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Comments
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Quest for Knowledge and Pursuit of Grades: Information, Course Selection, and Grade Inflation at an Ivy League School

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Abstract: This paper exploits a unique natural experiment – Cornell University's 1996 decision to publish course median grades online - to examine the effect of grade information on course selection and grade inflation. We model students' course selection as dependent on their tastes, abilities, and expected grades. The model yields three testable hypotheses: (1) students will tend to be drawn to leniently graded courses once exposed to grade information; (2) the most talented students will be less drawn to leniently graded courses than their peers; (3) the change in students' behavior will contribute to grade inflation. Examining a large dataset that covers the period 1990-2004 our study provides evidence consistent with these predictions.

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1 Introduction

In April 1996 Cornell University's Senate voted in favor of adopting a new a grade reporting policy which consisted of two parts: (1) the publication of course median grades on the internet; (2) the reporting of course median grades in students' transcripts. The policy change followed the determination of the Committee on Academic Programs and Policies that "it is desirable for Cornell university to provide more information to the reader of a transcript and produce more meaningful letter grades." The rationale section of the policy stated that "students will get a more accurate idea of their performance, and they will be assured that users of the transcript will also have this knowledge. A grade of B- in a course of substantial enrollment in which the median was C+ will often indicate a stronger performance than, e.g., a B+ in a large course in which the median is A. *More accurate recognition of performance may encourage students to take courses in which the median grade is relatively low* [emphasis ours]."[2]

The publication of median grades on the internet started in the fall semester of 1997. For technical reasons, however, the reporting of course median grades in transcripts has not been implemented yet.[3] The (partial) implementation of the policy allows us to compare patterns of course selection and grade inflation under two distinct levels of information. Prior to the implementation of the policy students could learn about grades mostly through the grapevine. Since 1997 whatever grade information was available through this informal channel was augmented by easily accessible official information.

Our study examines the effect of the policy change both theoretically and empirically. We provide a simple model of course selection. Students have to choose between two (horizontally differentiated)

[2] The quotes are taken from Cornell's "Median Grade Reports" website: http://registrar.sas.cornell.edu/Student/mediangrades.html

[3] According to the University Registrar the inclusion of median grades in transcripts is planned to take place in late 2005.

courses according to their tastes, abilities, and the grades they expect to receive. Absent any information on grades students choose courses solely based on their tastes. In contrast, once exposed to grade information students tend to trade off tastes for higher grades. This tendency, which affects more strongly less capable students, results in grade inflation.

We then turn to the empirical analysis. First we investigate patterns of access to the median grades website. We demonstrate that the daily number of hits on this website peaks immediately before and during periods of course registration. This pattern is consistent with our assumption that students use the online information to choose courses. In our examination of course selection and grade inflation we employ a large dataset containing student grades in courses taken at Cornell's College of Arts and Sciences in the period 1990-2004. Our analysis shows that whereas prior to the online publication of grades course enrollment was not sensitive to past median grades the two variables have become positively and significantly correlated since then. As predicted by our model we find that the most talented students tend to be less drawn to leniently graded courses than their peers. We then show that the change in students' behavior following the online publication of grades may have contributed to grade inflation, a decrease in the information content of grades, and an increased bias in the ranking of graduating students.

Grade inflation is a subject of concern in the academic world.[4] Over the past few decades students' grades have increased considerably in many institutions of higher-education, most notably in the Ivy League. Since grades are bounded from above grade inflation is accompanied by a compression of grades at the top. The resultant reduction in the information content of grades is a major cost of grade inflation.

Several explanations for the grade inflation phenomenon have been suggested over the years.[5] There

[4] Goldman (1985) defines grade inflation as "an upward shift in the grade point average of students (GPA) over an extended period of time without a corresponding increase in students' achievement."

[5] See, for example, Johnson (2003) and Rosovsky and Hartley (2002). A recent review of the literature is provided by

seems to be an agreement that grade inflation originated in the 1960s with a reluctance of instructors to give male students low grades that would perhaps force them into the Vietnam War draft. Other proposed explanations include: the widespread use of student evaluations of instructors in promotion decisions (student evaluations have been shown to be positively correlated with expected course grades)[6]; changes in the internal structure of college faculties, with adjunct faculty members and those with high work loads more inclined to grade leniently; institutions' competition for students; and a rise in the "student as a consumer" culture.

Our paper focuses on one potential reason for grade inflation: students' grade-driven course selection. Grade-driven course selection has been mentioned in the discussion of grade inflation in the past. However, until now it has received almost no formal treatment. Notable exceptions are Sabot and Wakeman-Linn (1991) and Johnson (2003). Sabot and Wakeman-Linn (1991) used a sample of 376 students in Williams College during the 1985-86 academic year to study the effect of grades on course choice. They show that a decline in the grade received by a student decreases the probability of her taking a second course in the same department. Their main concern is whether differences in grading policies among departments results in skewed enrollment, particularly away from sciences. Johnson (2003) used data from an experiment conducted at Duke University during the 1998-99 academic year. In the experiment students were provided with historical course information and were then asked to choose among courses. The study provided evidence that students tend to elect courses with leniently grading instructors. While Johnson is better able to observe the set of courses from which the students selected, his study, like Wakenman-Linn (1991), is based on a relatively small number of observations (500 students) and may be subject to potential sample selection biases. Our analysis is based on a much larger dataset covering many students, courses and years - in total we have more than 800,000 observations at the student-course level.

Manhire (2005).

[6] See, for example, Evans and McNelis (2000).

The paper proceeds as follows. Section 2 introduces our course selection model. Section 3 examines patterns of access to the median grades website. Section 4 analyzes the effect of the median grade policy on course enrollment. In section 5 we examine which students tend to be more drawn to leniently graded courses. Section 6 looks at grade inflation and its consequences. In section 7 we investigate alternative explanations for grade inflation. Section 8 concludes

2 Course selection and Compositional Grade Inflation

In this section we illustrate the possible effect of grade information and grade-driven course selection on course enrollment and grade inflation. We demonstrate that in the presence of variations in grading policies an increase in the level of information results in increased enrollment of students into leniently graded courses and an increase in the overall average grade. We refer to this phenomenon as *compositional grade inflation*. We also examine how grade information affects differently students of different intellectual abilities.

2.1 Model

We assume that there are two courses available, A and B. The courses are horizontally differentiated and located at the end points of a line segment $[0, 1]$ as in Hotelling (1929). Students are heterogeneous. They differ in their intellectual abilities and in their tastes for courses. A student's taste for courses is denoted by $\tau \in [0, 1]$. The parameter τ measures the distance of the student's ideal course from the location of course A, and $1 - \tau$ measures the distance from course B. Students incur a cost (or a disutility) associated with choosing a course, $c(d)$ where d denotes the distance between a student's ideal course and the one she chooses to take. We assume $c(0) = 0$, and that $c(d)$ is increasing in distance $c'(d) > 0$. Particularly we will assume $c(d) = kd$ where $k \geq 1$. We denote a student's ability by the parameter $\theta \in [0, 1]$. A higher ability level is characterized by a higher θ. Hence every student's type is

a pair (θ, τ). The population of students is uniformly distributed on the two dimensional space $[0,1]^2$ of pairs (θ, τ).

Each student enrolls in one course. Grades depend on the grading policy represented by a course specific parameter M_i and on the student's rank in the course. The student's rank is in turn a function of her ability and that of her classmates. A student of ability θ enrolled in course i is ranked

$$r(S_i, \theta) = prob(\theta' \leq \theta | (\theta', \tau) \in S_i)$$

where S_i is the population of students in course i. Each student then receives an expected grade $g(M_i, r(S_i, \theta))$ for that course. A course with a larger parameter M_i is said to be more leniently graded if it yields a higher expected grade for every rank r,

$$M_i \geq M_j \Rightarrow g(M_i, r) \geq g(M_j, r) \quad \forall r.$$

For simplicity we assume for the most part a linear grading policy:

$$g(M_i, r) = 2(1 - M_i)r + 2M_i - 1,$$

where $M_i \in [\frac{1}{2}, 1]$.[7] Note that the grading policy parameter M_i represents the median grade: $g(M_i, \frac{1}{2}) = M_i$. This grading policy is increasing in a student's rank in the course and the highest ranking student receives the highest grade: $g(M_i, 1) = 1$ for any M_i. The most talented student $\theta = 1$ would receive the highest possible rank $r(S_i, 1) = 1$ for any composition of students S_i and therefore the highest grade.

We assume a separable utility in grades and tastes:

$$u(M_i, S_i, \theta, \tau) = g(M_i, r(S_i, \theta)) - c(d(i, \tau)).$$

Students maximize their expected utility.

[7] Course grades in higher education are often given in discrete grade categories such as A, B, C. Our grading policy is continuous and can be interpreted as an expected grade for any rank. A higher rank in a course increases the probability of a higher letter grade.

If the grading policies in the two courses are the same, $M_A = M_B$, then a student's decision as to which course to select would only depend on the student's taste τ. A student selects course i over j if

$$c(d(i,\tau)) < c(d(j,\tau)). \tag{1}$$

There is a cutoff point τ_0 defined as the solution to

$$c(\tau) = c(1-\tau),$$

such that students of taste $\tau < \tau_0$ select course A and students of taste $\tau > \tau_0$ select course B. For a linear cost $\tau_0 = \frac{1}{2}$.

If grading policies differ, e.g. $M_A > M_B$, but students are uninformed of this difference and have the same prior probability over the distribution of grading policy parameters for both courses, their expected grade in both courses would be equal. Hence students would select courses according to their tastes only, as in the situation when grading policies are the same. However, when a student is informed of the grading policy, consideration of grades becomes relevant for course selection. Students would then trade off some of their academic interest for higher grades.

2.2 Equilibrium

Suppose for a moment that grades were independent of student ability and rank and all students in a course would receive the same grade. In this simple case, clearly an increase in the of proportion λ of students informed about these grading policies would increase enrollment into the leniently graded course and raise the overall mean grade, i.e. create grade inflation. This rise in the mean grade is not driven by a change in the grading policies or in the ability of students, but rather by the selection of students into leniently graded courses, i.e. it is a result of compositional grade inflation.

Generally, however, grades depend on a student's ability and that of her classmates. An informed student's expected grade in a course depends not only on the grading policy but also on the composition

of students in the course. Hence the reaction of students to information on grading policies may depend on their ability and the composition of students in each course may be different when students are informed and can respond to grading policies in their course selection. We define an equilibrium notion in which students form beliefs over their rank in each course. We denote their expected rank by $\widehat{r}_i(\theta|a_i, a_j)$. Course i is selected by an informed student (θ, τ) if

$$2(1 - M_i)\widehat{r}_i(\theta|M_A, M_B) + 2M_i - 1 - c(d(i, \tau)) > 2(1 - M_j)\widehat{r}_j(\theta|M_A, M_B) + 2M_j - 1 - c(d(j, \tau)). \quad (2)$$

In the event the student is indifferent we assume that she randomly selects each course with a probability $\frac{1}{2}$. In equilibrium all students informed and uninformed maximize their expected utilities. Uninformed students expect the same grade in both courses. Informed students have rational expectations regarding their grades. We denote the probability that a student is informed by λ, and assume that it is independent of type.

Definition 1 *Given parameters M_A, M_B, λ an equilibrium is defined as:*

Course selection functions for informed and uninformed students

$$\sigma_{un}, \sigma_{in} : (\theta, \tau) \to \{A, B\},$$

probability distributions $H_i(\theta)$ for the distribution of abilities in each course,

and expected ranks for informed students $\widehat{r}_i(\theta|M_A, M_B)$ in each course such that for all (θ, τ):

(i) Students maximize utility given their information and beliefs: $\sigma_{un}(\theta, \tau) = i$ whenever (1) and $\sigma_{in}(\theta, \tau) = i$ whenever (2).

