Quest for Knowledge and Pursuit of Grades:
Grade Information and 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 main predictions of the model are that students will be drawn to high grading courses and that this will contribute to grade inflation. Examining a large individual-level dataset for the period 1990-2004, our study provides evidence consistent with these predictions. Since the adoption of the policy the rate of grade inflation at Cornell has doubled and course enrollment has become much more positively related to grades. We document a significant decline in the information content of grades and an increased bias in the ranking of students.

Key words: grade inflation, course selection, information

JEL classification: I21

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1 Introduction

Grade inflation is a subject of concern in the academic world.\footnote{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”}. Over the past few decades students’ grades have increased considerably in many higher-education institutions, most notably in the Ivy League. Since grades are bounded form above, grade inflation is accompanied by a compression of grades at the top. The resultant reduction in the information content of grades is the main cost of grade inflation.

Several explanations have been offered for the grade inflation phenomenon.\footnote{See for example Johnson (2003) and Rosovsky and Hartley (2002).} There 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: a high positive correlation between student evaluations of instructors and grades combined with the widespread use of evaluations in promotion decisions; changes in the internal structure of college faculties, with adjunct faculty members and those with high work loads more inclined to give high grades; institutions’ competition for students and a rise in the ”student as a consumer” culture.

This paper focuses on one potential reason for grade inflation: students’ grade-driven course selection. A student’s Grade Point Average (GPA) is crucial for her career prospects. All else being equal, a student may attempt to increase her GPA by selecting courses in which she expects to obtain a high grade. The ability of the student to forecast her grade depends on the availability of course grade information. An increase in the availability of information would enable the student to increase her
GPA. To the extent that past course grades provide information on future course grades, there may be a positive correlation between past grades and course enrollment. We examine these relationships by exploiting a unique natural experiment.

In 1996 Cornell University adopted a new grade reporting policy. This policy consisted of two parts: (1) online publication of course median grades; (2) reporting of course median grades in students’ transcripts. The online publication of median grades started in the fall semester of 1997. However, for technical reasons the reporting of course median grades in transcripts has not been implemented yet.4

Cornell’s policy change followed the determination of the Committee on Academic Programs and Policies that it is desirable for the university to provide more information to the reader of a transcript and produce more meaningful letter grades. The rationale for the policy change was that “more accurate recognition of performance may encourage students to take courses in which the median grade is relatively low.”

The partial implementation of the policy change allows us to compare course selection patterns and the rates of grade inflation under two distinct levels of information. Prior to the policy change students could learn about grades mostly through the grapevine. Since 1997 the grade information available through this informal channel was augmented by easily accessible official information.

Our research 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) 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. Once grade information is available they trade off tastes for higher grades. This grade-driven course selection results in grade inflation.

We then turn to an empirical analysis. We employ a large dataset containing student grades in courses taken at Cornell’s College of Arts and Sciences in the period 1990-2004. We first document a

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4 According to the university registrar the change in the structure of the transcript is planned to take place in late 2005.
significant rise in the rate of grade inflation at Cornell following the adoption of the new policy. We then explore the relationship between course enrollment and past median grades. Our analysis shows that prior to the policy change the two variables were not related. After the policy change, however, course enrollment became positively related to past median grades.

Grade-driven course selection has been mentioned in the discussion of grade inflation in the past. However, it received almost no formal treatment. A notable exception is the work of Johnson (2003). His research uses data from an experiment conducted in Duke University during the 1998-1999 academic year. In the experiment students were provided with historical course information and were then asked to choose among courses. The study provides evidence that students tended 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 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 close to 800,000 observations at the student-course level.

The paper proceeds as follows. Section 2 introduces our course selection model. Section 3 describes the data. Section 4 presents results on the effects of the median grade policy on course selection and grade inflation in the College of Arts and Sciences. Section 5 focuses on the Department of Economics, where these effects were particularly significant and for which we have more detailed data. Section 6 concludes.

2 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 students’ selection into courses with high expected
grades and causes grade inflation. We refer to this phenomenon as *compositional grade inflation*.

### 2.1 Model

We assume 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 $\tau$ 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’ll assume $c(d) = kd$ where $k > 0$. We denote a student’s ability by the parameter $\theta \in [0, 1]$. A higher ability is denoted by a higher $\theta$. Hence every student’s type is a pair $(\theta, \tau)$. The population of students is uniformly distributed on the two dimensional space $[0, 1]^2$ of pairs $(\theta, \tau)$.

Each student enrolls in one course. Grades depend on the grading policy represented by a course specific parameter $a_i$ 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 $\theta$ enrolled in course $i$ is ranked

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

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

$$a_i \geq a_j \Rightarrow g(a_i, r) \geq g(a_j, r) \ \forall r.$$
For simplicity we assume for the most part a linear grading policy:

\[ g(a_i, r) = (1 - a_i)r + a_i, \]

where \( a_i \in [0, 1] \). This form of grading policy is increasing in a student’s rank in the course and the highest ranking student receives the highest grade: \( g(a_i, 1) = 1 \) for any \( a_i \). 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:

\[ u(a_i, S_i, \theta, \tau) = g(a_i, r(S_i, \theta)) - c(d(i, \tau)). \]

Students maximize their expected utility.

If the grading policies in the two courses are the same, \( a_A = a_B \), then a student’s decision as to which course to select would only depend on the student’s taste \( \tau \). A student selects course \( i \) over \( j \) if

\[ c(d(i, \tau)) < c(d(j, \tau)). \]

There is a cutoff point \( \tau_0 \) defined as the solution to

\[ c(\tau_0) = c(1 - \tau_0), \]

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. \( a_A > a_B \), 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 are independent of student ability and rank and are equal for all students in a course. It is easy to see that an increase in the number of students informed about grading policies would effect enrollment and increase the overall mean grade, i.e. create grade inflation. In the following proposition we show that when the number of informed students increases and course A is more leniently graded, more students select course A and thus the overall mean grade increases. This increase in mean grade is not driven by a change in grading policy or in the ability of students, but rather by the selection of students into leniently graded courses. This is compositional grade inflation.

