Dynamic Estimation of the Incentive Schemes and Signalling Costs of Grade Inflation

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Abstract

Higher education is a subject of continual interest. It is marked as an area to propel growth and equality, and public monies in the many billions of dollars are spent annually for its support. Over the past half century, there is evidence of grade inflation within these universities and colleges. However, the potential and actual costs of this grade inflation have been understudied, as well as the feedback effects of changes in the labor market. This paper first examines grading, enrollment, and quality trends in UCLA from 1980-2007. The data demonstrates that there is inflation, even likely when controlling for improvement in student quality. The data also shows that there is a lot of movement in grading patterns over the period; some departments are choosing not to inflate. I construct a stochastic dynamic model which demonstrates the tensions that encourages and discourages grade inflation. It also shows that grade inflation can cause higher variance in initial wages, which might induce some to pursue graduate degrees as an additional signal. The paper then provides suggestions of how it might be estimated with the proper data. Given that the UCLA data does not have all of the information necessary to estimate this model, the paper concludes by making suggestions for a model that can be constructed with the current data, with the intention of so doing.

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1 Overview

In the fiscal year 2009, the US Department of Education allotted 2.4 billion USD for higher education (US Department of Education, 2009). Even more is spent at the state level, where university and college systems are administered. The California Governor's Budget 2009-10 reported a higher education budget of 13.1 billion USD (California Department of Finance, 2009). With little doubt, higher education is a priority of the United States of America.

There is evidence that the second half of the 20th century was a period of increasing Grade Point Averages (GPAs) in selective universities in the United States. Figure 1 shows this overall trend starkly, from data collected by Rojstaczer (2009) from publicly available University Registrar Data. This phenomenon, typically called grade inflation, is neither clearly bad nor good. However, grade inflation can potentially be important insofar as grades are signals of student quality. With inflation that is independent of quality increases, those particularly at the higher end of the skill distribution are affected. As grades are discrete and bounded, higher grades imply those at the top end of the distribution become indistinguishable. While a GPA of 4.0 might have before signaled that an individual is in the top 5%, with grade inflation it might only signal that the individual is in the top 10%. Given grade inflation's potential importance, economists would be interested in finding some of the causes of this grade inflation, and how departments react to changes in the labor market landscape that their students will compete in after graduation.

Should there be measurable costs to signaling via grade inflation, being able to estimate these costs would help in the decisions that departments make. There are at least two such costs: a worker attaining more education than is optimal, and the costs of misallocating a low skill worker to the high skill firms (mismatching costs). I am not interested in explaining all of the reasons for the seemingly secular increase in grades over the last half century, but in exploring the implications of movements. In light of the importance of higher education, any further understanding of grade inflation will be helpful.

There are two potential questions we would want to answer. First, can grade inflation cause movement in the top of the skill distribution to go to these newly created masters programs so as to differentiate themselves with an additional signal in the reality of post-inflation fuzziness of grade's signal? Is there evidence that these masters programs are just signalling, and not human capital development? Figure 2 shows an overall increase of graduate schooling in the United States, using the US Census. Second, do departments react to changes in expected students wages by changes in grading patterns (to improve matches of their students in the labor force)?

I first look at UCLA data and see that there is inflation over the last 25 years in many of the departments, even potentially when controlling for student quality improvements. I also find that smaller departments tend to award higher grades. I construct a stochastic dynamic model. The inflation decision happens within an environment of counteracting incentives. There is a short term benefit to the school's low-skill students, but at a short term cost to the high skill student (of lower expected wages in high skill firms) and long term cost of credibility that affects all future high mark earners. I show that the model implies that increases in mean grades can increase the variance of the initial wage distribution even while lowering its mean, which might be strong enough to induce some marginal high skill students to pursue a graduate degree to improve their perceived ordering in the distribution. I offer suggestions of how the model might be estimated with the proper data; given that I do not have the appropriate data, I conclude by making suggestions for the model that can be constructed with the current data, which works from student course decisions as endogenous.

1.1 Relevant Literature

There is some progress in researching the topic, although most of it is theoretical. Chan, Hao, and Suen (2007) create a static model that has, as its implication, an equilibrium with grade inflation. It is a simple but interesting model, and the model that I start with as my basis. I incorporate some of their basic modeling decisions, while expanding in many areas. Chan et al build on the basis of their 2002 working paper, which details some of the mathematics involved in their model.