(ii) $H_i(\theta) = prob\{\theta' \leq \theta|(\theta', \tau) \in S_i\}$ where $S_i = \{(\theta, \tau)|\sigma_{un}(\theta, \tau) = i$ and (θ, τ) is uninformed or $\sigma_{in}(\theta, \tau) = i$ and (θ, τ) is informed.$\}$

(iii) Informed students' expectations about their rank are correct: $\widehat{r}_i(\theta|a_A, a_B) = H_i(\theta)$.

We investigate the effects of grade information on course selection. We show that when students are informed enrollment into the leniently graded course and the overall mean grade increase.

2.2.1 Information, Course Selection and Grade Inflation

Uninformed students assign the same prior probability distribution to the difficulty of grading and to their rank in each course. They have the same expected grade in both courses. Thus, only students' tastes determine their course selection. For all ability levels θ, students with $\tau < \tau_0 = \frac{1}{2}$ enroll in course A.

For informed students course A is selected if

$$2(1 - M_A)\widehat{r}_A(\theta|M_A, M_B) + 2M_A - 1 - c(d(A, \tau)) > 2(1 - M_B)\widehat{r}_B(\theta|M_A, M_B) + 2M_B - 1 - c(d(B, \tau)).$$

Note that a student of ability $\theta = 1$ will have the highest grade regardless of the grading policy. Therefore, the highest capability student, even when she is informed, chooses a course according to her taste only.

Suppose that course A is more leniently graded, $g(M_A, r) > g(M_B, r)$ for all $r < 1$. We show that for each θ all students with low taste parameters choose course A and those with high values of τ choose course B. However, for informed students the cutoff point between the selection of the two courses depends on the student's ability θ. To derive the equilibrium enrollment, the composition of students in each course, and the overall mean grade we find a boundary curve $\tau_1(\theta)$ which in equilibrium separates the types (θ, τ) that would enroll in each course. In proposition 1 we characterize this curve. An example is provided at the end of this section and illustrated graphically in Figure 1.

Proposition 1 *Assume parameter values $0 < M_A - M_B < \frac{k}{4}$. When a proportion λ of students of each type are informed, there exists a function $\tau_\lambda : [0, 1] \to [0, 1]$ and an equilibrium such that, in the equilibrium, for all types (θ, τ), if $\tau < \tau_\lambda(\theta)$ then $\sigma_{in}(\theta, \tau) = A$ and if $\tau > \tau_\lambda(\theta)$ then $\sigma_{in}(\theta, \tau) = B$. Moreover, for all θ, $\tau_\lambda(\theta) \geq \tau_0 = \frac{1}{2}$ and $\tau_\lambda(\theta)$ is decreasing in θ.*

All proofs are provided in the Appendix. The assumption $M_A - M_B > 0$ simply states that course A is the leniently graded course. The assumption $M_A - M_B < \frac{k}{4}$ (which is sufficient but not necessary)

implies that some low ability students select course B due to their tastes, even if they are informed of the grading policy. It guaranties an interior cutoff point for each ability level.

Proposition 1 allows us to reach important conclusions on the selection of courses by informed students. Since we find that $\tau_\lambda(\theta) \geq \tau_0$ for all θ, enrollment into the leniently graded course is larger when some students are informed than when all students are uninformed about the grading policy. For all abilities $\theta < 1$, when some students are informed, there is an increased tendency to choose the high grade course over the low grade course. Moreover, since the boundary of course selection $\tau_\lambda(\theta)$ is decreasing in θ, high ability students are less inclined to choose leniently graded courses. The proportion of high ability students in the leniently graded course is lower than in the stringently graded course. The attractiveness of the leniently graded course is reinforced by the expected composition of abilities in the course.

To prove the proposition, we conjecture the existence of a function $\tau_\lambda(\theta)$ as described in the proposition. We then solve for the function using a differential equation defined by the indifference of an informed student of type $(\tau_\lambda(\theta), \theta)$ between choosing course A and course B.

The next proposition shows that enrollment into the leniently graded course is higher the higher the proportion of informed students.

Proposition 2 *For parameter values $0 < M_A - M_B < \frac{k}{4}$, enrollment into the leniently graded course $N_A(\lambda)$ is higher the higher the proportion of informed students λ.*

In the third proposition we show that the overall mean grade is higher when all students are informed than it is when all students are uninformed.

Proposition 3 *When all students are informed about the grading policy, the overall mean grade is higher compared to the case where students are uninformed.*

To illustrate the results we provide a numerical example of course selection by informed students.

The example is derived following the proofs of propositions 1-3 for particular parameter values. The results are illustrated in Figure 1.

Example 1 *Let* $M_A = \frac{7}{8}, M_B = \frac{5}{8}$ *and* $k = 1$. *We compare the extreme cases* $\lambda = 0$ *or* 1.

The boundary between selection of the two courses in the case of informed students ($\lambda = 1$*) is given by:*

$$\tau_1(\theta) = 0.848\,22 - 9.\,821\,7 \times 10^{-2} \exp\left(1.\,265\,6\theta\right)$$

Informed students with type (τ, θ) *such that* $\tau < \tau_1(\theta)$ *(points below the* $\tau_1(\theta)$ *curve) enroll into course* A*, and those above the curve enroll into course* B*. For uninformed students, only types* (τ, θ) *such that* $\tau < \frac{1}{2}$ *enroll into course* A*. When the students are uninformed, enrollment into course* A *is* $N_A(0) = 0.5$ *and the overall mean grade is is* $M(0) = 0.75$*. When the students are informed, enrollment into course* A *is* $N_A(1) = 0.650\,69$ *and the overall mean grade is* $M(1) = 0.787\,67$.

In the following sections we test the predictions derived from the model. We examine whether students respond to information on grading policies by selecting into leniently graded courses and whether highly capable students are less drawn to such courses than their peers. We also explore the connection between grade-driven course selection and grade inflation. First, however, we examine patterns of access to the median grades website.

3 Patterns of Access to the Median Grades Website

Since the adoption of the policy course median grades are reported on the website of the Office of the Registrar. The registrar has provided us with daily data on the number of visits (hits) to the median grades website from May 2002 to December 2004. We examine the patterns of access to the median grade website and show that the site is visited more frequently during periods of course registration.

This evidence seems is consistent with our hypothesis that students use the information for selecting courses.

There are two periods of registration in every semester at Cornell. The first, called the "add/drop" period, starts at the beginning of each semester and lasts several weeks.[8] The second period of registration, called the "pre-enrollment" period, lasts 25 days. It starts either 3 days (Fall semester) or 24 days (Spring semester) after the end of the "add/drop" period. During this period students pre-enroll for courses offered in the next semester.

During the period that we study there were 63,540 visits to the website or an average of 65 visits per day. There are large differences in the average number of visits between registration and non-regisration periods. The average number of visits in non-registration periods is 48. In contrast, during the "add-drop" periods the average number of visits is 85 and during the "pre-enrollment" periods the average is 103. These differences in the average number of visits between registration and non-registration periods are highly significant statistically.[9]

Figure 2 displays the daily number of visits to the median grades website from May 2002 to December 2004. We combine the two registration periods to increase the clarity of the figure. The starting day of every semester is highlighted on the horizontal axis. The figure clearly demonstrates that the median grades website experiences much more traffic during registration periods than during non-registration periods. It is also interesting to note that the number of visits seems to be higher than normal just prior to the start of registration periods. One possible interpretation of this pattern is that students gather information about grades in order to be well prepared to select courses once registration starts.

[8] The "add/drop" period is itself divided into two subperiods. In the first subperiod, which lasts either 22 days (Spring semester) or 23 days (Fall semester), students are allowed to add or drop courses for the current semester. In the second subperiod, which lasts 28 days, students are allowed only to drop courses for that semester.

[9] Regressing the daily number of visits on two dummy variables for the "add/drop" and "pre-enrollment" periods and a constant yields coefficients that are all statistically significant at the 1 percent level.

Overall, the data on the daily number of visits strongly suggest that the online grade information is used by students in selecting courses.

4 The Effect of Grade Information on Course Selection

In order to study the effect of grade information on course selection we utilize a large dataset provided to us by the registrar. The dataset contains grade information on all the students who attended courses at the College of Arts and Sciences between the Spring semester of 1990 and the Fall semester of 2004. We focus our attention on undergraduate level courses.[10] The dataset contains more than 800,000 observations of students attending such courses. Each observation has information on an individual student taking a specific course. The observation includes course characteristics and student characteristics, including, most importantly, her final grade in the course.[11]

We propose to study the effect of the median grade reporting policy by examining course enrollment patterns. According to our model when students do not have information about grading policies they choose courses solely according to their tastes. Thus, all else being equal (e.g. constant tastes and total aggregate enrollment), in such circumstances variations in grades have no effect on course enrollment. In contrast, the model predicts that course enrollment would be positively correlated with median grades once grade information becomes available.[12]

[10] According to the median grade reporting policy grades for graduate level courses were not supposed to be reported in transcripts or published online.

[11] In this section we restrict our investigation to the original grades given to students at the end of each semester and ignore ex-post grade changes. The same restriction is applied by the registrar in computing course median grades.

[12] We are assuming that a high median grade signals a lenient grading policy. However, one could legitimately argue that a high median grade may instead signal a high instructor quality. Given the data that we have we cannot rule out this interpretation. However, even if course grades signal instructor quality and not grading leniency the results that we obtain below still support our central thesis which is that grade information matters for course selection.

Table 1 reports results of regressions that test this hypothesis. The dependent variable in all the regressions reported in the table is the natural logarithm of course enrollment. There are two key explanatory variables in these regressions. The first is the lagged course median grade.[13] The second is an interaction variable between the lagged median grade and a dummy variable, *policy*. Since the online publication of median grades started at the end of 1997 (the first set of median grades to be published was that of the Spring semester of that year) the dummy variable takes the value of 0 during 1990-97 and 1 during 1998-2004.[14] Additionally, the regressions allow for period specific course fixed effects. These capture characteristics that are unique to each course while allowing for a structural break between the pre-policy-change and the post-policy-change eras.

We focus our analysis on annual courses (offered either every Fall or every Spring semester) at the lower or upper division level (200-400 level) with enrollment of at least 10 students. We chose to focus on these courses for the following reasons. First, median grades are typically published with a lag of about one year. This means that when a student registers for a course she is able to observe last year's median grades but not last semester's grades. Moreover, semestral courses (offered every semester) are often required courses where there is less freedom to choose. Second, the primary audience of introductory (100 level) courses are freshmen students who may be less knowledgeable about the median grades website relative to other students. Third, according to the median grades policy only courses with at least 10 students have their grades published online.

[13] The course median grade in the previous period provides a good estimate for the median grade in the current period. In about one half of the cases we examine the grade does not change from one period to the next and in about a quarter of the cases the grade increases. Thus a student choosing a course should have a high degree of confidence that the median grade in the current period would be at least as high as that of the previous one.

[14] The Office of the Registrar does not keep a record of the publication dates of the median grade reports. However, we were able to estimate these dates by inspecting electronic file property characteristics and by other means. Reports are typically published with a lag of about one year. From the Fall semester of 1999 to the Spring semester of 2002 the publication lag was longer than one year. We account for these longer lags in our analysis.

