{Mi}^2/100 + \phi Y_{Mi} + \mathbf{X}_i \boldsymbol{\delta} + \epsilon_i, \quad (7)$$

where  $Y_{Fi}$  and  $Y_{Mi}$  denote the respective scores in the final and the midterm examinations for student  $i$ ,  $Y_{Mi}^2/100$  is the squared midterm score for student  $i$ , divided by 100.  $D_i$  is a dummy variable equal to one if student  $i$  is given information on her relative rank in the midterm examination (i.e., the student is in the treatment group), and zero if

student  $i$  is not given this information (i.e., in the control group).  $Y_{Mi}^2/100 \times D_i$  and  $Y_{Mi} \times D_i$  are interaction terms for both variables.<sup>21</sup> The vector  $\mathbf{X}_i$  contains the student characteristics, including the final scores for Economics I, the Pretest of Mathematics, the number of homework submissions, dummy variables for male students and students in different classrooms, and a constant term.  $\epsilon_i$  are disturbances, which we assume are distributed  $N(0, \sigma^2)$ .

The coefficients upon which we focus are  $\alpha$  and  $\beta$ , which are the estimated coefficients for the interaction terms. These coefficients enable us to determine whether the impact of information on a student’s relative rank in the midterm examination and the improvement (if any) in the final examination score vary in accordance with the midterm examination score.<sup>22</sup>

## 5.2 Descriptive Statistics

Comparing the mean scores in the midterm examination  $Y_M$  for the control and treatment groups in Table 1, the means (standard deviations) for the control and treatment groups are 53.35 (18.09) and 50.15 (14.94), respectively. However, we fail to reject the null hypothesis that “the mean values of the two groups are not different” (Welch’s t-test: p-value is 0.14).

[Insert Table 1 here]

To visualize the relationship between the midterm and final examination scores, we show a scatterplot for the control and treatment groups in Figure 2. We can see that improvements in the final examination scores depend on the range of midterm examination scores. For example, students in the control group with a score of 60 or more in the midterm examination tend to obtain higher scores in the final examination than comparable students in the treatment group. Moreover, control group students with a midterm examination score of less than 30 show greater improvement in their final examination scores than do students in the treatment group. These observations suggest

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<sup>21</sup>As Barnett et al. (2005) argue, randomized experiments can reduce the effect of the regression to the mean (RTM). As the responses from both the control and treatment groups are equally affected by RTM, the differences between the treatment group and the control group, that is, the coefficients for  $D_i$  and the interaction terms, comprise the treatment effect after adjusting for the RTM.

<sup>22</sup>All regression results reported in this section are estimated using STATA version 14.

that the impact of information on a student’s relative rank in the midterm examination on the extent of improvement in the final examination varies according to the midterm examination score.

[Insert Figure 2 here]

### 5.3 Estimation Results

The estimation results following Equation (7) are shown in Column (1) in Table 2. The coefficient for  $Y_{Mi}^2/100 \times D_i$  is significantly negative and the coefficients for  $Y_{Mi} \times D_i$  are significantly positive. This indicates that the impact of information on the student’s relative performance in the midterm examination on the final score varies according to the midterm score. That is, relative performance information feedback on the midterm examination exerts asymmetric effects on the final scores for the control and treatment groups.<sup>23</sup>

One point to note is that we excluded from our sample the 5% of students who took the midterm examination and received a letter, but who did not subsequently sit the final examination. The average score for these students in the midterm examination was 28.7, suggesting that sample attrition correlates with lower scores in the midterm examination. However, among these students, the average midterm score in the treatment group was 29.3, while that in the control group was 28.4. As for the average midterm score, we cannot readily observe a distinct difference between the two groups.

[Insert Table 2 here]

We calculate the fitted values of the final score, categorized by the control and treatment groups, using the estimated coefficients of the variables in Column (1) of Table 2. As shown in Figure 3, we clearly see that for students with intermediate midterm scores (scores between 28 and 67), the more precise the relative performance information provided, the higher the score in the final examination. In contrast, for students with relatively high scores in the midterm examination, those in the treatment group obtained lower scores in the final examination than those in the control group.