An alternative model of grade in inflation is presented by Ostrovsky and Schwarz (2003). They are more interested in seeing how the accuracy of grade signals affects the timing of contracting between students and the labor market. They argue that noisy signals are perhaps a result of a fully rational equilibrium. Their model implies that, under a certain level of ability, it is optimal for the school to reveal the truth; above that level, schools find it optimal to lump all of the students together. Their paper is relevant to this project because of their modeling decisions and because they identify another possible incentive avenue for grade inflation.

Sabot and Wakeman-Linn (1991) look at the impact of grade inflation as a signal to the student of their relative ability. My research will not address this aspect at all (I will assume students know their ability); however, as far as Sabot and Wakeman-Linn are correct, any estimated cost of grade inflation that I find would be underestimating the true cost. It is another source of inefficiency, and potentially a more lasting effect (insofar as students do not recover from mis-assigning themselves to a major).

Of potential interest is the work by Nelson and Lynch (1984). They instrument to find the effect of teacher evaluations on grade inflation. They hypothesize that teachers being evaluated might increase the grades of their student to barter for better evaluations, and find this result in estimating a model using data from Penn State economics department classes. This would suggest that grade inflation is potentially driven in part by teachers' responses to student demands, so that changes in student demands might shift the grade distribution.

Further, Wikström and Wikström (2005), on the other hand, have an empirical analysis of secondary schools in Norway. They provide evidence that higher levels of competition are correlated with, and potentially cause, higher levels of grade inflation. While our framework is in tertiary education, this offers one reason departments might inflate grades (to attract students), and motivates the use of a game model, as well as the model that I suggest in conclusion.

Tracy and Waldfogel (1997) address another aspect of the problem this paper faces. They establish an objective indexing of business schools based on factors which include labor market outcomes of graduates. This paper is directly interested in labor market outcomes; while not ranking the different departments, this paper will attempt to make similar forecasts about value-added implicitly.

1.2 Outline

The rest of the paper will proceed in the following manner: Section 2 takes a preliminary look at the data which will be my primary source. It comes from the population of University of California Los Angeles (UCLA) students from 1966-2007. I will examine some of the overall trends that will motivate the questions and suggest the formation of the model. Section 3 then will present the first main attempt at a model to answer these questions. First I create a model which does not allow for graduate schooling, and then relax this assumption in a model extension. I will then discuss the grade inflation and graduate program implications of the model. I look at what additional data is necessary for estimating the model, and other limitations of the data. Section 4 will then look at what are the next steps in the research, both in terms of data and modeling. Section 5 will then conclude.

2 UCLA Data

2.1 Data Preview

In the case of this paper, the main definition for grade inflation we will be working with is an increase in the mean grade awarded conditional on the quality of the students. The preliminary model adopts language such as more grades awarded than deserved. This is slightly different, but can be encompassed within the original definition by considering a baseline at any given point (of awarding a certain level, whether that is more or less than is "deserved"). The model is still primarily interested with changes from such a point, which is the definition as first stated.

The primary data source which I will use comes from UCLA. The data source has observations from 1966-2007. However, as Figure 3 suggests, the data set seems to be a sample before 1980. This creates a lot of noise in estimates of the grade distribution. For that reason, I will use only data from 1980-2008, when the data is a full census of course activity and students. This is still a sufficient length of time for movement in the data, and allows us to have better assurance, given that we are observing the actual grade distributions, and not very small-size samples.

There are a few interesting trends in the data. First, we are able to see that in UCLA there is overall grade inflation over the time period referenced. However, there is variation between departments in the grade trends–some have even overall decreased over the period. Looking at which departments are the highest graders at the beginning of the data's time and at the end, we see both that there is overall stability, but changes in the ordering that suggests relative grade inflation might be important as well. I further find that smaller departments tend to give out higher grades, and that there is increases in the SAT scores over time, but these don't seem to be immediately correlated with growth in mean grade awarded.

2.2 Summary Statistics

Table 1 presents the summary statistics. UCLA is on a quarter system, and the data is available for the three main quarters of each year (Fall, Winter, and Spring). For the rest of the analysis, I divide the population into two groups: graduate students and undergraduate classes. For undergraduate classes, the measure will select any observation (a student's course enrollment) that is in an undergraduate class. This could potentially include graduate students. As for graduate students, I only include graduate students here, not graduate classes.

One variable that will come up again is the class enrollments. This is the basic observational unit in the data. It measures when one student takes one course. The data has almost ten million undergraduate observations (after keeping only classes that have assigned at least one grade in a given quarter). A given student who attended four years and enrolled in forty classes during that period would be forty observations. Thus, in a given quarter, the average program is teaching about 3000 students in undergraduate classes.

