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Econ 312

Assessing Grade Inflation in Post-Secondary Institutions

Introduction:

In this paper, we examine the statistical determinants of grade inflation in a group of US colleges.

Using an unbalanced panel of 39 colleges, we analyze our data with a number of regressions, primarily using random effects. Our data was obtained from Gradeinflation.com, US News and World Report, and the IPEDS database.

There are several different things to which "grade inflation" might refer. In this study, we look only at the proportion of A's/B's/C's/D's/F's given and summary statistics of these data.

Our goal is to find college characteristics associated with grade inflation. To this end, we look at changes over time, but we also look at different factors that are associated with institutions having different "baseline" grading practices. Since different institutions have very different average grade distributions, some colleges that have experienced grade inflation still have lower overall grades than schools that already had higher grades, overall. Thus, while these baseline differences do not pertain to inflation over time, they are still an important part of the picture.

Looking at baseline grading practices, we find that schools with lower acceptance rates gave out more A's and fewer C's, and that larger schools and private schools gave out fewer F's. Our results also show that schools in the south had more C's, fewer D's, and lower grades overall.

Looking at the changes in grading practices, we confirmed the existence of a general grade inflation trend. We also found a trend of increasingly more A's being awarded instead of B's. We were unable to find significant results relating college characteristics to changes in grading practices.

Data:

Our dependent variables were descriptive statistics of the grade distributions of 39 colleges taken from an unbalanced panel with a total of 118 college-years. Our data included 2 community colleges, 16 liberal arts colleges, and 21 public universities; the earliest year in our sample was from 1944, though most of our colleges only had grade distribution information for the late 90's and 2000's. On average, each college had about 3 years of data. The vast majority of colleges had observations that were uniformly 10 years apart, but several observations did not fit this pattern.

This information was gathered primarily from two sources, the Department of Education's Integrated Postsecondary Education Data System (IPEDS) for school-years in 2007 and 2008, and the US News & World Report ranking data for the years of 1997 and 1998. Because of time and schedule constraints, earlier data was unavailable. IPEDS data is only available back to 2001, and the Reed College library does not have US News on shelf from before 1992. When we had grade distribution data for years before the 90's, we assumed that the earliest data we had available was the case in earlier years. Overall, we imposed later data on 41 school-years.

In order to examine the correlates of grade inflation by school, we gathered data on the type of institution, number of students, faculty to student ratio, acceptance and retention rates, the region of the institution, and the 75th percentile of its students' composite SAT scores. Each school was coded according to whether it was a private school, public university, or community college. These schools were also categorized according to region in four categories: West, Midwest, South, and Northeast; the northeast variable was omitted binary variable in this case. Faculty-to-student ratios and number of students were included as well. Also included were the acceptance rate, the percentage of applicants admitted in a given year, and the retention rate, the percentage of freshmen that returned for their sophomore year.

Modeling Grade Inflation:

There are several different things to which "grade inflation" might refer. The distribution of grades given at a college can be considered a function of student performance and school standards. Grade inflation could refer to:

(1) An absolute decrease in standards
(2) A decrease in standards relative to performance.
(3) An increase in average GPA
(4) An increase in average assigned grade (overall GPA)
(5) An increase in the number of A's or B's assigned relative to lower grades
(6) A decreased in ability to distinguish between student performance on the basis of students grades.

Note that (3) and (4) are not the same. While we average across all grades assigned to get (4), we average across students to get (3). This means that, if students take different numbers of classes, those grades received by students who have taken fewer classes are given more weight in (3), but not in (4). The gpa variable is (4), the overall GPA for the institution, *not* the average of the GPA's of the students at the institution, (3).

Also, since complete measures of standards and performance would not be single quantities, what exactly (1) or (2) mean would need to be further elucidated.

In the case of (2), standards could be absolutely increasing, decreasing, or constant. Performance and standards can be defined relative to the total population of humanity, America, or college students, or relative to some objective criteria.