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<sup>23</sup>When we exclude students whose scores in the midterm examination are more two standard deviations from the mean from our analysis as potential outliers, the estimation results are almost identical to those shown in Column (1).

[Insert Figure 3 here]

To confirm whether these results are robust, we identify three groups corresponding to students with low (less than 28), intermediate (between 28 and 67), and high (68 and above) scores in the midterm examination, and examine whether the impact of relative performance information feedback on the final examination differs between these groups. If the impact of the relative performance information feedback depends on the midterm score, we should be able to observe a varying impact between these groups. The estimation results are shown in Column (2) of Table 2. For the intermediate midterm scores group, relative performance information feedback has a significantly positive effect on the final examination scores (the coefficient for  $D$  is 3.25). This indicates that for students with an intermediate midterm score, information about their relative performance in the midterm examination improved their score in the final examination.

In contrast, relative performance information feedback has a significantly negative effect on the final examination scores for the high midterm examination scores group. The magnitude of the coefficient for *High* is 8.24, while the magnitude of the coefficient for  $(1 + High) \times D$  is  $-6.00$  ( $= -9.25 + 3.25$ ), which is statistically significant (f-value is 4.01). That is, for students with high midterm examination scores, on average, the final examination scores among the treatment group are 14.24 points significantly lower than those among the control group (f-value is 8.24). For students with low scores in the midterm examination, the magnitude of the coefficient for  $(1 + Low) \times D$  is  $-10.00$  ( $= -13.25 + 3.25$ ), which is statistically significant (f-value is 2.88), but there are no significant differences in the final examination scores between the treatment and control groups (f-value is 0.31). For students with high scores in the midterm examination, information on their relative performance in the course could reduce their incentive to study for the final examination. In other words, relative performance information discourages student incentives to study given just-pass behavior. On the other hand, there is no clear difference between the control and treatment groups with low scores in the midterm examination. This is somewhat expected because according to the theoretical model, some of the students in both groups belong to class  $L$ , in which students exert no effort and accordingly receive a minimal score.

In terms of other research considerations, similar to the experimental design employed by Tran and Zeckhauser (2012), we divided students into control and treatment groups

within each classroom. Because of this, we cannot rule out the possibility that students shared their ranks with classmates because we are unable to restrict student actions outside the classroom entirely. However, it would be generally difficult for a student in the control group to identify a student in the treatment group with exactly the same score.<sup>24</sup> In addition, when students exchange information to determine their own rank, this leads to an underestimation (toward zero) in the estimated treatment effects. If so, our estimated treatment effects—that for students with intermediate (high) midterm examination scores, the more precise the information provided, the higher (lower) their score in the final examination—might be smaller than the true treatment effects. Our empirical results demonstrate that the relative performance information feedback has a substantial impact on student incentives to learn.

## 6 Concluding Remarks

Our findings demonstrate that the impact of relative performance information on final scores has opposing effects depending on a student's midterm score. The results seem reasonable if students are interested in passing the course with minimal effort provision and do not take getting a higher grade into account. That is, students adopt just-pass behavior. When the decision on the borderline between pass and fail depends on the students' relative scores, whether students can pass or not depends not only on their own ability, but also on the abilities of other students. Therefore, we considered relative performance information on the midterm examination as a proxy for borderline uncertainty. For marginal students, that is, those whose scores in the midterm examination lie around the borderline, relative performance information serves as a signal indicating that they will need to work harder to pass the course. In contrast, for students with sufficiently high scores in the midterm examination, relative performance information is a signal that they can pass with only moderate effort. Thus, knowledge of relative performance information from the midterm examination will affect student attitudes concerning the final examination.

Overall, our study reveals that information on relative performance is not necessarily

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<sup>24</sup>Further, we also note that many Japanese students do not like revealing their grades to friends. As observed by Benedict (1946), Japan has a long tradition as a shame society where students receiving higher (lower) grades prefer to avoid the envy (derision) of those with lower (higher) grades.

beneficial in incentivizing students to study. For students with intermediate midterm examination scores, it is beneficial to inform them of their performance ranking as a means of decreasing uncertainty. In contrast, for students with high midterm examination scores, providing their own relative performance information could be detrimental to their overall performance in the course.