The summary statistics offer the first hint of grade inflation. The mean grade awarded over the early period was over 0.1 grade points lower than in the late period. If the mean grade awarded is regressed within each department on time and a constant, 79% and 76% of the departments have positive coefficients on time for graduate and undergraduate, respectively.

2.3 Mean Grade Awarded Trends

There is evidence of a lot of movement in the data, as regards departments mean grade awarded. This can be seen in Figure 4, which is a histogram of the coefficients from department regressions of mean grade awarded on time and a constant (to see the overall trend). There are many coefficients are greater (in absolute value) than 0.01. A coefficient of 0.01 implies that, over a decade, the mean grade awarded would increase from 3.3 to 3.4, for example. 25 years then implies a full letter grade change. There are many departments that have even higher levels of inflation or deflation. Even within departments, there is a good amount of variation over time. Figure 5 shows the largest change within a department. This movement in the data encourages identification as well as motivating the overall question.

Figure 6 shows the estimated distribution of mean grades awarded calculated for every year in the sample across the entire university, estimated using an Epanechnikov Kernel. Figure 7 shows the contours. Both show slight upward movement in distribution over time. Also, the means for graduate students are both more concentrated and higher. The distribution for graduate students represents a possible future outcome for undergraduate students if grades continue to increase. While the shapes of the distributions are relatively consistent over time, there does seem to be a small decrease in the variance of the undergraduate distribution towards the end of the sample. This could perhaps be the result of the grade inflation or independent.

Tables 3 and 4 show the bottom and top 20 departments, by mean grades, in the beginning and ending periods.There is relative continuity as the departments in each group generally stayed the same from the earlier period to the later period. Also, the departments with lower mean grade awarded tend to be the more mathematical and scientific disciplines, while higher grades are given out by liberal arts departments, in general. The model should somehow reflect this distinction, why some departments might have lower incentives to systematically inflate, given their labor market outcomes and student demand. Note too that ranking comes from relative grade inflation, not absolute. Thus, mathematics for example, inflated grades over the period, but dropped in the ordering to the second lowest grade-givers because they did not inflate as much as economics.

2.4 Class Enrollments Trends

We are interested in the class enrollment trends for a few reasons. First of all, we might think that the changes in grades awarded are just reflective of changes in the composition. This presents a first stage to that query by looking at how many students are taking classes in the department. Second, we might think that departments use grade levels as incentives to attract students.

Figure 8 is a histogram of the coefficients from doing department regressions of class enrollments in a quarter on time and a constant, to find the trends. Interestingly, it is not just a season of growth or stagnation. There is good variation, as some departments are shrinking while others are expanding. This will be valuable in a model that predicted departments were using grades at least partially in attempts to attract (potentially specific) students bases.

What is the relationship between mean grades awarded and the number of students enrolled in classes? Figures 9 and 10 show this by department. There is overall a downwards trend–larger departments are handing out lower grades. This relationship is consistent across time, as the two cross-sections of time demonstrates. There are various conclusions that can be drawn: one, that higher grades do not unconditionally attract students, or two, that smaller departments are trying to attract students by raising grades (whether or not they are successful). This would require more investigation, but could be an important part of a model that considers the motivations for grading decisions of the department (as will be suggested in the remodeling).

2.5 SAT Trends

We might be concerned that increases in grades are just an indication of increases in student quality. The data has information concerning the SAT scores of incoming students. The SATs are standardized, and so can offer insight into the changing quality of the students at UCLA over the relevant time period. Figures 11 and 12 present non-perimetrically estimated distributions over cross-sections of time using an Epanechnikov Kernel.

SAT scores seem to have increased for graduates in both math and verbal, but only in verbal for undergraduates. Also, there is an interesting bimodality for the undergraduates in math SAT that is consistent over time. One interesting next step would be to see which departments are in the upper mode, and which the lower, and if there is any correlation between this and the grades that are awarded.

Overall though, the improvement for undergraduates is small for either measure. This suggests that potentially the increased grades observed is actually inflation, and not compositional changes in quality. To see a little more carefully if changes in student quality are driving changes in grade, Figures 13 and 14 are scatter plots which look at first differences within a department over a year. The interpretation of a point is, for a given increase/decrease over a year of the mean SAT score in the classes taught in a department, the associated change in mean grades handed out in the department. The trends are all non-existent, implying on a first-step level that increases in the quality of students do not drive changes in grades awarded. The truth might still be obscured, but this gives initial confidence that we are actually observing inflation. The future model development will discuss how to use the SAT scores to standardize the grades over time.