**Proposition 1** 1. For constant grading policies $g_i = a_i$, if $a_A > a_B$ there exists $\tau_1 > \tau_0$ such that all informed students of type $\tau < \tau_1$ select course A and all informed students of type $\tau > \tau_1$ select course B.

2. When over time the proportion of informed students $\lambda_t$ increases, enrollment into the leniently graded course increases and grade inflation is generated.

All proofs are provided in the Appendix.

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. In the equilibrium notion we define bellow students form beliefs over their rank in each course. We denote their expected rank by $\hat{r}_i(\theta|a_i, a_j)$. We consider now the linear grading policy. In this case course $i$ is selected by an informed student $(\theta, \tau)$ if

$$
(1 - a_i)\hat{r}_i(\theta|a_A, a_B) + a_i - c(d(i, \tau)) > (1 - a_j)\hat{r}_j(\theta|a_A, a_B) + a_j - c(d(j, \tau)). \tag{2}
$$

In the event the student is indifferent we assume that she randomly selects each course with a probability $\frac{1}{2}$. 
We now define an equilibrium. In equilibrium all students informed and uninformed maximize their expected utilities. Informed students form a correct expectation regarding their grades.

**Definition 1** Given parameters $a_A, a_B, \lambda$ 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 $\widehat{r}_i(\theta|a_A, a_B)$ in each course such that for all $(\theta, \tau)$:

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

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

Under linear grading policies we now investigate the effects of grade information on course selection. For simplicity, we compare equilibria for the two extreme cases where all students are uninformed, or when all students are informed. 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. In this case since they have the same expected grade only students’ taste determines their selection of course. Hence For all ability levels $\theta$, students with $\tau < \tau_0 = \frac{1}{2}$ enroll in course $A$. 
For informed students course A is selected if

\[(1 - a_A)\hat{r}_A(\theta|a_A, a_B) + a_A] - [(1 - a_B)\hat{r}_B(\theta|a_A, a_B) + a_B] > c(\tau) - c(1 - \tau).\]

Note that a student of type \( \theta = 1 \) will have the same 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 without loss of generality that course A is more leniently graded, i.e. \( g(a_A, r) \geq g(a_B, r) \) for all \( r \). We show that for each \( \theta \) all students with low taste parameters choose course A and those with high values of \( \tau \) choose course B. However for informed students the cutoff point between the selection of the two courses depends on the student’s ability \( \theta \). 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 \((\theta, \tau)\) that would enroll in each course. In proposition 2 we characterize this curve.

**Proposition 2** For parameter values \( 0 < a_A - a_B < k \) there exists a function \( \tau_1 : [0, 1] \rightarrow [0, 1] \) such that for all types \((\theta, \tau)\) if \( \tau < \tau_1(\theta) \) then \( \sigma_{in}(\theta, \tau) = A \) and if \( \tau > \tau_1(\theta) \) then \( \sigma_{in}(\theta, \tau) = B \). Moreover, for all \( \theta \), \( \tau_1(\theta) \geq \tau_0 = \frac{1}{2} \) and \( \tau_1(\theta) \) is decreasing in \( \theta \).

The assumption \( 0 < a_A - a_B \) states without loss of generality that course A is the leniently graded course. The assumption \( a_A - a_B < k \) implies that \( \tau_1(0) < 1 \) which means that some low ability students would select course B due to their tastes even if they are informed of the grading policy.

Proposition 2 allows us to reach important conclusions on the selection of courses by informed students. Since we find that \( \tau_1(\theta) \geq \tau_0 \), enrollment into the easier course is larger when the students are informed than when students are uninformed about the grading policy. For all abilities \( \theta < 1 \) there is an increased tendency to choose the high grade course over the low grade course. Moreover, since the boundary of course selection \( \tau_1(\theta) \) is decreasing in \( \theta \), high ability students are less inclined to choose
leniently graded courses. The attractiveness of the more 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 $\tau_1(\theta)$ as described in the proposition. We then solve for the function using a differential equation defined by the indifference of a student $(\tau_1(\theta), \theta)$ between choosing course $A$ and $B$.

**Corollary 1** When students are informed about the grading policy, enrollment to the leniently graded course is higher compared to the case where students are uninformed.

We now show that the mean grade of all students is higher when the students are informed.

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

To clarify the results we provide a numerical example of course selection by informed students. The example is derived following the proofs of propositions 2 and 3 for particular parameter values.

**Example 1** Let $a_A = \frac{3}{4}, a_B = \frac{1}{4}$ and $k = 1$.

The boundary between selection of the two courses in the case of informed students is given by:

$$
\tau_1(\theta) = 0.84822 - 9.8217 \times 10^{-2} \exp (1.2656 \theta)
$$

Graphically:

The division of students between courses

10
Informed students with type \((\tau, \theta)\) which lie below the solid line enroll into course A, and those above the solid line enroll into course B. Uninformed students with type \((\tau, \theta)\) which lie below the dotted line enroll into course A (the lower half of the square). When the students are uninformed, enrollment into course A is \(N_A(0) = 0.5\) and the overall mean grade is \(M(0) = 0.75\). When the students are informed, enrollment into course A is \(N_A(1) = 0.65069\) and the overall mean grade is \(M(1) = 0.78767\).

In the following sections we test the predictions derived from the model. We show that students respond to information on grading policies by selecting into leniently graded courses. Such selection results in grade inflation during a period of dissemination of grading information. We leave the testing of the prediction that highly capable students are less drawn to leniently graded courses than their peers to future research.