## Appendix A Derivation of the Functional Form of $U(e)$

For the case of  $1 - \varepsilon > \hat{A}(e)$  (if and only if  $e < \underline{e}$ ), the student fails the examination for certain. Therefore,  $U(e) = -\frac{e^2}{2}$ . At the same time,  $1 + \varepsilon \leq \hat{A}(e)$  (if and only if  $e \geq \bar{e}$ ) ensures that the student passes the examination, that is,  $U(e) = 1 - \frac{e^2}{2}$ . If  $\underline{e} \leq e < \bar{e}$ , whether a student passes or fails the examination depends on the realized  $A$ .  $U(e)$  can be written as follows:

$$\begin{aligned} U(e) &= \int_{1-\varepsilon}^{\hat{A}(e)} 1 \times \frac{1}{2\varepsilon} dA + \int_{\hat{A}(e)}^{1+\varepsilon} 0 \times \frac{1}{2\varepsilon} dA - \frac{e^2}{2} \\ &= \frac{(s_0 - S_0) - (1 - \varepsilon)}{2\varepsilon} + \frac{s_0}{2\varepsilon} e - \frac{e^2}{2}. \end{aligned}$$

## Appendix B Proof of Proposition

To prove the proposition, we use the inequality

$$\varepsilon > (\sqrt{2} - 1)^2(1 + S_0), \quad (8)$$

which holds under the assumption in the text. Define  $\tilde{U}(e) = \frac{(s_0 - S_0) - (1 - \varepsilon)}{2\varepsilon} + \frac{s_0}{2\varepsilon} e - \frac{e^2}{2}$  for  $e \in \mathbb{R}$ . Put  $\tilde{e} = \frac{s_0}{2\varepsilon}$ , which is the unique maximizer of  $\tilde{U}$ . As  $U$  is decreasing in  $[0, \underline{e}]$  and  $[\bar{e}, +\infty)$ ,  $U$  can be maximized only at 0,  $\tilde{e}$  or  $\bar{e}$ .

**Case 1:**  $\tilde{e} < \underline{e}$

In this case,  $e^* = 0$  because  $U$  is decreasing throughout the domain. We obtain that  $\tilde{e} < \underline{e}$  if and only if

$$s_0 < -\varepsilon + \sqrt{\varepsilon^2 + 2\varepsilon(1 - \varepsilon + S_0)} \equiv s_0^1.$$

**Case 2:**  $\underline{e} \leq \tilde{e} < \bar{e}$

The condition  $\underline{e} \leq \tilde{e} < \bar{e}$  is equivalent to

$$s_0^1 \leq s_0 < -\varepsilon + \sqrt{\varepsilon^2 + 2\varepsilon(1 + \varepsilon + S_0)} \equiv s_0^2.$$

In this case,  $e^* = 0$  or  $\tilde{e}$  because  $U$  is decreasing for  $e \geq \tilde{e}$ . The condition for  $e^* = \tilde{e}$  is  $U(0) \leq U(\tilde{e})$ , which can be reduced to

$$s_0 \geq 2 \left[ -\varepsilon + \sqrt{(1 + S_0)\varepsilon} \right] \equiv s_0^3.$$

We can show that  $s_0^1 < s_0^3$  for any parameter value.<sup>25</sup> Besides,  $s_0^3 < s_0^2$  under (8). Therefore,  $e^* = 0$  if  $s_0 < s_0^3$  and  $e^* = \tilde{e}$  if  $s_0^3 \leq s_0 < s_0^2$ .

**Case 3:**  $\bar{e} \leq \tilde{e}$

By Case 2,  $\bar{e} \leq \tilde{e}$  if and only if  $s_0 \geq s_0^2$ . In this case,  $e^* = 0$  or  $\bar{e}$  because  $U$  is increasing in  $[e, \bar{e})$ . The condition for  $e^* = \bar{e}$  is  $U(\bar{e}) \geq U(0)$  and it is equivalent to

$$s_0 \geq (-1 + \sqrt{2})(1 + \varepsilon + S_0) \equiv s_0^4.$$

By tedious but straightforward calculations, we find that  $s_0^4 < s_0^2$  under (8). Hence,  $e^* = \bar{e}$  if  $s_0 \geq s_0^2$ .