Although it makes theoretical sense to model grades as a function of school standards and student performance, this approach requires instrumental variables that only affect performance and/or only instruments that only affect standards, or a good way to directly appraise either of these. Since we do not have appropriate instruments[1], we focus on real changes in grades given in this project, specifically, we investigate (4), (5), and (6).

[1] We could use SAT's as an instrument for performance, but this is measure of ability (and hence a predictor of performance) only relative to the population taking the SAT, since the test is normalized. Furthermore, it is likely that SAT scores would be correlated with grading standards, since colleges chose who to accept to their student body and hence institutional factors which would be related to grading standards, would influence the SAT scores of the student population, so SAT scores are probably not a good enough instrument.

To quantitatively assess (6), we look at the entropy of the grade distribution for each data point. Entropy is a concept from information theory. Intuitively, the entropy measures the expected gain in information from learning what grade a student received in a class. Higher entropy corresponds to more information. One potential problem with inflating grades is an inability to distinguish student quality based on their grades. Entropy provides a measure of how well the school's grading practices distinguish between their students' performances. Analytically, entropy represents the "flatness" of distribution. The lowest entropy and most distinguishing power comes from a completely flat distribution where 1/5 of grades given are A's, 1/5 are B's, &c.

Methods and Results:

We ran two groups of regressions. In the first group, dependent variables are the proportion of each grade given, the grade point average of the college, calculated by gpa = (4a+3b+2c+d)/100, and the entropy of the grade distribution, calculated by:

entropy[2] = - [a ln(a) + b ln(b) + c ln(c) + d ln(d) + f ln(f)].

In the second group of regressions, the dependent variables were differences of these over ten year time periods.

The first group of regressions deals with:

(1) The existence of grade inflation trends at a global level
(2) The characteristics associated with higher or lower levels of baseline grade inflation.

The second group deals with:

(1) Non-linearity of the grade-inflation trend
(2) The characteristics associated with changes in grading practices over time.

Group 1:

Before we dive into the panel analysis of data, we perform an OLS regression of our dependent variables. This regression confirms a global pattern of grade inflation (in our dataset at least). Relative to the year, there is an upward trend in overall GPA and percentage of A's given, and a downward trend in C's, D's, and F's, given and the entropy of the distribution of grades. Thus grades are increasing, a trend accounted for almost exclusively by an increase in the number of A's given. Since the distribution of grades is becoming more spiked (since A was already a more popular grade than C, D, or F) and less flat, the entropy decreases and the discriminatory power of grades is lessened.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	a	b	c	d	f	gpa	entropy
students	-4.17e-05	4.16e-05	3.75e-05	6.41e-06	-5.02e-05**	5.54e-07	-1.15e-05
	(6.53e-05)	(4.14e-05)	(3.91e-05)	(2.02e-05)	(2.18e-05)	(1.74e-06)	(0.000104)
private	2.817	2.487*	-2.368	-0.856	-2.104***	0.132**	-8.599***
	(2.178)	(1.342)	(1.492)	(0.736)	(0.565)	(0.0570)	(3.109)

[2] Properly, this is not the entropy, since we are using the percents, not the probabilities. This value is a scaling and translation of the true entropy measure, however, so the constant term and the coefficients will be different, but the t-statistics will be identical.