In column (1) of Table 1 we provide our first set of results. These show that enrollment was not sensitive to the lagged median grade prior to 1998: the coefficient on the median grade variable is very small in value and statistically indistinguishable from 0. In contrast, enrollment has become quite sensitive to the lagged median grade since 1998: the coefficient on the interaction variable is positive and highly significant. Since 1998 a one unit change in the lagged median grade (e.g. from a B to an A) is associated with an 18 percent increase in enrollment.

In column (2) we add to the regression two explanatory variables. The first is the natural logarithm of the number of student-course observations at the department level in a given semester. The second is the natural logarithm of the number of courses offered by the department in a given semester. Controlling for all other factors (including the number of courses) an increase in the number of students in a department should increase course enrollment. Similarly, controlling for all other factors (including the number of students) an increase in the number of courses should decrease course enrollment. Both variables have the expected signs and are highly significant.

In the last column of Table 1 we add time (semester-year) fixed effects to the regression. These are meant to capture the effect of all time specific potential determinants of enrollment. Results remain almost unchanged relative to column (2). Summarizing, Table 1 strongly suggests that whereas before 1998 enrollment was not sensitive to past median grades, since the adoption of the median grade reporting policy students tend to be drawn to leniently graded courses.

We next investigate the effects of removing the restrictions we have placed on the set of courses examined. Results are reported in Table 2. The dependent and the independent variables are the same as those of the last column of Table 1. Results for only the two main explanatory variables are reported. For ease of comparison the first column in Table 2 replicates the results presented in column (3) of Table 1 (where the sample consisted of annual courses at the 200-400 level with lagged enrollment of at least 10 students).

For the set of courses we used in Table 1 and for which we conjectured the information on grading policy would be most relevant we find the largest and most significant effect. Adding introductory level courses we still find a positive and significant effect, though lower in value and statistical significance. The coefficient of the policy variable becomes small and insignificant when we include semestral courses and courses with lagged enrollment of less than 10 students [see columns (3) and (4)]. This result is not surprising given the considerations discussed above.

In Table 3 we address the following question: Does the responsiveness of enrollment to past median grades change over time? All else being equal, we expect that when more students are informed the sensitivity of enrollment to grades would be larger. An increase in the share of informed students could be the result of several factors. First, more students may know of the existence of the median grades website. Second more students may have easy access to the internet. Third, it is possible that accessing this website seems more legitimate today than in the past.

To address the question at hand we construct a pair of dummy variables: *Policy1* takes the value of 1 from the Spring semester of 1998 to the Spring semester of 2001; *Policy2* takes the value of 1 from the Fall semester of 2001 to the Fall semester of 2004. Thus *Policy1* and *Policy2* capture two equal subperiods (of 7 semesters) within the post-policy-change era. We then interact the lagged median grade with the two dummy variables. In the regression reported in Table 3 the sample is of annual courses at the 200 to 400 levels with lagged enrollment of at least ten students, as in Table 1. All regressions include the same controls as in column (3) of Table 1.

In the first column of table (3) we examine courses offered in all departments at the College of Arts and Sciences. The coefficients on the two interaction variables are almost identical in magnitude. In column (2) we restrict our analysis to the ten departments with the largest course enrollment over the period examined.[15] Relative to the coefficient on the first interaction variable the coefficient on

[15] These departments are (in declining order of total enrollment): Chemistry, Mathematics, English, Economics, Psy-

the second interaction variable is larger and more highly significant. In the last column we examine the Department of Economics, one of the largest departments in the College. We chose to focus on this department for two reasons. First, for this department we have more detailed data which we analyze next. Second, economics students seem to display a higher degree of sensitivity to grades than students attending courses in other departments. Indeed, for courses in the Department of Economics the coefficients for both interaction variables are very large (a one unit change in the median grade is associated with an enrollment change of about 45 percent), but only the second interacton variable is significant. Taken together, the results reported in Table 3 do not provide strong evidence of an increase in the sensitivity of enrollment to grades between the first and the second post-policy-change periods.

We next incorporate into our analysis controls for course and instructor characteristics. This type of information is not available in the original dataset obtained from the registrar. We therefore hand-collected data on characteristics of courses offered at the Department of Economics from 1990 to 2004. The information includes year and term, course number and title, number of sections, meeting schedule, and instructor name and position. This data was then matched with the dataset used previously. In Table 4 we examine whether controlling for meeting schedule and instructor characteristics changes the results obtained previously. We use the regression that is reported in the last column of Table 3 as a basis for our analysis. Columns (1)-(3) report the results of a regression that includes the number of meetings per week, the length of each meeting in minutes, and class starting time. These variables do not seem to affect enrollment, possibly because they exhibit very little variation for a given course. Columns (4) and (5) examine the effect of instructor characteristics. We see that whether the instructor is a professor (at the assistant, associate, or full level) or not and whether the instructor has tenure or not has no influence on enrollment either.

chology, Physics, Government, History, Music, and Philosophy.

The most important conclusion to be drawn from Table 4 is evident in its top three rows: controlling for meeting schedule and instructor characteristics does not change our main results regarding the change over time in the sensitivity of enrollment to the lagged median grade.

5 Student Ability and Responsiveness to Grades

Our model predicts that when students do not have information about grading policies they select among courses solely based on their tastes. This is true for students of all ability levels. Once exposed to grade information, however, students tend to trade off tastes for grading leniency and this tendency is stronger for those with lower abilities. In this section we propose to test this prediction of the model. In order to do so we need to measure student ability. For this purpose we cannot rely on grades received in courses taken at Cornell as these may be biased along the lines we have discussed previously. Instead we rely on students' SAT scores. Using SAT scores makes sense for several reasons. First, SAT scores are based on a standardized test. Second, almost all students need to take the SAT test in order to be admitted to the university. Third, the test measures (undoubtedly in an imperfect manner) intellectual ability.

Our individual level dataset contains math and verbal SAT scores for the years 1996-2004. Unfortunately we cannot use some of this data because of the following complication. SAT scores were recentered by the Educational Testing Service in 1995.[16] The recentered math scores were raised relative to the original ones by up to 50 points (but could also drop by up to 10 points). The recentered verbal scores were raised relative to the original ones by up to 80 points. This means that scores of students that took the test before 1995 are not directly comparable to those of students that took the test since then.

[16] For details on this issue see the website of The College Board: http://www.collegeboard.com/

Since our data does not indicate whether the SAT score is based on a test that was taken before or after the recentering we needed to further restrict the time period to be examined. The last cohort of freshmen students with old (original) SAT scores entered Cornell in 1995. Almost all of these students graduated by the Spring semester of 1999. Thus in this section we focus our analysis on the period from the Fall semester of 1999 to the Fall semester of 2004.

In order to test the connection between student ability and responsiveness to grades we construct a new dependent variable. This variable measures for each course the share of students with a SAT score greater than or equal to a given threshold. In effect the threshold distinguishes between high and low ability students. If high ability students are less responsive to grades, as our model predicts, we should see their share in total enrollment decline as the lagged median grade increases.

The key explanatory variable in our regression is the lagged median grade. A second explanatory variable, *department SAT*, measures the share of students in a department in a given semester with a SAT score greater than or equal to the threshold applied to the dependent variable. By including this variable we are able to control for the fact that SAT scores of students have increased during the period examined (more on that later). All specifications also include, as before, course and time fixed effects. We restrict our focus to courses offered by the ten largest departments. We do so because the sensitivity of enrollment to grades is stronger in these departments than in the College as a whole. This fact should in principle assist us in finding ability-based differences in the responsiveness of students to grades.

Table 5 reports the results of this analysis. Each column in the table reports results of a regression that applies a different SAT threshold. The thresholds range from 1,430 in the first column (representing the 65th percentile in student level observations) to 1,490 in the last column (representing the 85th percentile). All the specifications have the same set of explanatory variables and are applied to the

same sample.[17] The results presented in table (5) support the prediction that the share of highly capable students decreases with an increase in the lagged median grade. For the 75th percentile threshold of 1,450, a one unit increase in the median grade decreases the share of high ability students by 4.5 percentage points. This figure can be compared to the mean of the dependent variable (reported in the last row) which is 35 percent. Combining these two figures implies that a one unit change in the median grade leads to about a 12 percent decrease in the share of high ability students in a course. A similar effect is obtained in the other columns.

The coefficient for the lagged median grade in the last column is negative but insignificant. One possible reason for this relatively weak result is that the threshold was set in this case at a level which is too high. When the threshold level is high only a few students in each course are classified as high ability and the share of those students in the course is close to zero. This implies that there may not be enough variation in the dependent variable to capture the effect of the lagged median grade.

In all the columns of Table 5 the second explanatory variable - capturing the quality of students in the department - has the predicted positive sign and is highly significant. All else being equal the quality of students in a given course depends positively on the quality of students in the department.

Overall, the results presented in Table 5 seem to complement those presented previously and are consistent with the theoretical predictions of our model. Once grade information is available to students, they tend to be drawn to leniently graded courses. This tendency is not uniform, however: high ability students tend to be less drawn to such courses than their peers. We now turn to an analysis that relates grade-driven course selection to grade inflation and its consequences.

[17] The sample is of annual courses at the 100 to 400 levels with lagged enrollment of at least ten students. If we further restrict the sample by eliminating the 100 level courses results remain qualitatively identical but somewhat less significant.

6 Grade Inflation and Its Consequences

6.1 Grade Inflation

Figure 3 shows the mean grade of students attending courses at the undergraduate level in the College of Arts and Sciences in each semester.[18] From the spring semester of 1990 to the Fall semester of 2004 the mean grade climbed from 3.10 (equivalent to a little more than a B) to around 3.30 (equivalent to a B+), an increase of more than 6 percent.[19] The early part of the period, between the Spring semester of 1990 and the Fall semester of 1992 witnessed a relatively significant increase in the mean grade. Then the mean grade remained stable for several years. From the Spring semester of 1998 until the spring semester of 2004 the mean grade has steadily increased.[20] The fact that the mean grade is higher in the post-policy-change era than in the pre-policy-change era is consistent with our model and with our previous empirical findings. However, other factors may have played a role in the increase in grades. We will return to this issue in section 7. Before that, however, we aim to highlight some of the consequences of grade inflation.

[18] The figures refer to all grades given (including ex-post changes) in courses at the 100 to 400 level. They represent a weighted average where the weights are the number of units (credits) for each grade observation.

[19] We should point out that grades at Cornell have been consistently lower than in some of the other Ivy League schools. The dean of the College of Arts and Sciences put it in the following way "Out here in the sticks, we haven't kept up with the modern trend of inflating grade" (taken from the minutes of the faculty senate, 3/13/1996). For data on grade inflation in U.S. colleges and universities see http://www.gradeinflation.com/.

[20] An interesting comparison is that between the grade distributions of the Spring semester of 1990 and the Fall semester of 2004 (the first and last semesters we have data for). During that period the share of F's decreased from 1.43% to 0.90%; the share of D's decreased from 2.86% to 1.58%; the share of C's decreased from 14.66% to 10.54%; the share of B's decreased from 44.63% to 38.31%; and the share of A's increased from 36.43% to 48.66%.

6.2 Grade Compression

Because grades are bounded from above (at A+ or 4.3) grade inflation implies grade compression: when grades increase their dispersion decreases. Figure 4 starkly demonstrates this phenomena. From the Spring Semester of 1990 to the Fall semester of 2004 the standard deviation of grades decreased by roughly 7 percent from 0.83 to 0.77. This decrease in the standard deviation of grades highlights one of the major costs of grade inflation: it leads to a reduction in the information content of grades. As the majority of students are assigned to a gradually diminishing set of grade categories the ability to differentiate between these students declines.