I also do simple first difference (fixed effects) panel regressions of mean grades and proportion of A's on Math and Verbal SAT scores (as well as a time trend and a constant). The results are in Table 2.

The time trend (term) dominates the other variables, implying that these upward movements are mostly not a result of the increased student quality. However, it is interesting to note that increases in the mean math SAT score within a given department is correlated with decreased mean grades awarded. As a given department becomes more mathematically adept, lower grades are given. On the other hand, we do seem to observe more dominant affects and in the positive direction for verbal SAT scores. It seems that these measures of quality are absorbed into the grades, while math scores are not. Perhaps departments make classes tougher in an attempt to attract bright, mathematically minded students who want to differentiate themselves. I hope to incorporate these trends somehow into the model as well.

In conclusion, the raw UCLA data suggests that there is overall grade inflation, with a lot of variation; that the shape of the mean grade distribution is mostly consistent over time; that larger departments tend to give lower grades; and that, while SAT scores are increasing somewhat, initial evidence is that the effect on grade inflation is small, so that something else must be introduced to explain the change in grades over time. The model should allow for incentives to inflate grades, provide quality of student benchmarks, and be able to lead to different outcomes given different department/labor market matchings. The preliminary model will try to incorporate some of these traits, while the suggested future model adds more.

3 Preliminary Model

The preliminary model is a stochastic dynamic model where the departments are the agents maximizing the total expected future wages of their students. There is aggregate uncertainty in the form of firms not knowing the skill distribution that students are being drawn from and the true quality of the students they hire. This is a first attempt for the uncertainty that is important. The uncertainty creates the signalling problem of grade inflation of firms being unsure of the true type of the new workers. Without this uncertainty, there would be no grade inflation problem. While it is not clear that this aggregate uncertainty is the best way to address the uncertainty, it provides a nice first attempt at it. Firms learn over time and adjust their expectations, thereby punishing inflators. Departments also have the short term incentive to inflate to help mediocre students while a short term disincentive to help out their high quality students (they cannot be differentiated and immediately rewarded for their quality). It is important to make the model dynamic in order to capture this reputation effect, which I feel is a strong disincentive to grade inflate. The literature has not addressed this issue, so modeling and estimation will give a more realistic understanding of the incentives at play, and hence the reactions to changes in the environment (such as changes in wages).

I then extend the model to include students' decision to attend graduate school, to see if increased grade inflation will cause adoption of this signal. Neither model can currently be estimated, because of a lack of data. Therefore, after the model development I will explain what data is necessary and, basically, how the model would be estimated. Then I will briefly explain the plan for a future incarnation of the model that can be estimated given the UCLA data that I already have.

In the preliminary model, there are 2 states of the world: $S = F$ (favorable), in which there is an expected proportion ϕ_F of high skill students in the college, and $S = U$ (unfavorable) where there is ϕ_U of high skill students. It is assumed that $\phi_U < \phi_F$. The idea behind there being high and low skill workers is not quite as drastic as it initially sounds. The parameter really measures compatibility with the highest skill occupations/firms. The model allows for considerable amounts of other achievement heterogeneity on observables, as will later be explained.

Departments choose ψ^*, the proportion of students to which they give high marks. There is also a shock η which will be associated with ψ^*. Departments set objective grading policy, but then professors deviate in a mean zero manner (in expectation). Therefore, the actual outcome will be $\psi = \psi^* + \eta$, where $E(\psi) = \psi^*$. All students that receive high marks are initially hired in the high skill sector, regardless of whether they are actually high skill or low skill (firms cannot distinguish). After τ_h time passes, firms learn who is high skill and who is low skill. In the low skill firm, after τ_l, the market learns whether these workers are low or high skill.

It is assumed that $\tau_l > \tau_h$. This is both intuitive and attractive; intuitive, because in low skill sectors, high skill workers are not able to show their high skill, and so it takes more time to demonstrate this ability; attractive, because it gives colleges incentive to always first place high skill workers in the high skill sector, so that they can be discovered earlier.

We next look at the agents in the model, and their respective (explicit or implicit) objective functions.

3.1 Workers

In this preliminary model, workers (students) have no modeled decision. They are exogenously given to departments, and given marks, after which their life path is determined. However, the next development in the model will be to give students the ability to choose whether, after graduating with an undergraduate degree and observing their grades, they want to pursue a masters degree or go to the workforce. The decision will still be static, made once and for all time when they graduate.