In sum, we obtain the characterization of  $e^*$  in the proposition by putting  $s_0^3 = \underline{s}_0$  and  $s_0^2 = \bar{s}_0$ . The continuity of  $e^*$  at  $\bar{s}_0$  is immediate from the construction. (QED)

## Appendix C Derivation of (5) and (6)

First, we can show that  $-\frac{\partial s_0}{\partial \varepsilon} \geq 0$  if and only if  $\varepsilon \geq \frac{1+S_0}{4}$ . This is the parameter condition imposed in the assumption.

Next, we obtain

$$\begin{aligned} \frac{\partial \bar{s}_0}{\partial \varepsilon} &= -1 + [3\varepsilon^2 + 2(1 + S_0)\varepsilon]^{-\frac{1}{2}} [3\varepsilon + (1 + S_0)], \\ \frac{\partial^2 \bar{s}_0}{\partial \varepsilon^2} &= -[3\varepsilon^2 + 2(1 + S_0)\varepsilon]^{-\frac{3}{2}} (1 + S_0)^2 < 0. \end{aligned}$$

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<sup>25</sup>  $s_0^1 < s_0^3$  is reduced to  $\sqrt{\varepsilon^2 + 2\varepsilon(1 - \varepsilon + S_0)} < -\varepsilon + 2\sqrt{(1 + S_0)\varepsilon}$ . Note that the right-hand side is positive by  $\varepsilon \in (0, 1)$ . Taking the square of both sides and rearranging, we obtain  $(\sqrt{\varepsilon} - \sqrt{1 + S_0})^2 > 0$ .

For every  $\varepsilon$ , since  $\frac{\partial^2 \bar{s}_0}{\partial \varepsilon^2} < 0$ , we have

$$\begin{aligned} \frac{\partial \bar{s}_0}{\partial \varepsilon} &> \lim_{\varepsilon \rightarrow 1} \frac{\partial \bar{s}_0}{\partial \varepsilon} \\ &= -1 + [3 + 2(1 + S_0)]^{-\frac{1}{2}} [3 + (1 + S_0)] \\ &\equiv F(S_0). \end{aligned}$$

By  $F'(S_0) = [3 + 2(1 + S_0)]^{-\frac{3}{2}}(1 + S_0) > 0$ , we obtain

$$\begin{aligned} \frac{\partial \bar{s}_0}{\partial \varepsilon} &> \lim_{S_0 \rightarrow 0} F(S_0) \\ &= -1 + \frac{4}{\sqrt{5}} \\ &> 0 \end{aligned}$$

for every  $\varepsilon$ .

## References

- [1] Abe, Yukiko. 2002. “Universities and the entry-level job market: Evidence from Japanese panel data.” *Labour Economics* 9(6): 699–715.
- [2] Aoyagi, Masaki. 2010. “Information feedback in a dynamic tournament.” *Games and Economic Behavior* 70(2): 242–260.
- [3] Ashraf, Nava, Oriana Bandiera, and Scott S. Lee. 2014. “Awards unbundled: Evidence from a natural field experiment.” *Journal of Economic Behavior & Organization* 100: 44–63.
- [4] Azmat, Ghazala, and Nagore Iriberry. 2010. “The importance of relative performance feedback information: Evidence from a natural experiment using high school students.” *Journal of Public Economics* 94(7): 435–452.
- [5] Azmat, Ghazala, and Nagore Iriberry. 2016. “The provision of relative performance feedback: An analysis of performance and satisfaction.” *Journal of Economics & Management Strategy* 25(1): 77–110.