6.3 Ranking Bias

Our analysis of grade-driven course selection points to another (potentially more severe) way in which the information content of grades might decline. By choosing leniently graded courses a student may be able to increase her GPA and improve her ranking relative to her peers. Departments vary in their leniency of grading, a fact which implies a certain kind of bias [see Sabot and Wakeman-Linn (1991)]. However, since the major of a student is easily observed, differences in grading policies within a major may be of grater concern. In this section we examine the question of ranking bias by focusing on the students majoring in the Department of Economics. We focus on this deparment for two reasons. First, economics has been the largest major in the College of Arts and Sciences in recent years. Second, for this department we found a relatively high level of sensitivity of enrollment to median grades.

We construct a measure of ranking bias in the following way. First, we standardize students' course grades by dividing each student's grade by the mean grade for the course. In each year we then rank graduating students twice: once according to their GPA and a second time according to their standardized GPA. We then compute the mean squared deviation between the rank according to the original GPA and the rank according to the standardized GPA. This is our index of ranking bias.

We differentiate students according to the last year of their studies. Students who graduated before 1994 are excluded from the analysis since we could not follow them through four years of studies. Students who graduated between 1994 and 1997 where never exposed to the online information on grades. Those who graduated between 1998 and 2000 were partially exposed to the online information. Lastly, students who graduated since 2001 could have had access to this information throughout their undergraduate academic career.

Figure 5 displays our ranking bias index together with the average value of the index for the three subperiods mentioned above. The results are striking. There is an increase in the index from the first subperiod to the second and a further increase from the second subperiod to the third. The ranking bias as measured by our index is more than three times larger in the third period than in the first.[21] It has to be noted that we obtain the increase in ranking bias despite the fact that grade inflation would tend to limit the scope for such biases. One implication of grade inflation is that more and more courses offer higher median grades. In such circumstances the ability of students to choose among courses with different median grades and therefore the scope for ranking biases is diminished.

Students' GPAs and class ranking play a role in hiring and graduate school admission decisions, in allocation of fellowships, and in other circumstances. Grade-driven course selection and grade inflation make these GPAs and class rankings much less useful.

7 Examining Alternative Explanations for Grade Inflation

Figure 3 clearly demonstrates the rise in the mean grade of students from 1990 to 2004. We have argued that a possible explanation for the higher grades in the second part of the period, from 1998 to 2004, is grade-driven course selection. However, other factors may be responsible for the increase in grades. In this section we examine two alternative explanations for the rise in grades: changing faculty

[21] Experimenting with several alternative ranking bias indices yielded similar results.

composition and an increase in the quality of students. We find that the first factor, faculty composition, cannot account for the rise of grades. In contrast, we find that the improved quality of students may be responsible for a significant share of the increase in grades. However, the increase in student quality does not explain all of the increase in grades: we show that grades have risen since the adoption of the median grade reporting policy even when we control for the rise in student quality. While we cannot reject the possibility that other changes occurred during this time period, our empirical findings are consistent with compositional grade inflation. In the concluding part of this section we provide a rough estimate (or an order of magnitude) for the potential effect of grade-driven course selection on grade inflation. Our findings suggest that grade-driven course selection may have played an important role in the rise of grades since 1998.

7.1 Faculty Composition

Changes in the internal structure of college faculties has been suggested as one possible explanation for the grade inflation phenomenon.[22] This explanation for grade inflation is built on two claims. First, the composition of the faculty (instructors) in universities changes over time. In specific the share of professors and tenured faculty tends to decline. Second, faculty members who have high teaching loads and those that are untenured tend to grade more leniently. High teaching loads, so the argument goes, leads instructors to lower standards and inflate grades; the lack of tenure makes instructors more reluctant to assign low grades as this practice may hurt their teaching evaluations and thereby jeopardize their careers. We now turn to an examination of the two claims in the context of Cornell's College of Arts and Sciences. Our analysis does not find support for either claim.

Table 6 displays a profile of the College's faculty from 1990 to 2004. Our data contains for each department and year the overall faculty size, the number of tenured and untenrured faculty, and the

[22] See, for example, Rosovsky and Hartley (2002).

number of faculty in each of the following 6 possible positions: full professor, associate professor, assistant professor, senior lecturer, lecturer, and other instructor. We divide these positions to professors (the first three) and others (the last three). The last two columns in Table 6 display for each year the shares of professors and tenured faculty. Neither displays much variation over time. From 1990 to 1997 the share of professors (assistant, associate and full professors) in the faculty declined slightly from 77.98 percent to 76.49 percent; from 1998 to 2004 it rose from 75.87 percent to 78.31 percent. From 1990 to 1997 the share of tenured faculty rose slightly from 61.24 percent to 62.44 percent; from 1998 to 2002 this share remained virtually constant (62.52 percent in the first year and 62.35 percent in the last); the last two years witnessed a small decline in this share - to 59.64 percent in 2004. Thus, the behavior of the two ratios over the 1990-2004 period and especially during the 1998-2004 period does not seem to lend support to the first part of the faculty composition explanation of grade inflation.

Table 7 examines the second part of the faculty composition explanation. Here we focus on the Department of Economics for which we have instructor information. The columns of Table 7 report results of regressions in which the dependent variable is the mean course grade. The explanatory variables include dummy variables for professors and for tenured faculty. The sample includes annual courses with one section at the 200-400 level with lagged enrollment of at least 10 students. In all the regressions reported in the table the explanatory variables are statistically insignificant. Taken together with our previous result this suggests that changes in faculty composition cannot account for the grade inflation at the College of Arts and Sciences

7.2 Student Quality

It has been argued that the observed increases in student grades may be explained by an improvement in the quality of students (as measured by an increase in SAT scores).[23] Whether or not an increase in

[23] See Johnson(2003), page 5.

student quality justifies an increase in grades is controversial. For example, Mansfield (2001), objecting to the student quality justifications for grade inflation, writes "Some say Harvard students are better these days and deserve higher grades. But if they are in some measure better, the proper response is to raise our standards and demand more of our students." Nevertheless, if instructors compare students to previous cohorts, a potential explanation for grade inflation is a rise in student quality. Student quality could rise for various reasons. One potential reason is that the increase in the size of freshmen classes in elite universities does not match the rise in the pool of high quality applicants. Under such circumstances the quality of each freshmen cohort in elite universities would tend to improve over time. As the quality of students improves grades rise. We next test this explanation for grade inflation and find that it is empirically valid. However, controlling for this factor we still find that grades are higher after the median grade reporting policy was adopted than before. This implies at a minimum that our grade-driven course selection explanation for Cornell's grade inflation cannot be ruled out.

As before we proxy student quality with SAT scores. What we would have liked to do is to examine the improvement in the SAT scores of entering freshmen classes and correlate it with the change in grades over the 1990-2004 period. Unfortunately, we do not have reliable individual level SAT scores for the period 1990-1995. Instead we use aggregate SAT information on entering freshmen classes. By examining this data we hope to track changes in the quality of students over time. We then use student level data for the years 1996-2004 to measure the effect of the increase in SAT scores on grades.

Table 8 reports the SAT profiles of freshmen students entering the College of Arts and Sciences in the Fall semester from 1988 to 2004. Each cell displays the share of students with a SAT score that falls within a given category. As was mentioned previously SAT scores of freshman entering Cornell before 1996 are not directly comparable to those entering since 1996 because of the 1995 recentering. We focus our analysis on the top (700-800) math and verbal score groups. From 1988 to 1995 the share of students in the top math group rose from 42 percent to 53 percent and the share of students

in the top verbal group declined from 16 to 14 percent. The recentering of scores in 1995 had a very large impact on verbal scores and a milder impact on the math scores. The share of students in the top verbal group increased from 14 percent in 1995 to 38 percent in 1996 while the share of students in the top math group declined from 53 percent to 47 percent. Both scores remained at almost the same level in 1997. From 1998 to 2004, the share of students in both top groups increased: For math it increased from 48 percent in 1998 to 65 percent in 2004; for verbal it increased from 38 percent to 54 percent during the same period. In summary, the quality of entering freshmen students seems to have increased over time and more so in the 1998-2004 period than in the 1988-1995 period. This pattern matches the overall behavior of students' grades in the 1990-2004 period. However, we next show that this does not fully account for the increase in grades since 1998.

Table 9 displays a set of regressions that examine the effect of SAT scores on students' grades. These regressions utilize individual level data. The dependent variable in all specifications is a student's course grade. The explanatory variables include the student's SAT math and verbal scores (the scores were divided by 1,000 for ease of exposition). In the first three columns we also include a dummy variable, *policy*, which takes the value of 0 from the Fall semester of 1996 to the Fall semester of 1997 and 1 from the Spring semester of 1998 onwards. The sample includes in all cases grades given in undergraduate level courses at the College of Arts and Sciences. In column (1) the sample is restricted to freshmen students from the Fall semester of 1996 onwards. Almost all of these students should have recentered SAT scores. Column (1) demonstrates that both SAT scores have a positive and highly significant effect on grades. Most importantly, however, the policy dummy variable also has a positive, large, and highly significant effect on grades. This implies that student quality cannot account for all the rise in grades since the adoption of the median grade reporting policy. Columns (2) and (3) repeat the analysis for two different samples. In column (2) the sample is restricted to sophomores and covers the period from the Fall semester of 1997 onwards (again, these students should almost all have recentered SAT

scores). In column (3) the sample includes both freshmen (from the Fall semester of 1996 onwards) and sophomores (from the Fall semester of 1997 onwards). Results in columns (2) and (3) are very similar to those of column (1). Most importantly, the policy variable has a positive, large, and highly significant effect on grades.

The next question that we address is: how much of the increase the mean grade in the College of Arts and Science can be attributed to the increase in student quality. To answer this question we conduct the following exercise. First, we measure the sensitivity of course grades to SAT scores at the individual level. Then we measure the aggregate improvement in SAT scores during the period examined. Combining the two sets of figures would allow us to estimate the aggregate effect of student quality on grades. At the last stage we can compare this estimate to the actual increase in the mean grade and determine how much of the grade inflation phenomena can be explained by the improved student quality.

Column (4) of Table 9 conducts the first part of the analysis. We estimate the same regression as in columns (1) to (3) for all undergraduate students (freshmen to seniors) in the years in the years 2000-2004. Almost all of these students should have recentered SAT scores. Now we have estimates of the marginal effects of the SAT math and verbal scores on course grades. Next we compute (from individual level SAT data) the increase over this period in the SAT scores of students. In 2000 the mean SAT math score was 686 and the mean SAT verbal score was 679. In 2004 the corresponding figures were 698 and 689. Putting the coefficients obtained from the regression in column (4) of Table 9 together with these figures implies that SAT scores could account for a rise in the mean grade of less than 0.03 grade points. During the same period (2000-2004) the mean grade has in fact increased by close to 0.08 grade points. Thus about one third of the rise in the mean grade can be accounted for by the rise in student quality. This leaves two thirds in the rise of grades unexplained. In the next section we argue that grade-driven course selection could account for a large part of this residual.

7.3 Simulating the Effect of Grade-Driven Course Selection

Our model predicts that in the presence of grade information students will tend to enroll in leniently graded courses and that this compositional effect will contribute to grade inflation. We have shown in the analysis above that even after controlling for student quality, the policy variable is positive and significant. We also found that intertemporal changes in faculty composition cannot explain the increase in grades. But, since the policy variable is a time period indicator we could not rule out that it may capture other changes that occur over the same time. Moreover, while we uncovered a positive and statistically significant response of enrollment to the lagged median grade after the implementation of the policy, this effect is not very large - we estimated that enrollment increases by only 18 percent per 1 point increase in the median grade. Given that the point differences between consecutive grade categories (e.g. between B and B+ and between B+ and A-) are either 0.3 or 0.4 points one might wonder if this response has the potential for notably effecting grade inflation. In this section we try to obtain a rough estimate of the possible contribution of grade-driven course selection to grade inflation.