ftsratio	0.209	-0.0736	-0.167	-0.0156	0.0695	0.00209	-0.0546
	(0.173)	(0.130)	(0.102)	(0.0517)	(0.0460)	(0.00420)	(0.276)
acceptance	-10.99**	0.515	8.459***	2.532*	-0.662	-0.229**	11.67*
	(4.401)	(3.718)	(2.703)	(1.485)	(1.281)	(0.112)	(6.340)
retention	0.119	0.0488	-0.0973	-0.0130	-0.0621	0.00430	-0.224
	(0.139)	(0.101)	(0.0807)	(0.0412)	(0.0465)	(0.00371)	(0.235)
west	2.129	2.106	-2.224*	-1.467***	-0.640*	0.0908*	-6.364**
	(2.714)	(2.050)	(1.200)	(0.546)	(0.384)	(0.0494)	(2.939)
midwest	2.008	1.254	-1.114	-1.194**	-1.035**	0.0862*	-7.695**
	(1.909)	(1.577)	(1.178)	(0.547)	(0.515)	(0.0450)	(2.983)
south	-5.339***	0.415	3.181***	1.081**	0.568	-0.125***	3.845
	(1.797)	(1.350)	(0.942)	(0.459)	(0.418)	(0.0398)	(2.565)
composite	-0.00608	0.0140*	-0.00119	-0.00386	-0.00266	0.000107	-0.0199
	(0.0122)	(0.00800)	(0.00715)	(0.00366)	(0.00336)	(0.000313)	(0.0178)
year	0.564***	0.00229	-0.406***	-0.125***	-0.0412***	0.0134***	-0.412***
	(0.0346)	(0.0301)	(0.0235)	(0.0141)	(0.00924)	(0.000888)	(0.0510)
Constant	-1,087***	8.119	834.6***	260.0***	95.41***	-24.25***	532.9***
	(70.62)	(62.76)	(49.20)	(28.97)	(19.42)	(1.843)	(109.3)
Observations	108	108	108	108	108	108	104
R-squared	0.755	0.375	0.847	0.741	0.668	0.810	0.727

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In this regression, we also find statistically significant effects for all but the B's regression. We find that acceptance rates were statistically significant correlates of the share of A's and C's in the overall grade distributions of schools. Schools that were more selective gave more A's and fewer C's. We find the same effect in the GPA regression: more selective schools give higher grades on average. Schools with more students and private institutions gave out fewer F's. Of the region variables, we find that the West and Midwest give a statistically significant smaller proportion of D's than the Northeast, that schools in the Midwest also give fewer F's, and that the South statistically gives fewer A's and more C's an D's. The South also has lower grades on average, compared to the NorthEast.

Now we turn to modeling the correlates of high grades using the panel nature of our data. We had to determine whether to use a fixed effects or a random effects model. It is appropriate to use a fixed effects model when there are characteristics that are common to all units but that vary across time, and we do this by treating the levels of the explanatory variables that we are interested in as fixed so that we have a different fixed constant error term for each unit.

When we are interested in each unit having a common error term drawn randomly from some distribution, we use the random effects model. The α_i error terms in this model

$$Y_{it} = \beta_0 + \beta_1 X_{1it} + \beta_2 X_{2it} + \ldots + \beta_k X_{kit} + (\alpha_i + u_{it})$$

are treated as random variables that are drawn from some common distribution rather than as fixed.

To choose between the two models, we use a Hausman test, which is a nested sub-model of the fixed-effects model to determine whether the random effects model is appropriate. This test compares the coefficients given by each model, and tests whether they are statistically different. We use random effects model over a fixed-effects model unless the Hausman test is rejected. This test is rejected when the estimates are sufficiently different and the fixed-effects estimators are sufficiently precise.

To do this we ran both fixed effects and random effects models and used a Hausman test to determine which specification was appropriate.