3 Data and Descriptive Analysis

Cornell’s Office of the University Registrar provided us with a dataset containing grade information on all the students who attended courses at the College of Arts and Sciences between the spring semester of 1990 and the spring semester of 2004. We focus our attention on undergraduate level courses. The dataset contains close to 800,000 observations in total. Each observation has information on an individual student taking a specific course. The observation includes the course’s number, title, and department, the year and term in which the course was taken by the student, and the student’s identification number, year, term, college, major, and final grade in the course.\(^5\)

Figure 1 shows the behavior over time of the mean grade of students in the College of Arts and Sciences. From the spring semester of 1990 to the spring semester of 2004 the mean grade climbed from

\(^5\)We restrict our investigation to the original grades given to students at the end of each semester. We ignore ex-post grade changes. The same restriction is applied by the registrar in computing course median grades.
3.1 (equivalent to a little more than a B) to 3.34 (a notch above a B+). A significant increase in the mean grade occurred in the early part of the period, between the spring semester of 1990 and the fall semester of 1992. Then the mean grade remained stable for several years at the level of 3.2. From the spring semester of 1998 until the spring semester of 2004 the mean grade has steadily increased.\(^6\)

The first set of median grades to be published online by Cornell’s registrar was that of the spring semester of 1997. Publication began in the fall semester of 1997. This seems to correspond well with the apparent break in the mean grade series. Table 1 provides econometric evidence pointing to acceleration in the pace of grade increases after the introduction of the new policy. The table is based on a linear regression where the mean grade in each semester is the dependent variable. The independent variables include a dummy variable (“Policy”) which takes the value of 0 for the period 1990-1998 and 1 afterwards, a time trend, and an interaction variable between the time trend and the dummy variable.\(^7\) Table 1 demonstrates that grade inflation existed even before the new median grade policy was adopted: the mean grade increased on average by 0.005 per semester. However, since the introduction of the new median grade policy the pace of grade increases more than doubled to 0.011 per semester.

Figure 2 demonstrates a corollary of grade inflation. Because grades are bounded from above (at A+ or 4.3) grade inflation implies grade compression: when grades increase their dispersion decreases. From 1990 to 2004 the standard deviation of grades decreased by 9 percent from 0.82 to 0.75. Figure 2 thus highlights one of the main costs of grade inflation: the process makes it harder to distinguish between students.

\(^6\)An interesting comparison is that between the grade distributions of the spring semester of 1990 and the spring semester of 2004 (the first and last semesters we have data for): during that period the share of F’s decreased from 1.36% to 0.98%; the share of D’s decreased from 2.84% to 1.29%; the share of C’s decreased from 14.68% to 9.28%; the share of B’s decreased from 44.68% to 37.95%; and the share of A’s increased from 36.44% to 50.50%.

\(^7\)As was noted above, median grades were first published online in the fall semester of 1997. It is reasonable to assume, however, that it took time for students to learn about the new system and to adjust to it. We therefore decided to designate the spring semester of 1999 as the first under the new information regime.
4 Course Enrollment and Median Grades

Our hypothesis is that the introduction of the new median grade policy exacerbated the grade inflation problem at Cornell. We claim that this could have happened through grade-driven course choice by students. Once the median grade information became available online it was easier for students to choose courses based on past grades. This section focuses on testing this hypothesis.

Before conducting the tests we need to consider two sample related issues. First, according to the university registrar the lag in the online publication of the median grades varied between one semester and one year. Because we want to capture the effect of the online publication of median grades on course enrollment we limit our investigation to courses that are offered at an annual frequency. Second, the online publication of median grades is done only for courses with at least 10 participants so we restrict our investigation to such courses.\(^8\)

Table 2 explores the relationship between course enrollment and the lagged median grade in two sub-periods: 1990-1998 and 1999-2004. Each row in the table reports the results of a linear regression in which the dependent variable is the natural log of enrollment. The independent variable is the lagged median grade in that course.\(^9\) All regressions include course fixed effects to capture fixed course characteristics.

Results in the top row demonstrate that during 1990-1998 the relationship between the two variables was weak and statistically not different from zero. In contrast, after the introduction of the new median grade policy

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\(^8\)We later examine the effect of lifting these two restrictions.

\(^9\)One might argue that if course grades change frequently (in both directions) it would not make sense for a student to choose a course based on the course’s previous median grade. This is because the grade in the previous period would not provide a good estimate for the grade in the current period. However, empirically this is not the case. In 52 percent of cases we examine the grade does not change from one period to the next and in 25 percent 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.
grade policy the relationship turned positive and statistically significant: a one unit increase in the median grade (e.g. from a B to an A) increased enrollment in the following year by 13 percent.\textsuperscript{10} The next row examines the relationship between lagged median grades and course enrollment for the ten departments with the largest enrollment.\textsuperscript{11} Results are similar to the ones reported when all departments are examined: during 1990-1998 the effect of the lagged median grade on enrollment is close to zero and insignificant; after the introduction of the online publication policy the effect is positive and significant.

One of the major departments in the College of Arts and Sciences is the department of economics. Results in the third row demonstrate that the sensitivity of course enrollment in the Department of Economics to the past median grade during the period 1999-2004 is particularly strong. We now turn to a more detailed investigation of the relationship between enrollment and past grades in this department.

5 The Department of Economics

5.1 Grade Information and Course Enrollment

The department of economics has provided us with detailed information on all courses offered by it during 1990-2004. The information includes course and section numbers, course title, instructor name, and course schedule. Figure 3 demonstrates the behavior of the mean grade of students attending courses at the department of economics from 1990 to 2004. In the spring semester of 1990 the mean grade was less than 2.8 (just above a B-). By the fall semester of 2003 the mean grade climbed to 3.2 (just below a B+). The mean grade was rising even before the online publication of median grades. However, the pace of increase accelerated during 1999-2004.

\textsuperscript{10}To make sure that our results are not driven by changes in the supply of students attending courses in the college we added a variable capturing this effect to the regressions we run. In all cases results remained practically unchanged.

\textsuperscript{11}The ten departments are Chemistry, Mathematics, English, Economics, Psychology, Physics, Government, History, Music, and Philosophy.
Table 3 explores the sensitivity of enrollment to lagged median grade both before and after the introduction of the new policy. Each column represents the result of a regression in which the dependent variable is the log of enrollment. The independent variables include in all cases the lagged median grade and an interaction variable between the lagged median grade and the policy dummy (taking the value of 1 in 1999-2004).