We divide all courses to categories according to their median grades, which we take as an indicator of grading policy. We compare two cohorts of students (assumed identical in tastes and abilities). For the first cohort we use actual data to find the share of students in each course category.[24] We then make the following counterfactual assumptions: suppose grading policies and the characteristics of students remain the same, but some students in the second cohort respond to information on grading policies. We assume each student either remains in a course with the same grade as his predecessor or switches to a course one grade category higher (e.g. B to B+). We utilize the estimate of enrollment sensitivity obtained in Table 1 to determine the volume of transition between grading categories. The point

[24] For the first cohort we use enrollment shares in each grade category in the 1998-2004 period. To obtain these values we use the same sample restrictions as in Table 1 - annual courses at the 200 to 400 levels with lagged enrollment of at least 10 students.

estimate was roughly 0.18 - implying that a one unit change in grade (e.g. from a B to an A) leads to an 18 percent change in enrollment, hence the change in one grade category leads to either a 5.4% or a 7.2% change in enrollment. We calculate the new shares of students in each grade category after the transitions and find the new estimated mean grade. We can then compare this simulated change in the university-wide mean grade to the actual one. This allows us to gauge the potential effect of compositional grade inflation.

Table 10 presents the results of the simulation. For each letter grade column (1) reports the equivalent numerical grade and column (2) the actual mean grade in the sample.[25] Column (3) reports the actual share of student enrollment in each category. We then apply our transition rules to obtain the values in the last column. The transition leads to a decline in the enrollment shares of courses with low median grades and an increase in enrollment shares of courses with high median grades.

The last row reports the university-wide mean grade before and after the change. The simulated grade (3.27) is higher than the actual one (3.25) by 0.02 grade points, which is similar in magnitude to the effect of the increase in student quality (0.03 grade points). Given the crudeness of the estimate we do not wish to make too much of this result. The important point that we would like to emphasize is that grade-driven course selection can have a non-negligble effect on grade inflation.

8 Concluding remarks

Cornell's policy change provided us with a unique opportunity to test the effect that grade information combined with non-uniform grading policies have on students' course selection. We use the discontinuity in policy to identify the effects of the institutional structure on course selection patterns and subsequent grading outcomes. Our study confirms intuition - grade information biases students' course selection towards leniently graded courses. Grade-driven course selection contributes to grade inflation and

[25] We use the mean instead of the median course grade in calculating the univeristy-wide mean grade.

compression, depreciating the information content of grades. We show that providing students with information on grading policies, when these differ by course, might increase the potential for bias in the ranking of students. Moreover, the provision of grade information encourages students to opt out of courses they would have selected absent considerations of grades. Pursuit of grades compromises the quest for knowledge.

Our paper provides an interesting example of how individuals respond to aggregate information on payoffs. We found no response to past median grades before the policy. This suggests that students were either not obtaining much information through the grapevine or not utilizing the information they did have. In contrast, when official aggregate information on grades became easily accessible students responded to it. If one assumes that grade inflation, grade compression, and ranking bias are socially undesirable, our exercise also demonstrates an interesting case where an increase in information may have had a negative effect on social welfare.

The median grade policy was only partially implemented: median grades have been reported online since 1997 but do not yet appear in transcripts. This partial implementation may be responsible for the fact that the policy did it not achieve one of its objective - enrollment into leniently graded courses increased rather than decreased. It is possible that the inclusion of median grades in students' transcripts (expected to take place by the end of 2005) would mitigate or even reverse this effect.

We hope that our analysis would help to stimulate research on related policy questions such as: What type of grading information should be provided to students, instructors, and others? Should uniform grading guidelines be imposed on instructors? Such questions are relevant for the entire academic community and not just for Cornell.

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10 Appendix

Proof of proposition 1. We first show in an equilibrium for every θ there is a level of taste $\tau_\lambda(\theta)$ such that an informed student of type (θ, τ) with taste $\tau < \tau_\lambda(\theta)$ would select course A and an informed student with taste $\tau > \tau_\lambda(\theta)$ would prefer course B. Fix an equilibrium with some division of students between the courses A and B. For a given θ, $\Delta g(\theta|M_A, M_B) = g(M_A, \widehat{r}_A(\theta)|M_A, M_B)) - g(M_B, \widehat{r}_B(\theta)|M_A, M_B))$ is constant with respect to τ. The difference in costs, $\Delta c(\tau) = c(\tau) - c(1-\tau)$ is an increasing function of τ. If $\Delta g(\theta) \geq \Delta c(1)$ then for all τ course A is preferred. In this case, let $\tau_\lambda(\theta) = 1$. If $\Delta g(\theta) \leq \Delta c(0)$ then for all τ course B is preferred. In this case, let $\tau_\lambda(\theta) = 0$. Otherwise, $\tau_\lambda(\theta)$ solves $\Delta g(\theta|M_A, M_B) = \Delta c(\tau)$. For all $\tau_\lambda(\theta) \in [0, 1]$ in equilibrium an informed student of type (θ, τ) with taste $\tau < \tau_\lambda(\theta)$ would select course A and an informed student with taste $\tau > \tau_\lambda(\theta)$ would prefer course B.

For convenience of notation we make a change in parametrization. Let

$$a_i = 2M_i - 1.$$

Hence the grading policy can be written as:

$$g_i(M_i, \widehat{r}_i(\theta)|a_A, a_B) = (1 - a_i)\widehat{r}_A(\theta|a_A, a_B) + a_i.$$

Let us assume that in the equilibrium $\tau_\lambda(\theta)$ is interior, $0 < \tau_\lambda(\theta) < 1$ (we later verify that this holds true under our assumptions on the parameters). A student of type $(\theta, \tau_\lambda(\theta))$ is indifferent between the two courses. For all θ, $\tau_\lambda(\theta)$ solves:

$$(1 - a_A)\widehat{r}_A(\theta|a_A, a_B) + a_A - (1 - a_B)\widehat{r}_B(\theta|a_A, a_B) - a_B + k - 2k\tau_\lambda(\theta) = 0.$$

An informed student's belief about his expected rank in equilibrium is correct and therefore:

$$\widehat{r}_i(\theta) = H_i(\theta) = prob(\theta' \leq \theta|(\theta', \tau) \in S_i)$$

$$H_i(\theta) = \frac{prob(\{(\theta', \tau) : \theta' \leq \theta\} \cap S_i)}{prob(S_i)}$$

By definition of $\tau_\lambda(\theta)$ and H

$$H_A(\theta) = \frac{(1-\lambda)\int_0^\theta\int_0^{\frac{1}{2}} 1 d\tau d\theta' + \lambda\int_0^\theta\int_0^{\tau(\theta')} 1 d\tau d\theta'}{(1-\lambda)\int_0^1\int_0^{\frac{1}{2}} 1 d\tau d\theta' + \lambda\int_0^1\int_0^{\tau(\theta')} 1 d\tau d\theta'} = \frac{(1-\lambda)\int_0^\theta \frac{1}{2} d\theta' + \lambda\int_0^\theta \tau(\theta') d\theta'}{(1-\lambda)\int_0^1 \frac{1}{2} d\theta' + \lambda\int_0^1 \tau(\theta') d\theta'}.$$

Let

$$T(\theta) = \int_0^\theta \tau(\theta') d\theta'.$$

Then

$$H_A(\theta) = \frac{(1-\lambda)\frac{\theta}{2} + \lambda T(\theta)}{(1-\lambda)\frac{1}{2} + \lambda T(1)}.$$

Similarly:

$$H_B(\theta) = \frac{(1-\lambda)\frac{\theta}{2} + \lambda[\theta - T(\theta)]}{(1-\lambda)\frac{\theta}{2} + \lambda[1 - T(1)]}.$$

We substitute these results into the identity defining $\tau_\lambda(\theta)$:

$$(1-a_A)\frac{(1-\lambda)\frac{\theta}{2} + \lambda T(\theta)}{(1-\lambda)\frac{1}{2} + \lambda T(1)} + a_A - (1-a_B)\frac{(1-\lambda)\frac{\theta}{2} + \lambda[\theta - T(\theta)]}{(1-\lambda)\frac{\theta}{2} + \lambda[1 - T(1)]} - a_B + k - 2k\tau_\lambda(\theta) = 0$$

Let $T(1)$ be a constant value T. Note that by definition of the function $T(\theta)$,

$$T'(\theta) = \tau_\lambda(\theta).$$

Thus, we obtain the following differential equation:

$$\alpha T(\theta) + \beta T'(\theta) + \gamma\theta + \delta = 0, \tag{3}$$

where,

$$\begin{aligned} \alpha &= \frac{(1-a_A)\lambda}{(1-\lambda)\frac{1}{2}+\lambda T} + \frac{(1-a_B)\lambda}{(1+\lambda)\frac{1}{2}-\lambda T}, \qquad \beta = -2k \\ \gamma &= \frac{(1-a_A)(1-\lambda)\frac{1}{2}}{(1-\lambda)\frac{1}{2}+\lambda T} - \frac{(1-a_B)(1+\lambda)\frac{1}{2}}{(1+\lambda)\frac{1}{2}-\lambda T} \text{ and } \delta = a_A - a_B + k. \end{aligned} \tag{4}$$

By the assumptions on the parameters of the model, $\alpha > 0, \beta < 0, \gamma < 0$ and $\delta > 0$.

Taking the derivative we find that

$$\alpha T'(\theta) + \beta T''(\theta) + \gamma = 0. \tag{5}$$

and

$$\alpha T''(\theta) + \beta T'''(\theta) = 0.$$

Therefore,

$$\frac{-T'''(\theta)}{-T''(\theta)} = \frac{\alpha}{-\beta}.$$

Let us guess (and later verify) that $\tau_\lambda(\theta)$ is decreasing. Hence, $T'' < 0$). We integrate to find that:

$$\ln(-T''(\theta)) = \frac{\alpha}{-\beta}\theta + e_0.$$

Taking the exponent of each side of the identity

$$-T''(\theta) = e^{\frac{\alpha}{-\beta}\theta + e_0} = e^{e_0} e^{\frac{\alpha}{-\beta}\theta}. \tag{6}$$

Rearrange to find

$$T''(\theta) = -e^{e_0} e^{\frac{\alpha}{-\beta}\theta}. \tag{7}$$

Integrating to find

$$T'(\theta) = \frac{\beta}{\alpha} e^{e_0} e^{\frac{\alpha}{-\beta}\theta} + e_2. \tag{8}$$

Integrating once more we find:

$$T(\theta) = -\frac{\beta^2}{\alpha^2} e^{e_0} e^{\frac{\alpha}{-\beta}\theta} + e_2\theta + e_3. \tag{9}$$

We now evaluate the functions at certain points to pin down the constants e_i.

At $\theta = 0$:

$$T(0) = \int_0^0 \tau(\theta')d\theta' = 0.$$

$$T'(0) = \tau(0).$$

But

$$\widehat{r}_A(0|a_A, a_B) = \widehat{r}_B(0|a_A, a_B) = 0,$$

and so

$$a_A - a_B + k - 2k\tau(0) = 0.$$

Thus,

$$\tau(0) = \frac{a_A - a_B + k}{2k}.$$

By the assumptions on parameters, $\frac{1}{2} < \tau(0) < 1$.