In these specifications we included all of the time dummies and excluded the variables that did not vary across time (type of school, location). Here are the results of the Hausman tests:

```
. xtreg pcnta students ftsratio acceptance retention composite i.year, fe
. estimates store fixedA
. xtreg pcnta students ftsratio acceptance retention composite i.year, re
. estimates store randomA
. hausman fixedA randomA
    Test:  Ho:  difference in coefficients not systematic

                 chi2(19) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       10.35
                Prob>chi2 =      0.9438

. xtreg pcntb students ftsratio acceptance retention composite i.year, fe
. estimates store fixedB
. xtreg pcntb students ftsratio acceptance retention composite i.year, re
. estimates store randomB
. hausman fixedB randomB
      Test:  Ho:  difference in coefficients not systematic

                 chi2(19) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        6.28
                Prob>chi2 =      0.9972

. xtreg pcntc students ftsratio acceptance retention composite i.year, fe
. estimates store fixedC
. xtreg pcntc students ftsratio acceptance retention composite i.year, re
. estimates store randomC
. hausman fixedC randomC
      Test:  Ho:  difference in coefficients not systematic

                 chi2(20) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        9.36
                Prob>chi2 =      0.9784

. xtreg pcntd students ftsratio acceptance retention composite i.year, fe
. estimates store fixedD
. xtreg pcntd students ftsratio acceptance retention composite i.year, re
. estimates store randomD
. hausman fixedD randomD
      Test:  Ho:  difference in coefficients not systematic

                 chi2(19) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       18.14
                Prob>chi2 =      0.5130

. xtreg pcntf students ftsratio acceptance retention composite i.year, fe
. estimates store fixedF
. xtreg pcntf students ftsratio acceptance retention composite i.year, re
. estimates store randomF
. hausman fixedF randomF
      Test:  Ho:  difference in coefficients not systematic

                 chi2(19) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       13.25
                Prob>chi2 =      0.8257

. xtreg gpa students ftsratio acceptance retention composite i.year, fe
. estimates store fixedgpa
```

```
. xtreg gpa students ftsratio acceptance retention composite i.year, re
. estimates store randomgpa
. hausman fixedgpa randomgpa
      Test:  Ho:  difference in coefficients not systematic

                 chi2(20) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       10.73
               Prob>chi2 =      0.9528

. xtreg entropy students ftsratio acceptance retention composite i.year, fe
. estimates store fixedentropy
. xtreg entropy students ftsratio acceptance retention composite i.year, re
. estimates store randomentropy
. hausman fixedentropy randomentropy
      Test:  Ho:  difference in coefficients not systematic

                 chi2(20) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =        5.34
               Prob>chi2 =      0.9995
```

All of the seven tests performed above have insignificant p-values (Prob>chi2 larger than .05) meaning that the coefficients are not statistically different and that the random-effects model is the appropriate one to use.

We also had to consider whether to include the time dummy variables in our regressions. Since we found at least some of the coefficients to be statistically significant in each of these regressions, we continued to include the time dummy variables in our models.

Now, we ran the random effects regressions, including independent variables private, west, midwest, and south, which were left out of our earlier regressions since they were perfectly colinear in the fixed effects models.

```
xtreg a students private ftsratio acceptance retention west midwest south composite i.year,
re

xtreg b students private ftsratio acceptance retention west midwest south composite i.year,
re

xtreg c students private ftsratio acceptance retention west midwest south composite i.year,
re

xtreg d students private ftsratio acceptance retention west midwest south composite i.year,
re

xtreg f students private ftsratio acceptance retention west midwest south composite i.year,
re

xtreg gpa students private ftsratio acceptance retention west midwest south composite
i.year, re

xtreg entropy students private ftsratio acceptance retention west midwest south composite
i.year, re
```

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	a	b	c	d	f	gpa	entropy
students	-1.18e-05	3.59e-05	4.98e-05	3.94e-06	-5.96e-05**	1.05e-06	-6.40e-05
	(0.000140)	(9.78e-05)	(6.54e-05)	(2.93e-05)	(3.03e-05)	(2.91e-06)	(0.000174)
private	3.034	2.561	-2.104	-0.432	-2.205***	0.130*	-10.34**
	(3.343)	(2.316)	(1.544)	(0.691)	(0.711)	(0.0690)	(4.071)