The first column demonstrates the change in sensitivity of enrollment to lagged median grade between 1990-1998 and 1999-2004. During 1990-1998 enrollment was not influenced by the lagged median grade. After the introduction of the policy enrollment became positively associated with the lagged median grade. In the latter period a one unit change in the median grade translated into a 15 percent rise in enrollment. The next columns add explanatory variables to the benchmark specification of column 1. In column 2 we see a strong positive relationship between enrollment in one year and the next. Column 3 shows that there is seasonality in enrollment: it is higher on average in the fall term than in the spring term.

Columns 4 and 5 examine the role of two characteristics of the lagged grade distribution. These two statistics are in principle unknown to students. However, information flows might enable students to guess the shape of the distribution and to choose courses based on their guesses. Column 4 shows that the lagged mean grade has a positive, although insignificant, effect on enrollment. In contrast, enrollment reacts in a negative and statistically significant way to the lagged standard deviation. This result suggests that students might be risk averse in the sense that, all else being equal, they prefer lower dispersion in grades.

The next four columns examine the effects of course scheduling on enrollment. In column 6 we

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12 The simple correlation coefficient between lagged median grade and lagged mean grade for the sample of courses is 0.87. This collinearity might help to explain the non-significance of the lagged mean grade in the regression.

13 It has to be noted that most courses do not undergo frequent scheduling changes. This implies that since we are using course fixed effects there may not be enough variation in the data to capture the effect of scheduling on enrollment.
add to the regression the number of course meetings per week. Almost all courses meet two or three times a week. This variable has no influence on enrollment. The next variable to be included in the regression is minutes per meeting. In the vast majority of cases the length of a meeting is fifty or seventy five minutes. This variable does not have an influence on results either. Next we examine the effect on enrollment of the start time of the course. This effect is positive but statistically insignificant. However, when we examine courses that start before 9:00AM (“Early Morning”), the effect turns out to be statistically significant and strong: all else being equal, if the course starts early in the morning enrollment drops by more than 30 percent.

The last column in the table includes all the previously significant additional variables. Results are almost identical to those obtained when the variables were added separately. Most importantly, table 3 demonstrates that our core results are not sensitive to changes in the specification of the regression. Under all specifications enrollment is not affected by the lagged median grade before 1999; under all specifications enrollment becomes positively related to grades after the introduction of the new median grade policy.

In table 4 we conduct a series of tests involving changes in the sample of courses examined. The first column includes, for the sake of comparison, results of the benchmark regression – this is the regression reported in the first column of table 3. In the next column we limit the investigation to courses with lagged enrollment of less than 10 students. Since the median grades in these courses are not reported online we expect not to see a change between 1990-1998 and 1999-2004 in the responsiveness of enrollment to the lagged median grade. Indeed, the results presented in column 2 lend strong support to this hypothesis.

Column 3 reports the results of examining courses that are offered every semester. We find that the change in the enrollment sensitivity to lagged median grades is similar to the one obtained for annual courses. This can be explained as reflecting either the short lag in online reporting of grades (as was
mentioned above, in some cases this lag was only one semester) or students’ perceptions regarding the persistency of grades (when the reporting lag was one year). Column 4 restricts the investigation to courses with the same instructor in the two consecutive years examined. Results are almost identical to those presented in column 1. In sum, the results presented in table 4 reinforce our previous conclusions regarding the effect of the availability of grade information on course selection.

5.2 Ranking Bias

Grade inflation leads to a decline in the information content of grades as we have demonstrated in figure 2: the standard deviation of grades declines as the average grade increases. As students are assigned to a gradually diminishing set of grade categories the ability to differentiate between them declines. Students’ GPAs are compressed into a narrow range. Our analysis of grade driven course selection points to another, potentially more severe, way in which the information content of grades declines. By choosing leniently graded courses a student may be able to increase his GPA and improve his ranking relative to his peers.

To examine this question we construct a measure of ranking bias in the following way. First, we standardize students’ course grades by subtracting the mean course grade from the student’s grade and then dividing by the standard deviation of the course grade.\(^{14}\) In each year we then rank graduating students according to their GPA and their standardized GPA. The ranking is performed only for undergraduate students majoring in economics who have completed four years of study. We 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 completed their studies before 1994 are excluded from the analysis since we could not follow them through four years.

\(^{14}\)If the standard deviation is equal to zero the standardized grade is set to zero.
of studies. Students who completed their studies between 1994 and 1997 were never exposed to the online information on grades. Those who completed their studies between 1998 and 2000 were partially exposed to the online information. Lastly, students who completed their studies since 2001 could have had access to this information throughout their undergraduate academic career.

Figure 4 displays our ranking bias index together with the average 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 even a larger increase from the second subperiod to the third. The ranking bias as measured by our index is almost twice as large during the internet era (2001-2004) as it was before grades were published online (1994-1997). 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 an important role in hiring and graduate admission decisions, allocation of fellowships, etc. Our study suggests that grade driven course selection implies that GPAs and class ranking are not only less and less informative, but can also be misleading.

6 Concluding remarks

Cornell’s policy change provided us with a unique opportunity to test the effect that grade information has on students' course selection. Our study confirms intuition - grade information biases students' course selection towards leniently graded courses. Grade driven course selection contributes to grade inflation and 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

\footnote{We experimented with several alternative ranking bias indices. Our results proved to be robust to these changes.}
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 analysis raises some interesting and important questions to be addressed in future work. First, while so far we have focused our investigation on average student behavior, our model predicts that high ability students would be less sensitive to the relative leniency of grading policies, while low ability students would be more likely to select into leniently graded courses. These differences in behavior may be hard to uncover due to the difficulty of measuring a student’s inherent academic ability and the possible positive correlation between a student’s academic ability and her information on grading policies.