At $\theta = 1$:

$$T'(1) = \tau(1) = \frac{1}{2}.$$

Since

$$\widehat{r}_A(1|a_A, a_B) = \widehat{r}_B(1|a_A, a_B).$$

We substitute these values into (9) and (8) to find the constants e_3 and e_2 and e^{e_0}:

$$T(0) = 0 \Rightarrow e_3 = \frac{\beta^2}{\alpha^2} e^{e_0}$$

$$T'(0) = \frac{a_A - a_B + k}{2k} \Rightarrow e_2 = \frac{a_A - a_B + k}{2k} - \frac{\beta}{\alpha} e^{e_0}$$

$$T'(1) = \frac{1}{2} \Rightarrow e^{e_0} = -\frac{\alpha}{\beta} \frac{\frac{a_A - a_B}{2k}}{e^{\frac{\alpha}{-\beta}} - 1}$$

We substitute the constants into (9) and (8) to obtain:

$$T(\theta) = \frac{\beta}{\alpha} \left(\frac{\frac{a_A - a_B}{2k}}{e^{\frac{\alpha}{-\beta}} - 1} \right) (e^{\frac{\alpha}{-\beta}\theta} - 1) + (\frac{a_A - a_B + k}{2k} + \frac{\frac{a_A - a_B}{2k}}{e^{\frac{\alpha}{-\beta}} - 1})\theta,$$

and

$$\tau_\lambda(\theta) = T'(\theta) = \left(\frac{\frac{a_A - a_B}{2k}}{e^{\frac{\alpha}{-\beta}} - 1} \right) (1 - e^{\frac{\alpha}{-\beta}\theta}) + \frac{a_A - a_B + k}{2k}.$$

The values of α, and β are given in (4) and $T(1) = T$ solves

$$T = \frac{\beta}{\alpha} \left(\frac{a_A - a_B}{2k} \right) + (\frac{a_A - a_B + k}{2k} + \frac{\frac{a_A - a_B}{2k}}{e^{\frac{\alpha}{-\beta}} - 1}).$$

We only need to argue that a solution T in the range $\frac{1}{2} < T < 1$ exists. Let $x(T) = \frac{\alpha}{-\beta}$. Consider the function:

$$f(T) = \left(\frac{a_A - a_B}{2k}\right)\left[-\frac{1}{x(T)} + \frac{1}{e^{x(T)} - 1}\right] + \frac{a_A - a_B + k}{2k} - T. \tag{10}$$

By the assumption on parameters, if $0 < \lambda < 1$:

$$f(1) < 0$$

since $\frac{a_A - a_B + k}{2k} - 1 < 0$, $x(T) > 0$ and $\left[-\frac{1}{x} + \frac{1}{e^x - 1}\right] < 0$ for any $x > 0$.

If $\lambda = 0$, then $x = 0$ and , $\lim_{x \to 0}\left[-\frac{1}{x} + \frac{1}{e^x - 1}\right] = -\frac{1}{2}$, hence $\lim_{T \to 1} f(T) < 0$.

On the other hand

$$f(\frac{1}{2}) = \left(\frac{a_A - a_B}{2k}\right)\left[\frac{\beta}{\alpha} + \frac{1}{e^{\frac{\alpha}{-\beta}} - 1} + 1\right] > 0,$$

since $\left[-\frac{1}{x} + \frac{1}{e^x - 1} + 1\right] > 0$ for any $x > 0$ particularly for $x(\frac{1}{2})$.

The function $f(T)$ is continuous on $[\frac{1}{2}, 1)$. Therefore there exists a solution $\frac{1}{2} < T < 1$ such that $f(T) = 0$.

Finally we verify the conjecture that $\tau_\lambda(\theta)$ is decreasing in θ:

$$\tau_\lambda(\theta) = T'(\theta) = \left(\frac{\frac{a_A - a_B}{2k}}{e^{\frac{\alpha}{-B}} - 1}\right)(1 - e^{\frac{\alpha}{-B}\theta}) + \frac{a_A - a_B + k}{2k}$$

$$\tau'_\lambda(\theta) = T''(\theta) = -\left(\frac{\alpha}{-\beta}\right)\left(\frac{\frac{a_A - a_B}{2k}}{e^{\frac{\alpha}{-\beta}} - 1}\right) e^{\frac{\alpha}{-\beta}\theta} < 0.$$

And that $\tau_\lambda(\theta)$ is interior: $\tau_\lambda(\theta) = \frac{1}{2} + \frac{a_A - a_B}{2k}\left[1 - \frac{e^{\frac{\alpha}{-B}\theta} - 1}{e^{\frac{\alpha}{-B}} - 1}\right] \in [\frac{1}{2}, \frac{3}{4}]$. ■

Proof of proposition 2. For convenience of notation we maintain the change in parametrization as in the previous proof:

$$a_i = 2M_i - 1.$$

We found in proposition 1 that, $T_\lambda(1) > \frac{1}{2}$ since $\tau_\lambda(\theta) > \frac{1}{2}$ for all θ. Enrollment into course A is

$$N_A(\lambda) = \lambda T_\lambda(1) + (1-\lambda)\frac{1}{2} = \lambda(T_\lambda(1) - \frac{1}{2}) + \frac{1}{2}.$$

Hence, enrollment for any level of information $\lambda > 0$ is larger than enrollment with no information.To show that enrollment in increasing in λ for $\lambda > 0$, it is sufficient to show $T_\lambda(1)$ is increasing in λ. Let

$$x = \frac{\alpha}{-\beta} = \frac{1}{2k}[\frac{(1-a_A)\lambda}{(1-\lambda)\frac{1}{2} + \lambda T(1)} + \frac{(1-a_B)\lambda}{(1+\lambda)\frac{1}{2} - \lambda T(1)}].$$

$T_\lambda(1)$ is the solution to (10), so

$$\frac{df(x,T)}{d\lambda} = \frac{\partial f(x,T)}{\partial x}\frac{\partial x}{\partial \lambda} + \frac{\partial f(x,T)}{\partial x}\frac{\partial x}{\partial T}\frac{dT_\lambda(1)}{d\lambda} + \frac{\partial f(x,T)}{\partial T}\frac{dT_\lambda(1)}{d\lambda} = 0.$$

Thus,

$$\frac{dT_\lambda(1)}{d\lambda} = \frac{\frac{\partial f(x,T)}{\partial x}\frac{\partial x}{\partial \lambda}}{1 - \frac{\partial f(x,T)}{\partial x}\frac{\partial x}{\partial T}}.$$

$$\frac{\partial f(x,T)}{\partial x} = \left(\frac{a_A - a_B}{2k}\right)\left[\frac{1}{x^2} - \frac{e^x}{(e^x-1)^2}\right] > 0.$$

$$\frac{\partial x}{\partial \lambda} = \frac{1}{2k}[\frac{(1-a_A)\frac{1}{2}}{\left[(1-\lambda)\frac{1}{2} + \lambda T(1)\right]^2} + \frac{(1-a_B)\frac{1}{2}}{\left[(1+\lambda)\frac{1}{2} - \lambda T(1)\right]^2}] > 0.$$

$$\frac{\partial x}{\partial T} = \frac{1}{2k}[\frac{-(1-a_A)\lambda^2}{\left[(1-\lambda)\frac{1}{2} + \lambda T(1)\right]^2} + \frac{(1-a_B)\lambda^2}{\left[(1+\lambda)\frac{1}{2} - \lambda T(1)\right]^2}] > 0.$$

We need to show

$$1 - \frac{\partial f(x,T)}{\partial x}\frac{\partial x}{\partial T} > 0.$$

From (10) and the assumption on parameters we find that $T \leq \frac{a_A - a_B + k}{2k} < \frac{3}{4}$. The $\lim_{x\to 0} \frac{1}{x^2} - \frac{e^x}{(e^x-1)^2} = \frac{1}{12}$

and for all x $\frac{1}{x^2} - \frac{e^x}{(e^x-1)^2} \leq \frac{1}{12}$. Hence,

$$\begin{aligned}
\frac{\partial f(x,T)}{\partial x}\frac{\partial x}{\partial T} &= \left(\frac{a_A - a_B}{2k}\right)\left[\frac{1}{x^2} - \frac{e^x}{(e^x-1)^2}\right]\frac{1}{2k}[\frac{-(1-a_A)\lambda^2}{\left[(1-\lambda)\frac{1}{2}+\lambda T(1)\right]^2} + \frac{(1-a_B)\lambda^2}{\left[(1+\lambda)\frac{1}{2}-\lambda T(1)\right]^2}] \\
&\leq \left(\frac{a_A - a_B}{2k}\right)\left[\frac{1}{x^2} - \frac{e^x}{(e^x-1)^2}\right]\frac{1}{2k}\lambda^2\frac{(1-a_B)}{\left[(1+\lambda)\frac{1}{2}-\lambda\frac{3}{4}\right]^2} \\
&= \left(\frac{a_A - a_B}{2k}\right)\left[\frac{1}{x^2} - \frac{e^x}{(e^x-1)^2}\right]\frac{1}{2k}\lambda^2[\frac{(1-a_B)}{\left[\frac{1}{4}\right]^2}] \\
&< \frac{1}{4}\times\frac{1}{12}\times\frac{1}{2}\times 16 < 1
\end{aligned}$$

We conclude that $\frac{dT_\lambda(1)}{d\lambda} > 0$ and that enrollment into the leniently graded course is increasing in the proportion of informed students. ■

Proof of proposition 3. Let us find the mean grade when students are informed.

$$\begin{aligned}
M(1) &= \int_0^1\int_0^{\tau(\theta)} g_A(\widehat{r}_A(\theta))d\tau d\theta + \int_0^1\int_{\tau(\theta)}^1 g_B(r_B(\theta))d\tau d\theta \\
&= \int_0^1\int_0^{\tau(\theta)}\left[(1-a_A)\frac{T(\theta)}{T(1)} + a_A\right]d\tau d\theta + \int_0^1\int_{\tau(\theta)}^1\left[(1-a_B)\frac{\theta - T(\theta)}{1-T(1)} + a_B\right]d\tau d\theta \\
&= \int_0^1\left[(1-a_A)\frac{T(\theta)}{T(1)} + a_A\right]\tau(\theta)d\theta + \int_0^1\left[(1-a_B)\frac{\theta - T(\theta)}{1-T(1)} + a_B\right](1-\tau(\theta))d\theta \\
&= (1+a_A)\frac{T(1)}{2} + (1+a_B)\frac{(1-T(1))}{2}
\end{aligned}$$

For uninformed students:

$$\begin{aligned}
M(0) &= \int_0^1\int_0^{\frac{1}{2}} g_A(\widehat{r}_A(\theta))d\tau d\theta + \int_0^1\int_{\frac{1}{2}}^1 g_B(r_B(\theta))d\tau d\theta \\
&= \int_0^1\int_0^{\frac{1}{2}}\left[(1-a_A)\theta + a_A\right]d\tau d\theta + \int_0^1\int_{\frac{1}{2}}^1\left[(1-a_B)\theta + a_B\right]d\tau d\theta \\
&= \int_0^1\left[(1-a_A)\theta + a_A\right]\frac{1}{2}d\theta + \int_0^1\left[(1-a_B)\theta + a_B\right]\frac{1}{2}d\theta \\
&= \frac{1}{4}(1+a_A) + \frac{1}{4}(1+a_B).
\end{aligned}$$

Since $T(1) > \frac{1}{2}$ and $a_A > a_B$, we find that $M(1) > M(0)$. ■

TABLE 1: ARE STUDENTS ATTRACTED TO LENIENTLY GRADED COURSES?