- [6] Bandiera, Oriana, Valentino Larcinese, and Imran Rasul. 2015. “Blissful ignorance? A natural experiment on the effect of feedback on students’ performance.” *Labour Economics* 34: 13–25.
- [7] Barnett, Adrian G., Jolieke C. Van Der Pols, and Annette J. Dobson. 2005. “Regression to the mean: What it is and how to deal with it.” *International Journal of Epidemiology* 34(1): 215–220.
- [8] Becker, William E., and Sherwin Rosen. 1992. “The learning effect of assessment and evaluation in high school.” *Economics of Education Review* 11(2): 107–118.
- [9] Benedict, Ruth. 1946. *The Chrysanthemum and the Sword: Patterns of Japanese Culture*. Mariner Books.
- [10] Brownback, Andy. 2014. “A field experiment on effort allocation under relative grading.” University of California, San Diego.
- [11] Czibor, Eszter, Sander Onderstal, Randolph Sloof, and Mirjam van Praag. 2014. “Does relative grading help male students? Evidence from a field experiment in the classroom.” *IZA Discussion Paper*, No. 8429.
- [12] De Paola, Maria, and Vincenzo Scoppa. 2011. “Frequency of examinations and student achievement in a randomized experiment.” *Economics of Education Review* 30(6): 1416–1429.
- [13] Dubey, Pradeep, and John Geanakoplos. 2010. “Grading exams: 100, 99, 98, ... or A, B, C?” *Games and Economic Behavior* 69(1): 72–94.
- [14] Ederer, Florian. 2010. “Feedback and motivation in dynamic tournaments.” *Journal of Economics & Management Strategy* 19(3): 733–769.
- [15] Eriksson, Tor, Anders Poulsen, and Marie Claire Villeval. 2009. “Feedback and incentives: Experimental evidence.” *Labour Economics* 16(6): 679–688.
- [16] Freeman, Richard B., and Alexander M. Gelber. 2010. “Prize structure and information in tournaments: Experimental evidence.” *American Economic Journal: Applied Economics* 2(1): 149–164.

- [17] Genda, Yuji, Ayako Kondo, and Souichi Ohta. 2010. “Long-term effects of a recession at labor market entry in Japan and the United States.” *Journal of Human Resources* 45(1): 157–196.
- [18] Grant, Adam. 2016. “Why we should stop grading students on a curve.” *The New York Times*, accessed January 6, 2017. Available from URL: [https://www.nytimes.com/2016/09/11/opinion/sunday/why-we-should-stop-grading-students-on-a-curve.html?smid=tw-share&\\_r=0](https://www.nytimes.com/2016/09/11/opinion/sunday/why-we-should-stop-grading-students-on-a-curve.html?smid=tw-share&_r=0)
- [19] Hammond, Robert G., and Xiaoyong Zheng. 2013. “Heterogeneity in tournaments with incomplete information: An experimental analysis.” *International Journal of Industrial Organization* 31(3): 248–260.
- [20] Jalava, Nina, Juanna Schrøter Joensen, and Elin Pellas. 2015. “Grades and rank: Impacts of non-financial incentives on test performance.” *Journal of Economic Behavior & Organization* 115: 161–196.
- [21] Kaji, Sahoko. 2015. “Japanese universities need brighter ideas.” *Financial Times*, accessed March 6, 2017. Available from URL: <https://www.ft.com/content/bb4cb810-7717-11e5-a95a-27d368e1ddf7>
- [22] Kawai-juku. 2016. *Annual Ranking of Difficulty of Entrance to Japanese Private Universities in 2017* (in Japanese), accessed March 6, 2017. Available from URL: <http://www.keinet.ne.jp/rank/17/ks04.pdf>
- [23] Lazear, Edward P., and Sherwin Rosen. 1981. “Rank-order tournament as optimum labor contracts.” *Journal of Political Economy* 89(5): 841–864.
- [24] Lise, Jeremy, Sudo Nao, Suzuki Michio, Yamada Ken and Yamada Tomoaki. 2014. “Wage, income and consumption inequality in Japan, 1981–2008: From boom to lost decades.” *Review of Economic Dynamics* 17: 582–612.
- [25] Ludwig, Sandra, and Gabriele K. Lünser. 2012. “Observing your competitor: The role of effort information in two-stage tournaments.” *Journal of Economic Psychology* 33: 166–182.
- [26] Paredes, Valentina. 2016. “Grading system and student effort.” *Education, Finance and Policy*. 12(1): 107–128.