Second, the results we found for the policy change in Cornell stand in contrast to the stated objective of the policy, in that implementation of the policy tended to increase, rather than decrease, enrollment in leniently graded courses. It is possible that the inclusion of median grades in students’ transcripts (expected to take place by the end of 2005) would mitigate some of this effect. We plan to investigate this question. Important policy issues that are relevant for the entire academic community are raised by our analysis. For example, what type of grading information should be provided to students, instructors, and others? Should uniform grading guidelines be imposed on instructors? Such questions demand further investigation.

7 References


8 Appendix

Proof of Proposition 1. 1. Students select course A if

\[ g_A - c(\tau) > g_B - c(1 - \tau), \]

or

\[ g_A - g_B > c(\tau) - c(1 - \tau). \]

Since course A is easier, \( g_A - g_B > 0 \). The difference in costs, \( \Delta c(\tau) = c(\tau) - c(1 - \tau) \) is an increasing function of \( \tau \) with a unique zero obtained at \( \tau_0 \in [0, 1] \) and \( \Delta c(\tau) < 0 \) for \( \tau < \tau_0 \). Therefore, for a student with taste \( \tau < \tau_0 \),

\[ g_A - g_B > 0 > c(\tau) - c(1 - \tau) \]

and course A is selected. If \( \Delta g \geq \Delta c(1) \) then for all \( \tau \) course A is preferred by all students, in this case, let \( \tau_1 = 1 \). Otherwise, let \( \tau_1 \) be the solution to \( g_A - g_B = c(\tau) - c(1 - \tau) \). For all students of taste \( \tau < \tau_1 \), \( g_A - g_B > c(\tau) - c(1 - \tau) \). Hence these students select course A.

2. Let \( \lambda_t \in [0, 1] \) be the proportion of students informed about the grading policies at time \( t \). Suppose the probability of becoming informed is independent of the student’s type. In this case, all uninformed students would select course A if \( \tau < \tau_0 \) and course B if \( \tau > \tau_0 \). While all informed students would select course A if \( \tau < \tau_1 \) and course B if \( \tau > \tau_1 \). Let \( f_1(\tau) \) denote the density if the distribution of types (\( f_1(\tau) = 1 \) in the uniform case). Enrollment in course A is thus given by:

\[
N_A(\lambda) = (1 - \lambda) \int_0^{\tau_0} f_1(\tau) d\tau + \lambda \int_0^{\tau_1} f_1(\tau) d\tau = \int_0^{\tau_0} f_1(\tau) d\tau + \lambda \int_{\tau_0}^{\tau_1} f_1(\tau) d\tau.
\]
The mean grade of all students is given by

\[ M(\lambda) = \int_{\tau_0}^{\tau_1} g_A f_1(\tau) d\tau + \lambda \int_{\tau_0}^{\tau_1} g_A f_1(\tau) d\tau + (1 - \lambda) \int_{\tau_0}^{\tau_1} g_B f_1(\tau) d\tau + \int_{\tau_0}^{\tau_1} g_B f_1(\tau) d\tau. \]

Or

\[ M(\lambda) = \int_{\tau_0}^{\tau_1} g_A f_1(\tau) d\tau + \int_{\tau_0}^{\tau_1} g_B f_1(\tau) d\tau + \lambda \int_{\tau_0}^{\tau_1} (g_A - g_B) f_1(\tau) d\tau. \]

Taking the derivatives of the functions \( N_A(\lambda) \) and \( M(\lambda) \) we find that

\[ N_A'(\lambda) = \int_{\tau_0}^{\tau_1} f_1(\tau) d\tau > 0 \text{ and } M'(\lambda) = \int_{\tau_0}^{\tau_1} (g_A - g_B) f_1(\tau) d\tau > 0. \]

Thus, enrolment into the leniently graded course and the overall mean grade are both increasing in the proportion of informed students. If we fix the grading policies but expect that the proportion of informed students would rise over time, \( \lambda_t \) is increasing in \( t \), then we would observe an increase in enrollment to the leniently graded course and an increase in the overall mean grade over time. ■

**Proof of proposition 2.** We first show that for every \( \theta \) there is a level of taste \( \tau_1(\theta) \) such that in equilibrium an informed student of type \((\theta, \tau)\) with taste \( \tau < \tau_1(\theta) \) would select course \( A \) and an informed student with taste \( \tau > \tau_1(\theta) \) would prefer course \( B \). For a given \( \theta \), \( \Delta g(\theta|a_A, a_B) = g(a_A, \tau_A(\theta)|a_A, a_B)) - g(a_B, \tau_B(\theta)|a_A, a_B) \) is constant with respect to \( \tau \). The difference in costs, \( \Delta c(\tau) = c(\tau) - c(1 - \tau) \) is an increasing function of \( \tau \). If \( \Delta g(\theta) \geq \Delta c(1) \) then for all \( \tau \) course \( A \) is preferred. In this case, let \( \tau_1(\theta) = 1 \). If \( \Delta g(\theta) \leq \Delta c(0) \) then for all \( \tau \) course \( B \) is preferred. In this case, let \( \tau_1(\theta) = 0 \). Otherwise, let \( \tau_1(\theta) \) be the solution to \( \Delta g(\theta|a_A, a_B) = \Delta c(\tau) \). For all \( \tau_1(\theta) \in [0, 1] \) in equilibrium an informed student of type \((\theta, \tau)\) with taste \( \tau < \tau_1(\theta) \) would select course \( A \) and an informed student with taste \( \tau > \tau_1(\theta) \) would prefer course \( B \).