	(1)	(2)	(3)
Median	-0.00	0.01	0.01
	(0.04)	(0.04)	(0.04)
Median*Policy	0.18***	0.14**	0.14**
	(0.07)	(0.07)	(0.07)
Department Enrollment		0.65***	0.64***
		(0.06)	(0.06)
Department Courses		-0.47***	-0.44***
		(0.07)	(0.07)
Course-Policy Fixed Effects	Yes	Yes	Yes
Time fixed Effects	No	No	Yes
Observations	4,318	4,318	4,318
R^2	0.91	0.91	0.91

Notes: The dependent variable is the natural logarithm of course enrollment. Median is the lagged course median grade. Policy is a dummy variable that takes the value of 0 from the Spring semester of 1990 to the Fall semester of 1997 and 1 from the Spring semester of 1998 to the Fall semester of 2004. Department enrollment is the natural logarithm of the number of student-course observations at the department level in a given semester. Department courses is the natural logarithm of the number of courses offered by the department in a given semester. Included in the sample are annual courses at the 200 to 400 levels with lagged enrollment of at least ten students. The regressions were estimated by ordinary least squares and include a constant (not reported). Robust standard errors are reported in parentheses. The symbols *, **, *** represent statistical significance at the 10, 5, and 1 percent levels in a one-sided t-test.

TABLE 2: ANALYZING ALTERNATIVE SETS OF COURSES

	Course Characteristics (Lagged Enrollment, Frequency, Level)			
	>=10 Annual 200-400	>=10 Annual 100-400	>=10 Annual/Semestral 100-400	>=0 Annual/Semestral 100-400
	(1)	(2)	(3)	(4)
Median	0.01	0.03	0.02	0.03
	(0.04)	(0.04)	(0.03)	(0.02)
Median*Policy	0.14**	0.09*	0.04	0.03
	(0.07)	(0.05)	(0.05)	(0.04)
Observations	4,318	5,524	9,017	14,116
R^2	0.91	0.93	0.90	0.92

Notes: The dependent variable is the natural logarithm of course enrollment. Median is the lagged course median grade. Policy is a dummy variable that takes the value of 0 from the Spring semester of 1990 to the Fall semester of 1997 and 1 from the Spring semester of 1998 to the Fall semester of 2004. All regressions were estimated by ordinary least squares and include the same controls as in column (3) of Table 1. Robust standard errors are reported in parentheses. The symbols *, **, *** represent statistical significance at the 10, 5, and 1 percent levels in a one-sided t-test.

TABLE 3: DOES THE RESPONSIVENESS OF ENROLLMENT TO GRADES CHANGE OVER TIME?

	All Departments in the College	Ten Largest Departments	Department of Economics
Median	0.01	0.05	0.09
	(0.05)	(0.06)	(0.14)
Median*policy1	0.18**	0.19*	0.44
	(0.10)	(0.14)	(0.42)
Median*policy2	0.17**	0.27***	0.45**
	(0.09)	(0.10)	(0.24)
Observations	4,318	2,500	253
R^2	0.93	0.93	0.91

Notes: The dependent variable is the natural logarithm of course enrollment. Median is the lagged course median grade. The period analyzed starts at the Spring semester of 1990 and ends at the Fall semester of 2004. Policy1 is a dummy variable that takes the value of 1 from the Spring semester of 1998 to the Spring semester of 2001. Policy2 is a dummy variable that takes the value of 1 from the Fall semester of 2001 to the Fall semester of 2004. In all columns the sample is of annual courses at the 200 to 400 levels with lagged enrollment of at least ten students. All regressions include the same controls as in column (3) of Table 1. The regressions were estimated by ordinary least squares. Robust standard errors are reported in parentheses. The symbols *, **, *** represent statistical significance at the 10, 5, and 1 percent levels in a one-sided t-test.

TABLE 4: THE EFFECT OF COURSE AND INSTRUCTOR CHARACTERISTICS
DEPARTMENT OF ECONOMICS

	(1)	(2)	(3)	(4)	(5)
Median	0.07	0.07	0.09	0.07	0.07
	(0.14)	(0.14)	(0.14)	(0.14)	(0.15)
Median*Policy1	0.40	0.40	0.37	0.42	0.41
	(0.39)	(0.39)	(0.38)	(0.38)	(0.38)
Median*Policy2	0.45**	0.45**	0.45**	0.48**	0.47**
	(0.23)	(0.23)	(0.24)	(0.24)	(0.25)
Meetings per week	0.04				
	(0.11)				
Minutes per meeting		-0.00			
		(0.00)			
Class starting time			0.02		
			(0.02)		
Professor				0.02	
				(0.09)	
Tenure					0.02
					(0.11)
Observations	245	245	245	243	243
R^2	0.91	0.91	0.91	0.91	0.91

Notes: The dependent variable is the natural logarithm of course enrollment. Median is the lagged course median grade. The period analyzed starts at the Spring semester of 1990 and ends at the Fall semester of 2004. Policy1 is a dummy variable that takes the value of 1 from the Spring semester of 1998 to the Spring semester of 2001. Policy2 is a dummy variable that takes the value of 1 from the Fall semester of 2001 to the Fall semester of 2004. In columns (1) through (5) the sample is of annual courses with one section at the 200 to 400 levels with lagged enrollment of at least ten students. All regressions include the same controls and fixed effects as in the last column of Table 3. The regressions were estimated by ordinary least squares. Robust standard errors are reported in parentheses. The symbols *, **, *** represent statistical significance at the 10, 5, and 1 percent levels in a one-sided t-test.

TABLE 5: ARE GOOD STUDENTS LESS ATTRACTED TO LENIENTLY GRADED COURSES?

	SAT Threshold (Percentile in Student Level Observations)				
	1,430	1,440	1,450	1,470	1,490
	(65)	(70)	(75)	(80)	(85)
Median	-4.36**	-3.65**	-4.50**	-3.87**	-1.14
	(2.08)	(2.07)	(2.11)	(1.96)	(1.82)
Department SAT	0.69**	1.05***	1.24***	1.38***	1.13***
	(0.32)	(0.30)	(0.32)	(0.33)	(0.33)
Observations	1,065	1,065	1,065	1,065	1,065
R^2	0.79	0.79	0.78	0.77	0.73
Dependent variable mean	42.4	38.7	35.0	27.4	20.9

Notes: The dependent variable is the share of students in a course with a SAT score at least equal to a given threshold. Median is the lagged course median grade. Department SAT is the share of students in a department in a given semester with a SAT score at least equal to the threshold. The sample includes courses offered at the ten largest departments in the College of Arts and Sciences. In all cases the sample is of annual courses at the 100 to 400 levels with lagged enrollment of at least ten students. All regressions include the same controls and fixed effects as in the last column of Table 3. The period covered is from the Fall semester of 1999 to the Fall semester of 2004. The regressions were estimated by ordinary least squares. Robust standard errors are reported in parentheses. The symbols *, **, *** represent statistical significance at the 10, 5, and 1 percent levels in a one-sided t-test.

TABLE 6: COLLEGE OF ARTS AND SCIENCES FACULTY PROFILE

Year	Faculty Size	Professor (%)	Tenured (%)
1990	663	77.98	61.24
1991	657	77.47	62.25
1992	666	75.08	60.81
1993	665	75.19	60.60
1994	658	75.99	61.85
1995	665	75.79	61.35
1996	663	76.02	61.09
1997	655	76.49	62.44
1998	659	75.87	62.52
1999	650	77.54	63.23
2000	645	77.36	62.02
2001	653	77.03	62.33
2002	656	78.05	62.35
2003	657	77.17	60.27
2004	664	78.31	59.64

Notes: The table reports the profile of the faculty (instructors) in the College of Arts and Sciences from 1990 to 2004. The first column reports the overall number of instructors. The second column reports the share of professors (at the assistant, associate, or full level) in the overall number of instructors. The last column reports the share of tenured faculty in the overall number of instructors.

TABLE 7: EFFECT OF PROFESSORSHIP AND TENURE ON MEAN GRADES DEPARTMENT OF ECONOMICS

	(1)	(2)	(3)
Professor	0.01		0.02
	(0.06)		(0.06)
Tenure		-0.02	-0.03
		(0.07)	(0.07)
Observations	243	243	243
R^2	0.71	0.71	0.71

Notes: The dependent variable is the mean course grade. In columns (1) through (3) the sample is of annual courses with one section at the 200 to 400 levels with lagged enrollment of at least ten students. All regressions were estimated by ordinary least squares and include course and time fixed effects. Robust standard errors are reported in parentheses. The symbols *, **, *** represent statistical significance at the 10, 5, and 1 percent levels in a one-sided t-test.

TABLE 8: ENTERING FRESHMEN CLASS SAT PROFILE

		<		Math		>	<		Verbal		>
Year	Enrolled	700-800	650-699	600-649	550-599	200-549	700-800	650-699	600-649	550-599	200-549
1988	944	42	30	19	6	3	16	26	27	18	13
1989	964	48	27	15	6	4	12	25	29	18	16
1990	964	46	28	14	7	5	15	25	28	17	15
1991	973	45	28	15	6	6	14	22	27	20	17
1992	992	45	28	15	7	5	14	23	26	19	18
1993	1,041	49	29	13	5	4	13	22	30	19	16
1994	1,003	49	25	15	7	4	14	24	29	18	15
1995	1,049	53	24	15	5	3	14	22	28	19	17
1996	1,092	47	28	13	8	4	38	27	18	10	7
1997	1,045	48	27	14	7	4	37	28	21	8	6
1998	1,093	48	26	15	8	3	38	30	19	9	4
1999	1,051	52	26	15	5	2	45	24	19	8	4
2000	1,028	52	24	14	6	4	49	24	14	8	5
2001	1,012	55	23	13	6	3	49	24	17	6	4
2002	1,004	57	22	13	5	3	48	25	17	7	3
2003	1,061	59	21	12	5	3	49	25	17	5	4
2004	1,013	65	22	8	3	2	54	25	14	4	3

Notes: The table reports the SAT profiles of freshmen students entering the College of Arts and Sciences in the Fall semester from 1988 to 2004. Each cell displays the share of students with a SAT score that falls within a given category. SAT scores of freshman entering Cornell before 1996 are not directly comparable to those entering after 1996 because SAT scores were recentered by the Educational Testing Service in 1995. The recentered math scores were raised relative to the original ones by up to 50 points (but could also drop by up to 10 points). The recentered verbal scores were raised relative to the original ones by up to 80 points.