- [27] Tran, Anh, and Richard Zeckhauser. 2012. “Rank as an inherent incentive: Evidence from a field experiment.” *Journal of Public Economics* 96(9): 645–650.
- [28] Volokh, Eugene. 2015. “In praise of grading on a curve.” *The Washington Post*, accessed March 6, 2017. Available from URL: [https://www.washingtonpost.com/news/volokh-conspiracy/wp/2015/02/09/in-praise-of-grading-on-a-curve/?utm\\_term=.63bfc5beb916](https://www.washingtonpost.com/news/volokh-conspiracy/wp/2015/02/09/in-praise-of-grading-on-a-curve/?utm_term=.63bfc5beb916)

Table 1: Descriptive statistics

	Variables	Definition	Mean.	S.D.	Min.	Max.
Total $n = 239$	$Y_F$	Score in the final examination	67.17	14.84	16	100
	$Y_M$	Score in the midterm examination	51.76	16.64	12	102
	$D$	=1 if student is given information on her relative rank in the midterm examination, =0 if elsewhere	0.50	0.50	0	1
	$Male$	=1 if male, =0 if female	0.87	0.34	0	1
	$Classroom2$	=1 if in the classroom A (small), =0 elsewhere	0.16	0.37	0	1
	$Classroom3$	=1 if in the classroom B (middle), =0 elsewhere	0.26	0.44	0	1
	$Classroom4$	=1 if in the classroom C (middle), =0 elsewhere	0.29	0.45	0	1
	$Math$	The pretest scores of mathematics	37.39	13.56	11	87
	$EconI$	Grades in the Introductory Economics I	63.57	13.43	26	96
	$Homework$	The number of homework submissions	5.39	3.60	0	10
Treatment $n = 119$	$Y_F$		66.72	14.19	16	92
	$Y_M$		50.15	14.94	12	95
	$D$		1.00	0.00	1	1
	$Male$		0.87	0.34	0	1
	$Classroom2$		0.13	0.33	0	1
	$Classroom3$		0.27	0.45	0	1
	$Classroom4$		0.31	0.46	0	1
	$Math$		35.81	10.72	12	67
	$EconI$		62.43	12.90	26	95
	$Homework$		5.38	3.58	0	10
Control $n = 120$	$Y_F$		67.61	15.50	26	100
	$Y_M$		53.35	18.09	18	102
	$D$		0.00	0.00	0	0
	$Male$		0.87	0.34	0	1
	$Classroom2$		0.19	0.40	0	1
	$Classroom3$		0.26	0.44	0	1
	$Classroom4$		0.27	0.44	0	1
	$Math$		38.96	15.78	11	87
	$EconI$		64.71	13.89	31	96
	$Homework$		5.41	3.63	0	10

Mean-comparison test (Welch t-test)

$H_0$ : there is no difference in the means of  $Y_M$  ; t-value= 1.49 (p-value= 0.14)

Table 2: Estimation results: the impact of information on a student's relative rank in the midterm examination on the final examination score

	(1)	(2)
$Y_M^2/100 \times D$	-0.89 (0.41)	
$Y_M \times D$	0.84 (0.46)	
$D$	-16.51 (12.37)	3.25 (1.64)
$Y_M^2/100$	0.09 (0.22)	
$Y_M$	0.19 (0.28)	
$Low \times D$		-13.25 (6.11)
$High \times D$		-9.25 (3.34)
$Low$		-4.44 (4.95)
$High$		8.24 (2.56)
Observations	239	239
Log likelihood	-900.1	-899.5
$R$ -squared	0.50	0.50
F-test		
$H_0$ : all coefficients except the constant=0.	20.76	21.57

Notes

- 1) Standard errors (in parentheses) are heteroskedasticity robust.
- 2) The models in Columns (1)–(2) also include the student characteristics  $\mathbf{X}$ . Estimates for these variables not reported.
- 3)  $Low$  is a 0–1 dummy taking a value of unity if the midterm examination score is less than 28 and zero otherwise.  $High$  is a 0–1 dummy taking a value of unity if the midterm examination score is 68 and above and zero otherwise.