ftsratio	0.117	-0.0860	-0.137	0.0406	0.0845	-0.000412	0.109
	(0.346)	(0.243)	(0.163)	(0.0732)	(0.0757)	(0.00724)	(0.433)
acceptance	-0.1529**	0.2052	0.8143**	0.1350	0.00197	-0.00269*	0.1688*
	(6.508)	(4.881)	(3.318)	(1.524)	(1.608)	(0.144)	(8.761)
retention	0.0118	0.0873	-0.0870	-0.00938	-0.0494	0.00272	-0.191
	(0.186)	(0.140)	(0.0954)	(0.0439)	(0.0466)	(0.00414)	(0.252)
west	-0.759	2.366	-0.756	-0.129	-0.277	0.00810	-4.379
	(3.906)	(2.704)	(1.803)	(0.806)	(0.829)	(0.0806)	(5.153)
midwest	1.951	1.205	-1.131	-0.319	-0.865	0.0607	-7.403
	(3.737)	(2.628)	(1.760)	(0.794)	(0.823)	(0.0781)	(4.840)
south	-6.113*	0.291	3.787**	1.456**	0.642	-0.152**	4.982
	(3.327)	(2.288)	(1.522)	(0.679)	(0.696)	(0.0682)	(4.267)
composite	-0.0114	0.0124	0.000466	-0.00405	-0.00110	-2.66e-05	-0.00524
	(0.0126)	(0.00962)	(0.00658)	(0.00305)	(0.00326)	(0.000284)	(0.0172)
1944b.year	0	0	0	0	0	0	0
	(0)	(0)	(0)	(0)	(0)	(0)	(0)
1947.year	2.116	-4.098	3.688	1.070	0.200	-0.0349	-22.50***
	(5.678)	(4.735)	(3.331)	(1.617)	(1.823)	(0.138)	(8.208)
1957.year	7.116	-6.098	-2.312	3.070*	0.200	0.0301	-10.86
	(5.678)	(4.735)	(3.331)	(1.617)	(1.823)	(0.138)	(8.208)
1958.year	1.627	-3.917	-2.314	4.908***	2.443	-0.125	-11.15
	(4.955)	(4.067)	(2.849)	(1.374)	(1.539)	(0.119)	(7.127)
1959.year	2	0	-1	-0	-0	0.0316	-4.041
	(5.201)	(4.351)	(3.064)	(1.491)	(1.686)	(0.127)	(7.473)
1967.year	5.708	2.010	-6.320**	-0.0747	0.346	0.116	-14.85**
	(4.368)	(3.642)	(2.562)	(1.244)	(1.404)	(0.106)	(6.317)
1968.year	8.103	-3.483	-6.368**	2.660*	1.377	0.0497	-11.27
	(5.325)	(4.372)	(3.062)	(1.477)	(1.654)	(0.128)	(7.663)
1969.year	-3.634	9.080*	-5.188	0.109	0.222	0.0104	-6.971
	(5.998)	(4.941)	(3.463)	(1.673)	(1.876)	(0.144)	(8.610)
1977.year	13.09***	3.835	-13.27***	-2.348*	-0.134	0.317***	-19.03***
	(4.370)	(3.645)	(2.565)	(1.246)	(1.405)	(0.106)	(6.317)
1978.year	13.79***	0.0101	-12.31***	-0.0912	0.723	0.249**	-12.58*
	(4.586)	(3.772)	(2.644)	(1.276)	(1.431)	(0.110)	(6.627)
1987.year	15.36***	1.869	-14.84***	-1.922	0.705	0.323***	-17.88***
	(4.225)	(3.523)	(2.479)	(1.204)	(1.358)	(0.103)	(6.127)
1988.year	15.70***	1.721	-14.35***	-1.602	0.502	0.323***	-16.23**
	(4.636)	(3.796)	(2.657)	(1.281)	(1.433)	(0.111)	(6.674)
1997.year	23.69***	1.834	-20.11***	-3.735***	-0.557	0.533***	-25.40***
	(4.158)	(3.461)	(2.433)	(1.180)	(1.329)	(0.101)	(6.052)
1998.year	23.81***	1.893	-19.53***	-3.352***	-0.695	0.525***	-25.21***
	(4.475)	(3.651)	(2.554)	(1.229)	(1.374)	(0.107)	(6.430)
2007.year	30.75***	-2.332	-22.51***	-4.175***	-0.680	0.640***	-29.36***
	(4.161)	(3.457)	(2.429)	(1.177)	(1.324)	(0.101)	(6.126)
2008.year	29.02***	0.662	-22.53***	-4.310***	-0.981	0.635***	-29.62***
	(4.468)	(3.644)	(2.548)	(1.227)	(1.371)	(0.107)	(6.426)
Constant	37.07**	10.03	39.46***	11.75***	9.608**	2.471***	-293.4***
	(18.63)	(13.87)	(9.423)	(4.337)	(4.598)	(0.410)	(24.43)
Observations	108	108	108	108	108	108	104
Number of id	35	35	35	35	35	35	34