TABLE 9: EFFECT OF SAT SCORES ON STUDENT GRADES

	Freshmen	Sophomores	Freshmen and Sophomores	Freshmen to Seniors
	(1)	(2)	(3)	(4)
SAT math score	1.33***	0.95***	1.15***	0.70***
	(0.05)	(0.05)	(0.04)	(0.03)
SAT verbal score	1.69***	1.66***	1.68***	1.64***
	(0.05)	(0.05)	(0.03)	(0.03)
Policy	0.08***	0.09***	0.09***	
	(0.01)	(0.01)	(0.01)	
Observations	59,564	49,361	108,925	118,175
R^2	0.06	0.05	0.05	0.04

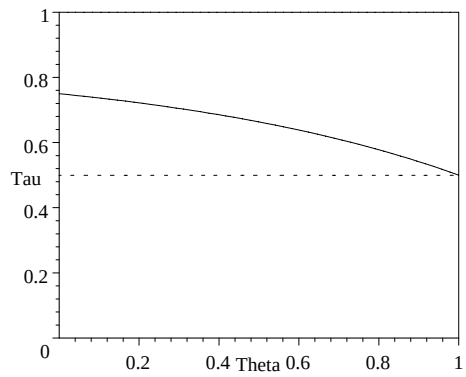
Notes: The dependent variable is a student's course grade. SAT scores were divided by 1,000. Policy is a dummy variable that takes the value of 0 before the Spring semester of 1998 and 1 since then. The sample includes in all cases grades given to Arts and Sciences students at undergraduate level courses (levels 100 to 400). In column (1) the sample is restricted to freshmen and covers the period from the Fall semester of 1996 onwards. In column (2) the sample is restricted to sophomores and covers the period from the Fall semester of 1997 onwards. In column (3) the sample includes both freshmen (from the Fall semester of 1996 onwards) and sophomores (from the Fall semester of 1997 onwards). In column (4) the sample is of all undergraduate students (freshmen to seniors) in the years 2000-2004. The regressions were estimated by ordinary least squares. Robust standard errors are reported in parentheses. The symbols *, **, *** represent statistical significance at the 10, 5, and 1 percent levels in a one-sided t-test.

TABLE 10: SIMULATING THE EFFECT OF GRADE-DRIVEN COURSE SELECTION

Course Median Letter Grade	Equivalent Point Grade	Course Mean Point Grade	Enrollment Shares (in %) Before Change	After Change
	(1)	(2)	(3)	(4)
C-	1.7	1.85	0.00	0.00
C	2	1.90	0.01	0.01
C+	2.3	2.50	0.05	0.04
B-	2.7	2.72	5.05	4.78
B	3	2.94	35.36	33.72
B+	3.3	3.25	25.92	25.96
A-	3.7	3.54	21.01	21.74
A	4	3.87	12.38	12.85
A+	4.3	4.12	0.22	0.89
Mean grade			3.25	3.27

Notes: The table reports a simulation of the effect of grade-driven course selection on grade inflation during the period 1998-2004. To conduct the simulation we use the sample of Table 1 - annual courses at the 200 to 400 levels with lagged enrollment of at least ten students. For each category of course median letter grade column (1) reports the equivalent numerical (point) grade and column (2) the actual mean grade for that category in the sample. Column (3) reports the mean share of student enrollment in each category during 1998-2004. We then use the value of the enrollment sensitivity parameter from column (1) of Table 1 to obtain the figures in column (4) as explained in the text.

FIGURE 1 - DIVISION OF STUDENTS BETWEEN COURSES



The solid line describes the curve $\tau_1(\theta)$ for the parameter values in example 1 ($M_A = \frac{7}{8}$, $M_B = \frac{5}{8}$, $k = 1$). When all students are informed, those with type (τ, θ) which lie below the solid curve $(\tau_1(\theta))$ enroll into course A, and those above the solid line enroll into course B. When all students are uninformed, students with type (τ, θ) which lie below the dotted line ($\tau = \frac{1}{2}$) enroll into course A, and those above the dotted line enroll into course B.

FIGURE 2 - INFORMATION GATHERING

daily visits to the median grades website: May 2002 - December 2004

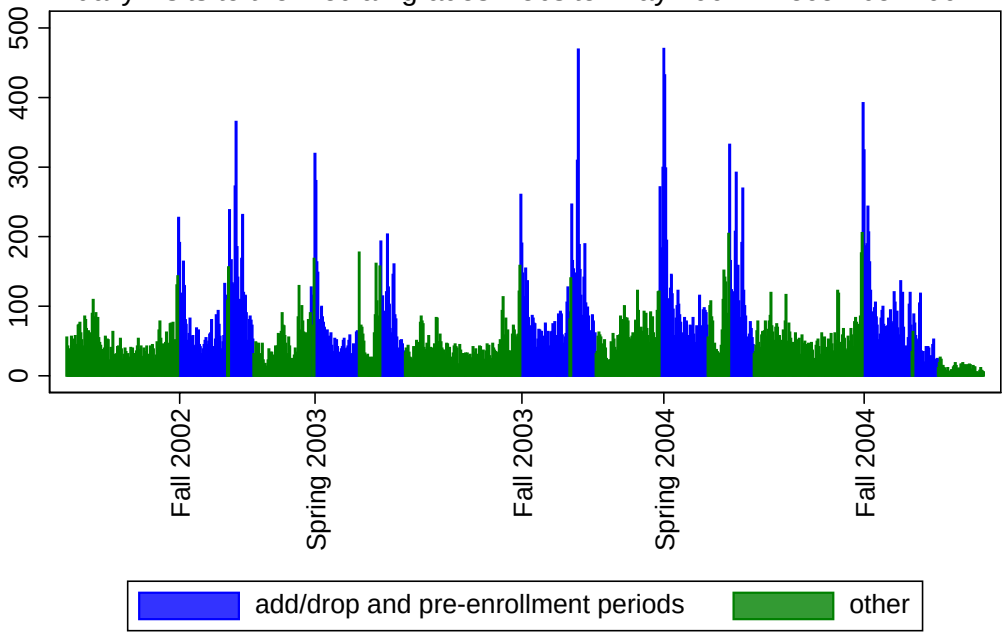


FIGURE 3 - GRADE INFLATION

mean grade 1990-2004

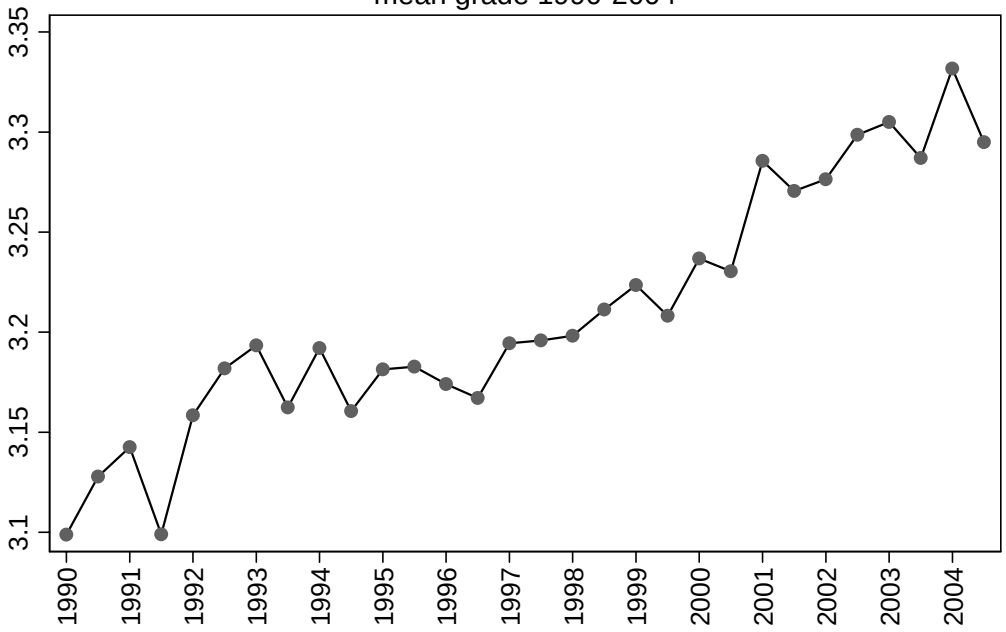


FIGURE 4 - GRADE COMPRESSION

mean and standard deviation of grades 1990-2004

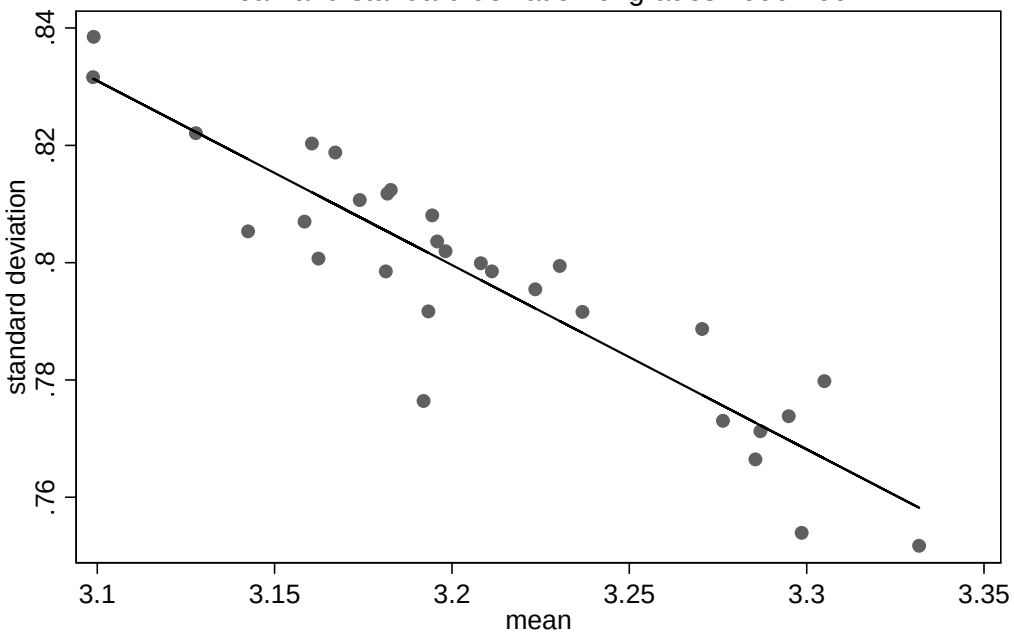
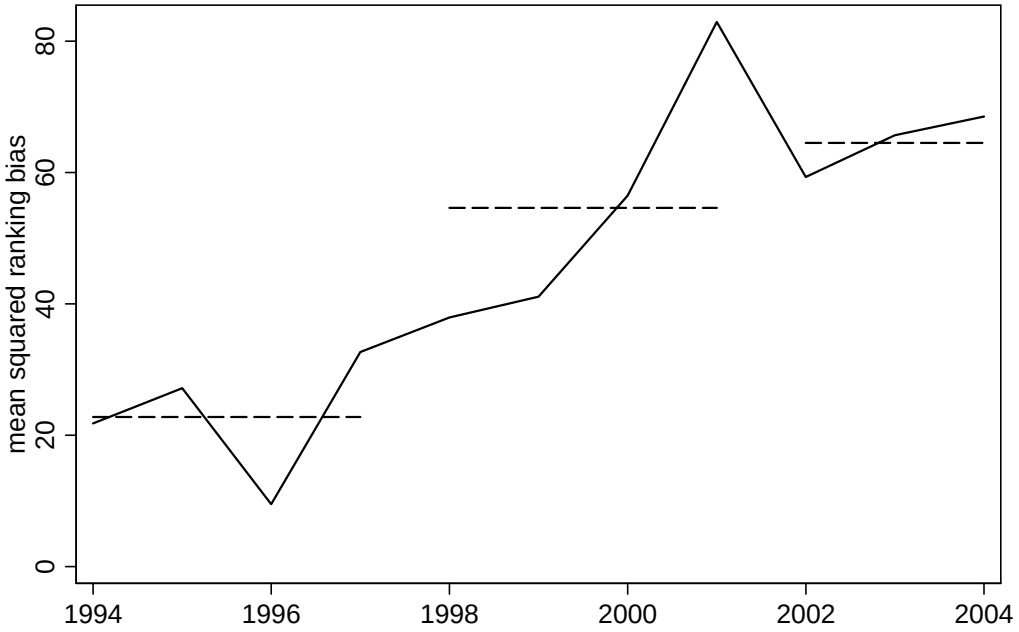


FIGURE 5 - RANKING BIAS

students majoring in economics