Figure 1: The relationship between midterm score and equilibrium final score

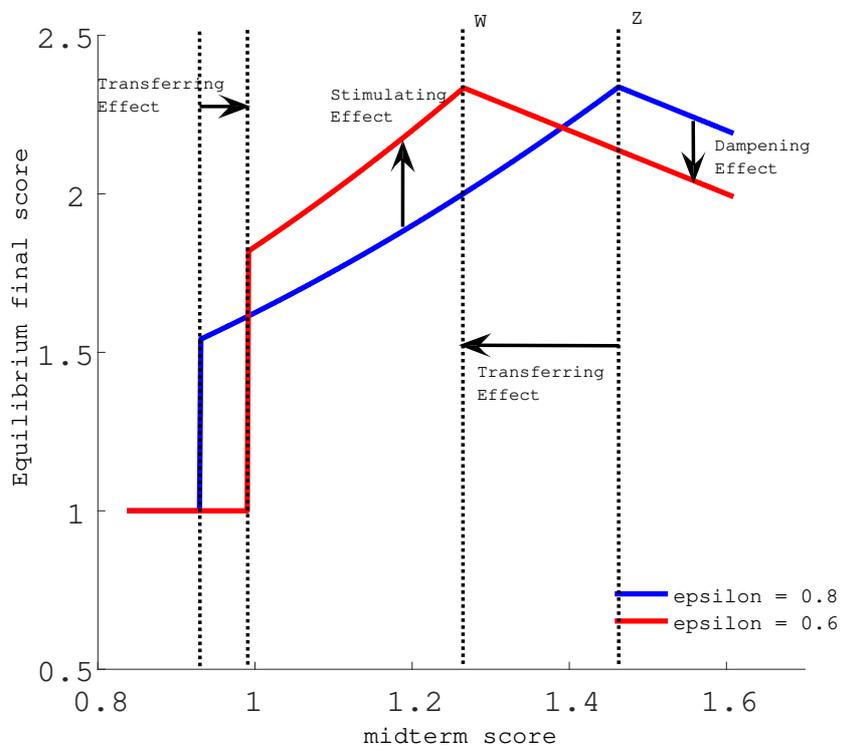


Figure 2: The relationship between the midterm examination and the final examination scores