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We were able to find results that were significant at the 5% level for all regressions except for the percentage of B's. There was a statistically significant negative effect of the acceptance rate on the percentage of grades that were A's. For every 10 point increase in the acceptance rate the percentage of grades that are A's decreases by

1.5%. There were no significant results for percentage of grades that were B's. For the percentage of grades that were C's, an acceptance rate increase of 10 points results in a 0.8 increase in the percentage of grades that are C's. The South on average also had 3.8% more C's than New England. For the percentage of grades that were D's, the South had on average 1.5% fewer grades than New England. The percentage of F's was affected by the number of students attending an institution; an increase of 10,000 students reduces the percent of F's by 0.596 percentage points. Private schools gave out 2.2 fewer F's than public schools. The only significant effect on GPA was that Southern schools have grades that are lower by .15 points on the 4-point GPA scale. We also found significant effects of private, acceptance, and year dummy variables. These indicate a decreasing ability to distinguish between students for later years, and also a decreased ability to distinguish between students for private institutions and for more selective institutions.
The significance of the time dummies varied among the models. We find that the percentage of A's has increased since 1977 and that the percentage of C's has decreased since that period. The percentage of grades that are D's has decreased since 1997, GPA has increased since 1977, and entropy has decreased since 1977 as well.

Group 2:

We now investigate patterns of inflation over time and attempt to find institutional factors that are associated with changes in the proportion of grades given, the average grade given, and the entropy of the distribution of grades given. We ran the same regressions as before, but using the differences as dependent variables. In order to have meaningful observations, we included only differences with a time lapse of 10 years. Also, for the fixed effects estimators, only schools with more than 2 observations provide relevant data; since the number of differences is the number of observations minus one, all these schools data will be fit by the constant term of the school.

First, we ran the pooled regressions using regular OLS and ignoring the fact that the data came from different schools. Here's an example:

```
. reg da year community private students ftsratio acceptance retention west midw
> est south composite, r
note: community omitted because of collinearity

Linear regression                                      Number of obs =      64
                                                       F( 10,    53) =    2.16
                                                       Prob > F      =  0.0349
                                                       R-squared     =  0.2229
                                                       Root MSE      =  4.3889

------------------------------------------------------------------------------
             |               Robust
          da |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        year |     .14502   .0479334     3.03   0.004      .0488778    .2411622
   community |  (omitted)
     private |   2.829511   2.156986     1.31   0.195     -1.496855    7.155878
    students |   .0000326   .0000812     0.40   0.689     -.0001302    .0001955
    ftsratio |  -.1234082    .207562    -0.59   0.555     -.5397249    .2929085
  acceptance |   1.500101   4.976401     0.30   0.764     -8.481296     11.4815
   retention |   .1811841    .126887     1.43   0.159      -.073319    .4356873
        west |   3.070261   2.389005     1.29   0.204     -1.721476    7.861998
     midwest |    2.81794   2.034214     1.39   0.172     -1.262177    6.898056
       south |   2.997098   1.786683     1.68   0.099      -.586535    6.580731
   composite |   -.010335   .0095838    -1.08   0.286     -.0295575    .0088876
       _cons |  -287.9116   95.30463    -3.02   0.004     -479.0685   -96.75473
------------------------------------------------------------------------------
```

We found significant effects of year on da and db, and of south on dc, dd, and dgpa.

The year coefficient for da was: .14502 and for db, it was: -.14122. These are almost exactly opposite. This suggests there is a general trend of increasingly more A's being awarded instead of B's.

The coefficient of south was negative for dc and dd and positive for dgpa. This suggests that there is an increasing trend in the decrease in C's and D's awarded in the south and, correspondingly, an increasing trend in the increase in overall gpa.