Under the assumption made \( \tau_1(\theta) \) is interior. Thus, for a student of type \((\theta, \tau_1(\theta))\) utility for taking either course is equal, that is, for all \( \theta \), \( \tau_1(\theta) \) solves:

\[ (1 - a_A)\hat{r}_A(\theta|a_A, a_B) + a_A - (1 - a_B)\hat{r}_B(\theta|a_A, a_B) - a_B + k - 2k\tau_1(\theta) = 0. \]
A student’s belief about his expected rank in equilibrium is correct and therefore:

\[
\hat{\tau}_i(\theta) = H_i(\theta) = \text{prob}(\theta' \leq \theta | S_i)
\]

\[
H_i(\theta) = \frac{\text{prob}(\theta' \leq \theta) \cap \text{prob}(S_i)}{\text{prob}(S_i)}
\]

By definition of \( \tau_1(\theta) \) and \( H \)

\[
H_A(\theta) = \frac{\int_0^{\theta} \int_0^{\theta'} 1 d\tau d\theta'}{\int_0^{\theta} \int_0^{\theta'} 1 d\tau d\theta'}
\]

Let

\[
T(\theta) = \int_0^{\theta} \tau(\theta') d\theta'.
\]

Then

\[
H_A(\theta) = \frac{T(\theta)}{T(1)}.
\]

Similarly:

\[
H_B(\theta) = \frac{\int_0^{\theta} \int_0^{\theta} 1 d\tau d\theta'}{\int_0^{\theta} \int_0^{\theta} 1 d\tau d\theta'}
\]

We substitute these results into the identity defining \( \tau_1(\theta) \):

\[
(1 - a_A) \frac{T(\theta)}{T(1)} + a_A - (1 - a_B) \frac{\theta - T(\theta)}{1 - T(1)} - a_B + k - 2k\tau_1(\theta) = 0
\]

Rearrange to find:

\[
\left[ \frac{(1 - a_A)}{T(1)} + \frac{(1 - a_B)}{1 - T(1)} \right]T(\theta) - 2k\tau_1(\theta) - \frac{(1 - a_B)}{1 - T(1)} \theta + a_A - a_B + k = 0.
\]

Note that by definition of the function \( T(\theta) \),

\[
T'(\theta) = \tau_1(\theta).
\]

Thus, we obtain the following differential equation:

\[
\alpha T(\theta) + \beta T'(\theta) + \gamma T(\theta) + \delta \theta + [a_A - a_B + k] = 0.
\]
or
\[ \alpha T(\theta) + \beta T'(\theta) + \gamma \theta + \delta = 0. \]

By the assumptions we made, \( \alpha > 0, \beta < 0, \gamma < 0 \) and \( \delta > 0 \).

Taking the derivative of this function we find that
\[ \alpha T'(\theta) + \beta T''(\theta) + \gamma = 0. \tag{3} \]

and
\[ \alpha T''(\theta) + \beta T'''(\theta) = 0. \]

Therefore,
\[ \frac{-T'''(\theta)}{-T''(\theta)} = \frac{\alpha}{-\beta}. \]

Let us guess (and later verify) that \( \tau_1(\theta) \) is decreasing. Hence, \( T'' < 0 \). We integrate to find that:

\[ \int \frac{-T'''(\theta)}{-T''(\theta)} d\theta = \int \frac{\alpha}{-\beta} d\theta + c_0, \]

or
\[ \ln(-T''(\theta)) = \frac{\alpha}{-\beta} \theta + c_0. \]

Taking the exponent of each side of the identity
\[ -T''(\theta) = e^{\frac{\alpha}{-\beta} \theta + c_0} = e^{c_0} e^{\frac{\alpha}{-\beta} \theta}. \tag{4} \]

Rearrange to find
\[ T''(\theta) = -e^{c_0} e^{\frac{\alpha}{-\beta} \theta}. \tag{5} \]

Integrating to find
\[ T'(\theta) = \frac{\beta}{\alpha} e^{c_0} e^{\frac{\alpha}{-\beta} \theta} + e_2. \]

Finally integrating once more we find:
\[ T(\theta) = \int \left[ \frac{\beta}{\alpha} e^{c_0} e^{\frac{\alpha}{-\beta} \theta} + e_2 \right] d\theta + c_3 = -\frac{\beta^2}{\alpha^2} e^{c_0} e^{\frac{\alpha}{-\beta} \theta} + e_2 \theta + e_3. \]
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

$$\hat{\tau}_A(0|a_A, a_B) = \hat{\tau}_B(0|a_A, a_B) = 0,$$

and so

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

Thus,

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

Since A is the easier course, $a_A > a_B$, $\tau(0) > \frac{1}{2}$. Additionally we assumed $\frac{a_A - a_B + k}{2k} < 1$ or $a_A - a_B < k$.

At $\theta = 1$:

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

Since

$$\hat{\tau}_A(1|a_A, a_B) = \hat{\tau}_B(1|a_A, a_B).$$

We substitute these values into

$$T(\theta) = -\frac{\beta^2}{\alpha^2} e^{x_0} e^{\frac{\alpha}{\beta} \theta} + e_2 \theta + e_3$$

and

$$T'(\theta) = \frac{\beta}{\alpha} e^{x_0} e^{\frac{\alpha}{\beta} \theta} + e_2.$$  

We obtain the parameters $e_3$ and $e_2$:

$$T(0) = 0 \Rightarrow e_3 = \frac{\beta^2}{\alpha^2} e^{x_0}$$
Substitute the constants

We substitute the constants into the function to obtain:

\[
T'(0) = \frac{a_A - a_B + k}{2k} \Rightarrow e_2 = \frac{a_A - a_B + k}{2k} - \frac{\beta}{\alpha} e^{\alpha_0}
\]

\[
T'(1) = \frac{1}{2} \Rightarrow \frac{\beta}{\alpha} e^{\alpha_0} e^{-\beta} + e_2 = \frac{1}{2}
\]

\[
\Rightarrow \frac{\beta}{\alpha} e^{\alpha_0} e^{-\beta} + \frac{a_A - a_B + k}{2k} - \frac{\beta}{\alpha} e^{\alpha_0} = \frac{1}{2}
\]

\[
\Rightarrow \frac{\beta}{\alpha} (e^{-\beta} - 1) e^{\alpha_0} + \frac{a_A - a_B}{2k} = 0
\]

\[
T'(1) = \frac{1}{2} \Rightarrow e^{\alpha_0} = -\frac{\alpha a_A - a_B}{\beta} e^{-\beta} - 1
\]