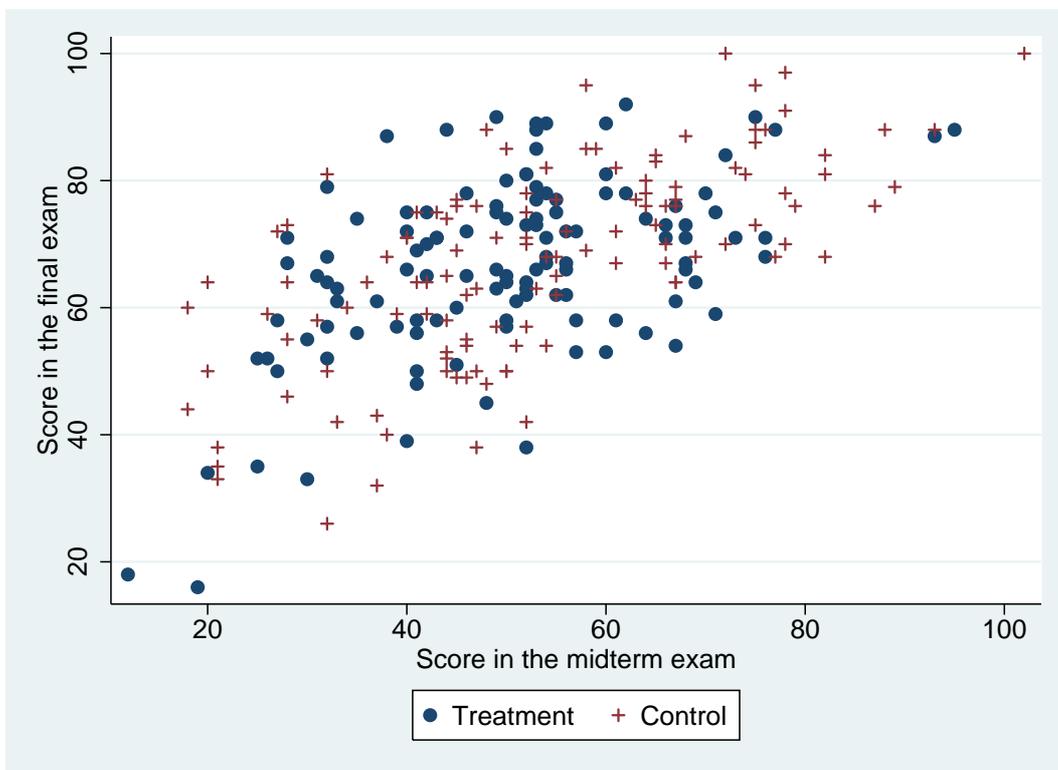
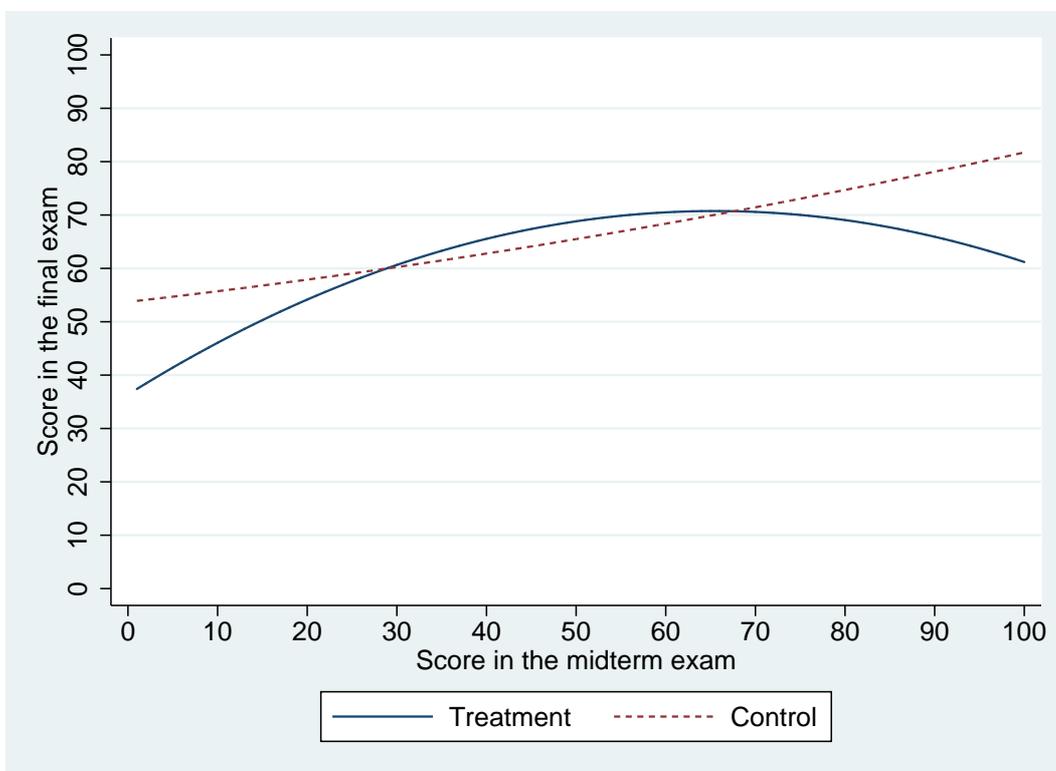


Figure 3: The relationship between the midterm examination scores and improvements in the final examination scores



Note: We calculate the fitted values of final examination score using the coefficients in Column (1) in Table 2. The student characteristics  $\mathbf{X}$  are evaluated at the sample mean values.

Appendix Figure 1: The letter to students (originally written in Japanese)

Panel A: Treatment group

Introductory Economics, Second Semester, 2012			
A report on the result of your midterm examination			
<u>Student ID</u>	<u>7 digit ID</u>	<u>Name</u>	<u>Name of the student</u>
<u>Classroom</u>	<u>Instructor's name</u>		
Your score in the midterm examination is		49/110	
Your score in problems of mathematics is		6/10	
Within four classrooms, you are 146 <sup>th</sup> out of 285 students.			

Panel B: Control group

Introductory Economics, Second Semester, 2012			
A report on the result of your midterm examination			
<u>Student ID</u>	<u>7 digit ID</u>	<u>Name</u>	<u>Name of the student</u>
<u>Classroom</u>	<u>Instructor's name</u>		
Your score in the midterm examination is		49/110	
Your score in problems of mathematics is		6/10	

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