Now, we also ran fixed effects and random effects regressions treating our data as panel data, and ran Hausman tests, just as in group 1. We found that random effects was a good specification, except for dgpa, for which we strongly rejected the random effects hypothesis:

```
. hausman fixedgpa randomgpa

                 ---- Coefficients ----
             |      (b)          (B)            (b-B)     sqrt(diag(V_b-V_B))
             |    fixedgpa    randomgpa      Difference          S.E.
-------------+----------------------------------------------------------------
    students |   -.0001085    -2.94e-06       -.0001056        .0001867
   composite |    .0004725    -.0002518        .0007244        .0004059
 1957bn.year |    -.025049     -.025049        1.03e-15               .
   1958.year |     -.34293    -.0274572       -.3154728               .
   1967.year |     .086201     .0827137        .0034873               .
   1977.year |   -.0151858    -.0598236        .0446378        .0043189
   1978.year |   -.2905318     .0383468       -.3288786        .0152863
   1987.year |    .1781881     .1422097        .0359783        .0118495
   1988.year |   -.1561236     .1734433       -.3295669        .0174718
   1997.year |    .0906007     .0935262       -.0029255        .0280253
   1998.year |   -.2745216     .0586604        -.333182         .030323
------------------------------------------------------------------------------
                           b = consistent under Ho and Ha; obtained from xtreg
            B = inconsistent under Ha, efficient under Ho; obtained from xtreg

    Test:  Ho:  difference in coefficients not systematic

                 chi2(11) = (b-B)'[(V_b-V_B)^(-1)](b-B)
                          =       61.59
                Prob>chi2 =      0.0000
                (V_b-V_B is not positive definite)
```

Now, as before, we ran a time random effects regressions for all of these dependent variables (except dgpa), including the regional and private independent variables. We found that at least one of the time dummies was significant in all the regressions except for da, db, and dentropy. We also found significant effects of retention on da and db, and a marginally significant coefficient for dc in these regressions. However, when we ran random effects regressions for da and db without the time dummies (since they were not significant in these regressions), we found no significance. Here is the regression for dc:

```
. xtreg dc community private west midwest south students ftsratio acceptance ret
> ention composite i.year, re
note: community omitted because of collinearity

Random-effects GLS regression                   Number of obs      =        64
Group variable: id                              Number of groups   =        35

R-sq:  within  = 0.5546                         Obs per group: min =         1
       between = 0.2544                                        avg =       1.8
       overall = 0.5021                                        max =         6

Random effects u_i ~ Gaussian                   Wald chi2(19)      =     44.36
```

```
corr(u_i, X)       = 0 (assumed)                Prob > chi2       =    0.0008

------------------------------------------------------------------------------
          dc |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
   community |  (omitted)
     private |  -1.107121   .9925635    -1.12   0.265     -3.05251     .838268
        west |   -.487694   1.197351    -0.41   0.684    -2.834459    1.859071
     midwest |  -.7871543   1.386968    -0.57   0.570    -3.505562    1.931254
       south |  -1.264637   1.052412    -1.20   0.229    -3.327327    .7980525
    students |   .0000139   .0000427     0.32   0.745    -.0000698    .0000976
    ftsratio |  -.0327266   .1166512    -0.28   0.779    -.2613586    .1959055
  acceptance |  -1.396649   2.422482    -0.58   0.564    -6.144627    3.351328
   retention |   -.123809   .0680912    -1.82   0.069    -.2572653    .0096473
   composite |   .0046829   .0049563     0.94   0.345    -.0050312     .014397
             |
        year |
       1957  |          3    2.89557     1.04   0.300    -2.675212    8.675212
       1958  |   7.016804   3.070743     2.29   0.022     .9982592    13.03535
       1967  |   .0576191   2.563245     0.02   0.982    -4.966248    5.081486
       1968  |    .016804   3.070743     0.01   0.996    -6.001741    6.035349
       1977  |   5.256578   2.386134     2.20   0.028     .5798408    9.933316
       1978  |   4.120799   2.340648     1.76   0.078    -.4667865    8.708385
       1987  |   .3557651   2.305769     0.15   0.877     -4.16346     4.87499
       1988  |    .069863   2.298303     0.03   0.976    -4.434728    4.574454
       1997  |   1.996036   2.197877     0.91   0.364    -2.311724    6.303797
       1998  |   2.472232   2.189722     1.13   0.259    -1.819545    6.764008
             |
       _cons |   1.350484   7.244213     0.19   0.852    -12.84791    15.54888
-------------+----------------------------------------------------------------
     sigma_u |          0
     sigma_e |  2.4417787
         rho |          0   (fraction of variance due to u_i)
------------------------------------------------------------------------------
```