We substitute the constants into the function to obtain:

\[
T(\theta) = -\frac{\beta^2}{\alpha^2} e^{\alpha_0} e^{-\beta} + e_2 \theta + e_3
\]

\[
T(\theta) = -\frac{\beta^2}{\alpha^2} e^{\alpha_0} e^{-\beta} + \left(\frac{a_A - a_B + k}{2k} - \frac{\beta}{\alpha} e^{\alpha_0}\right) \theta + \frac{\beta^2}{\alpha^2} e^{\alpha_0} =
\]

\[
-\frac{\beta^2}{\alpha^2} \left(\frac{\alpha}{\beta} \frac{a_A - a_B}{2k} e^{-\beta} - 1\right) e^{\alpha_0} + \left(\frac{a_A - a_B + k}{2k} - \frac{\beta}{\alpha} \frac{a_A - a_B}{2k} e^{-\beta} - 1\right) \theta + \frac{\beta^2}{\alpha^2} e^{\alpha_0} =
\]

\[
\frac{\beta}{\alpha} \left(\frac{a_A - a_B}{2k} e^{-\beta} - 1\right) e^{\alpha_0} + \left(\frac{a_A - a_B + k}{2k} + \frac{a_A - a_B}{2k} e^{-\beta} - 1\right) \theta - \frac{\beta}{\alpha} \left(\frac{a_A - a_B}{2k} e^{-\beta} - 1\right) =
\]

\[
\frac{\beta}{\alpha} \left(\frac{a_A - a_B}{2k} e^{-\beta} - 1\right) (e^{-\beta} - 1) + \left(\frac{a_A - a_B + k}{2k} + \frac{a_A - a_B}{2k} e^{-\beta} - 1\right) \theta
\]

And we find that

\[
T'(\theta) = \frac{\beta}{\alpha} e^{\alpha_0} e^{-\beta} + e_2.
\]

Substitute the constants \(e^{\alpha_0}, e_2\):

\[
\tau_1(\theta) = T'(\theta) = -\left(\frac{a_A - a_B}{2k} e^{-\beta} - 1\right) e^{\alpha_0} + \frac{a_A - a_B + k}{2k} + \frac{a_A - a_B}{2k} e^{-\beta} - 1.
\]

\[
\tau_1(\theta) = T'(\theta) = \left(\frac{a_A - a_B}{2k} e^{-\beta} - 1\right) (1 - e^{-\beta} \theta) + \frac{a_A - a_B + k}{2k}
\]

where \(T(1) = T\) solves

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

25
\[
T = \frac{-2k}{(1-a_A) + (1-a_B)} \left( \frac{a_A-a_B}{2k} \right) (e^{-\frac{\alpha}{\beta}} - 1) + \left( \frac{a_A-a_B+k}{2k} \right) \left( \frac{a_A-a_B}{2k} \right),
\]

or
\[
\frac{a_A-a_B}{2k} \left[ \frac{e^{\frac{(1-a_A)}{2kT}} + (1-a_B)}{e^{\frac{(1-a_A)}{2kT}} + (1-a_B)} - 1 \right] - \frac{1}{\frac{(1-a_A)}{2kT} + (1-a_B)} + \frac{1}{2} - T = 0.
\]

We only need to argue that a solution \( T \) in the range \( \frac{1}{2} < T < 1 \) exists. Consider the function of \( T \):

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

By the assumption on parameters:

\[
\lim_{T \to 1} f(T) = \frac{a_A-a_B+k}{2k} - 1 < 0.
\]

On the other hand \( f\left(\frac{1}{2}\right) > 0 \) since

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

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

Finally verify the conjecture that \( \tau \) is decreasing:

\[
\tau_1(\theta) = T'(\theta) = \left( \frac{a_A-a_B}{2k} \right) (1 - e^{-\frac{\alpha}{\beta} \theta}) + \frac{a_A-a_B+k}{2k} \left( \frac{a_A-a_B}{2k} \right),
\]

\[
\tau'_1(\theta) = T''(\theta) = -\frac{\alpha}{\beta} \left( \frac{a_A-a_B}{2k} \right) e^{-\frac{\alpha}{\beta} \theta} < 0
\]

\[\blacksquare\]
Proof of proposition 3. Let us find the mean grade when students are informed.

\[
M(1) = \int \int g_A(\tau_A(\theta))d\tau d\theta + \int \int g_B(r_B(\theta))d\tau d\theta
\]

\[
= \int \int \left[ (1 - a_A)\frac{T(\theta)}{T(1)} + a_A \right] d\tau d\theta + \int \int \left[ (1 - a_B)\frac{\theta - T(\theta)}{1 - T(1)} + a_B \right] d\tau d\theta
\]

\[
= \int \left[ (1 - a_A)\frac{T(\theta)}{T(1)} + a_A \right] \tau(\theta) d\theta + \int \left[ (1 - a_B)\frac{\theta - T(\theta)}{1 - T(1)} + a_B \right] (1 - \tau(\theta)) d\theta
\]

\[
= \left[ \frac{(1 - a_A) T^2(\theta)}{T(1)} + a_A T(1) \right]_0^1 + \left[ \frac{(1 - a_B) (\theta - T(\theta))^2}{1 - T(1)} + a_B (\theta - T(\theta)) \right]_0^1
\]

\[
= \left[ \frac{(1 - a_A) T^2(1)}{2} + a_A T(1) \right] + \left[ \frac{(1 - a_B) (1 - T(1))^2}{2} + a_B (1 - T(1)) \right]
\]

\[
= (1 + a_A)\frac{T(1)}{2} + (1 + a_B)\frac{(1 - T(1))}{2}
\]