If this coefficient were significant, it would imply that having a higher retention rate is associated with a decrease in the number of C's given over time. By itself, we cannot interpret this result as deflation or inflation, however.

For dgpa, the Hausman test was rejected and so we stuck with a fixed effects model, which, unsurprisingly given our small sample, did not show any significant results, except for year dummies.

```
. xtreg dgpa students ftsratio acceptance retention composite i.year, fe
note: ftsratio omitted because of collinearity
note: acceptance omitted because of collinearity
note: retention omitted because of collinearity
note: 1968.year omitted because of collinearity

Fixed-effects (within) regression               Number of obs      =        64
Group variable: id                              Number of groups   =        35

R-sq:  within  = 0.7296                         Obs per group: min =         1
       between = 0.0071                                        avg =       1.8
       overall = 0.0277                                        max =         6

                                                F(11,18)           =      4.42
corr(u_i, Xb)  = -0.9983                        Prob > F           =    0.0027

------------------------------------------------------------------------------
        dgpa |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
    students |  -.0001085   .0001867    -0.58   0.568    -.0005007    .0002836
    ftsratio |  (omitted)
```

```
  acceptance |  (omitted)
   retention |  (omitted)
   composite |   .0004725   .0004412     1.07   0.298    -.0004544    .0013994
             |
        year |
       1957  |   -.025049   .1002934    -0.25   0.806    -.2357575    .1856595
       1958  |    -.34293   .1002934    -3.42   0.003    -.5536385   -.1322215
       1967  |    .086201   .0904032     0.95   0.353    -.1037291    .2761311
       1968  |  (omitted)
       1977  |  -.0151858   .0862938    -0.18   0.862    -.1964823    .1661108
       1978  |  -.2905318   .0867301    -3.35   0.004    -.4727451   -.1083185
       1987  |   .1781881   .0840569     2.12   0.048     .0015911    .3547851
       1988  |  -.1561236    .085107    -1.83   0.083    -.3349267    .0226794
       1997  |   .0906007   .0848077     1.07   0.300    -.0875738    .2687751
       1998  |  -.2745216   .0855031    -3.21   0.005     -.454157   -.0948862
             |
       _cons |   .9139055   2.310237     0.40   0.697    -3.939722    5.767533
-------------+----------------------------------------------------------------
     sigma_u |   1.429163
     sigma_e |  .07091811
         rho |  .99754369   (fraction of variance due to u_i)
------------------------------------------------------------------------------
F test that all u_i=0:     F(34, 18) =     1.16             Prob > F = 0.3766
```

Conclusion

To summarize, while we found that more selective schools gave higher grades, on average, that larger schools and private schools gave fewer F's, and that the South had lower grades overall. We were unable to find variables that had statistically significant effects on the grade inflation over time, due probably to the paucity of our data.

The largest obstacle in our study was a lack of data, both explanatory variables and data points. Any study of grade inflation must identify what it seeks to measure. Some may argue that any raise in grades is a bad thing since it makes students less distinguishable, but if grades are to distinguish between students at different schools, grades should at least reflect a student's performance or ability relative to the entire population of college students at similar institutions. A more thorough way to address the question is to attempt to distinguish between student performance and/or ability, and grading standards. An instrumental variables approach could help disambiguate here, but since colleges have control over who they admit as students, institutional character will affect the characteristics, including performance and ability, of the student body as well as the way in which they are evaluated, it would take some degree of cleverness to make such an approach feasible.