For uninformed students:

\[
M(0) = \int \int g_A(\tau_A(\theta))d\tau d\theta + \int \int g_B(r_B(\theta))d\tau d\theta
\]

\[
= \int \int \left[ (1 - a_A)\theta + a_A \right] d\tau d\theta + \int \int \left[ (1 - a_B)\theta + a_B \right] d\tau d\theta
\]

\[
= \int \left[ (1 - a_A)\theta + a_A \right] \frac{1}{2} d\theta + \int \left[ (1 - a_B)\theta + a_B \right] \frac{1}{2} d\theta
\]

\[
= \frac{1}{2} \left[ (1 - a_A)\frac{\theta^2}{2} + a_A \theta \right]_0^1 + \frac{1}{2} \left[ (1 - a_B)\frac{\theta^2}{2} + a_B \theta \right]_0^1
\]

\[
= \frac{1}{2} \left[ (1 - a_A)\frac{1}{2} + a_A \right] + \frac{1}{2} \left[ (1 - a_B)\frac{1}{2} + a_B \right]
\]

\[
= \frac{1}{4} (1 + a_A) + \frac{1}{4} (1 + a_B)
\]

\[
= \frac{1}{4} (1 + a_A) + \frac{1}{4} (1 + a_B)
\]
Since $T(1) > \frac{1}{T}$ and $a_A > a_B$, we find that $M(1) > M(0)$. ■
**Table 1: Grade Inflation and the Median Grade Reports Policy**

<table>
<thead>
<tr>
<th>Dependent variable: mean grade of all undergraduates</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>0.005***</td>
</tr>
<tr>
<td></td>
<td>(5.85)</td>
</tr>
<tr>
<td>Time*Policy</td>
<td>0.006***</td>
</tr>
<tr>
<td></td>
<td>(3.79)</td>
</tr>
<tr>
<td>Policy</td>
<td>-0.12***</td>
</tr>
<tr>
<td></td>
<td>(3.55)</td>
</tr>
<tr>
<td>Constant</td>
<td>3.13***</td>
</tr>
<tr>
<td></td>
<td>(249.60)</td>
</tr>
</tbody>
</table>

Observations 29
R-squared 0.91

Notes:
Estimated by ordinary least squares with robust standard errors.
Absolute values of t-statistics in parentheses.
*, **, *** represent statistical significance at the 10, 5, and 1 percent levels.
Table 2: Course Enrollment as a Function of Lagged Median Grade

<table>
<thead>
<tr>
<th></th>
<th>1990-1998</th>
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<th></th>
<th>1999-2004</th>
<th></th>
<th></th>
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<tbody>
<tr>
<td></td>
<td>Lagged</td>
<td>Constant</td>
<td>N₁</td>
<td>R²</td>
<td>Lagged</td>
<td>Constant</td>
</tr>
<tr>
<td></td>
<td>Median</td>
<td></td>
<td>(N₂)</td>
<td></td>
<td>Median</td>
<td></td>
</tr>
<tr>
<td>All departments</td>
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<td>3.41***</td>
<td>3269</td>
<td>0.91</td>
<td>0.13***</td>
<td>2.84***</td>
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<tr>
<td></td>
<td>(0.59)</td>
<td>(27.98)</td>
<td>(938)</td>
<td></td>
<td>(2.96)</td>
<td>(19.04)</td>
</tr>
<tr>
<td>Ten Largest Departments</td>
<td>0.03</td>
<td>3.51***</td>
<td>1686</td>
<td>0.92</td>
<td>0.14**</td>
<td>3.02***</td>
</tr>
<tr>
<td></td>
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<td>(20.87)</td>
<td>(463)</td>
<td></td>
<td>(2.24)</td>
<td>(13.59)</td>
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<tr>
<td>Department of Economics</td>
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<td>144</td>
<td>0.78</td>
<td>0.23**</td>
<td>2.97***</td>
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<tr>
<td></td>
<td>(0.35)</td>
<td>(7.22)</td>
<td>(38)</td>
<td></td>
<td>(2.12)</td>
<td>(8.10)</td>
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</tbody>
</table>

Notes:
N₁ is the number of observations
N₂ is the number of distinct courses
Estimated by ordinary least squares with robust standard errors
Course fixed effects included in all regressions
Absolute values of t-statistics in parentheses
*, **, *** represent statistical significance at the 10, 5, and 1 percent levels
Table 3: Determinants of Course Enrollment  
Department of Economics, 1990-2004

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
<th>(10)</th>
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</thead>
<tbody>
<tr>
<td>Dependent variable: log of enrollment</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lagged Median</td>
<td>0.04</td>
<td>0.13</td>
<td>0.07</td>
<td>-0.08</td>
<td>-0.03</td>
<td>0.05</td>
<td>0.05</td>
<td>0.05</td>
<td>-0.01</td>
<td>0.06</td>
</tr>
<tr>
<td></td>
<td>(0.34)</td>
<td>(1.28)</td>
<td>(0.68)</td>
<td>(0.43)</td>
<td>(0.27)</td>
<td>(0.45)</td>
<td>(0.45)</td>
<td>(0.44)</td>
<td>(0.05)</td>
<td>(0.59)</td>
</tr>
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<td>Lagged Median*Policy</td>
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Notes: Estimated by ordinary least squares with robust standard errors; Course fixed effects included in all regressions; Absolute values of t-statistics in parentheses.; *, **, *** represent statistical significance at the 10, 5, and 1 percent levels
### Table 4: Course Enrollment as a Function of Lagged Median Grade

#### Additional Tests

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<th>Dependent variable: log of enrollment</th>
<th>(1) Benchmark Regression</th>
<th>(2) Lagged enrollment &lt;10</th>
<th>(3) Semester based courses</th>
<th>(4) Same instructor</th>
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**Notes:**
- Estimated by ordinary least squares with robust standard errors.
- Course fixed effects included in all regressions.
- Absolute values of t-statistics in parentheses.
- *, **, *** represent statistical significance at the 10, 5, and 1 percent levels.
FIGURE 2 - GRADE COMPRESSION
mean and standard deviation of grades 1990-2004
FIGURE 3 - THE ECONOMICS DEPARTMENT

mean grade 1990-2004
FIGURE 4: RANKING BIAS
UNDERGRADUATE ECONOMICS MAJORS

mean squared ranking bias