3.2 Firms

I do not explicitly model the firms decision process. Rather, following the lead of Chan et al, I assume sufficiently thick labor markets and perfect competition. These will imply that there is no strategic pricing of wages by the firms, that they pay the marginal product of the workers and wages are not a function of how many people are already working. Decisions are static and, in terms of this model, already decided.

I assume two types: great workers (g) and mediocre (m). Further, I assume that the expected wages unconditioned on observables is stochastic, and given by

$$w_{ic}^{g} = \begin{bmatrix} w_{hic}^{g} \\ w_{lic} \end{bmatrix} \sim N\left(\begin{bmatrix} \mu_{hc}^{g} \\ \mu_{lc} \end{bmatrix}, \Sigma_c \right)$$
$$w_{ic}^{m} = \begin{bmatrix} w_{hic}^{m} \\ w_{lic} \end{bmatrix} \sim N\left(\begin{bmatrix} \mu_{hc}^{m} \\ \mu_{lc} \end{bmatrix}, \Sigma_c \right)$$

where i indexes the worker, c the labor market entry cohort, and h vs l the high skill vs. low skill sector. Note that the mean for great and mediocre workers is the same in low-skill occupations. Also, note that I allow for the possibility of cohorts having different distributions. This will be reflective of the changing marginal product of workers across time, and the parameters can potentially be estimated outside of the dynamic program from census data.

The wage distribution conditional on observables within a cohort is generated from order statistics. Therefore, high skill individuals (g) expect, once type is learned, to receive wages $w_{hic(k:n)}^{g}$ if they believe that they are ranked k^{th} out of n. Low skill individuals expect, once type is learned, to be offered wages $w_{hic(k:n)}^{m}$, and choose low skill position at wage $w_{lic(k:n)}$. I assume that high skill firms offer such low wages that it is optimal for low skill workers to switch.

The order statistic index k is generated by a reduced form indexing of predicted wages from observables. For example, in a given year we can look at the Current Population Survey and find through regressions predicted wages based on observables. Do this for all individuals in the graduating cohort and rank them from highest and lowest, and this generates their respective k. This is important for when the model allows for graduate school attendance, to allow the students to not just randomly choose to go to grad school, but the ones for whom it is optimal. Graduate school both changes their cohort and their observables and so their ranking, both of which might offer incentive. These will require additional expectations, both on the part of the students and the college departments.

It still remains to be shown what wage the high skill firms offer before they realize the types of the workers. This will just be a reflection of the weights of each type. These will be given by

$$\begin{aligned} w_{ic}(A|\psi) = &\sigma_F(\psi, \sigma_{F,-1}) w_{ic}(A|\psi, \phi_F) \\ &+ (1 - \sigma_F(\psi, \sigma_{F,-1})) w_{ic}(A|\psi, \phi_U) \end{aligned}$$

where

$$\begin{aligned} &\sigma_F(\psi, \sigma_{F,-1}) = Pr(S = F|\psi, \Pi, \sigma_{F,-1}) \\ &w_{ic}(A|\psi, \phi_S) = \min\left\{\frac{\phi_S}{\psi}, 1\right\} w^g_{hic(k:n)} + \left(1 - \min\left\{\frac{\phi_S}{\psi}, 1\right\}\right) w^m_{hic(k:n)} \end{aligned}$$

Then, by Bayes' Law

$$\sigma_F(\psi, \sigma_{F,-1}) = \frac{Pr(\psi|S = F, \sigma_{F,-1}) Pr(S = F)}{\sum_{s=U,F} Pr(\psi|S = s, \sigma_{F,-1}) Pr(S = s)}$$

The question becomes, how do we handle these beliefs? One option, we assume that the initial belief is assuming truth-telling in expectation ($\psi = \phi_S$), and then the firms update each time types are learned by taking averages of all past actions (when state was S, what ψ was chosen by departments). This will allow for the evolution of beliefs over time, conditional on the college departments' actions.

3.3 Departments

Departments maximize total lifetime wealth of their students. This can be interpreted as maximizing total donations, altruism, increasing reputation, or other possible incentive structures. The timing becomes important, as colleges face a dynamic problem.

Departments solve a discrete, infinite horizon problem. In a given time period, they observe the state of the world and choose ψ, the proportion of students they will give high marks to. Then, responding to this, in the next period the high skill firms choose the wage to offer and the colleges receive the discounted expected future lifetime wealth of their students. At this point, all that is stochastic is the state of the world, as determined by a Markov transition matrix Π.

3.3.1 Value Functions

Case I: $\psi > \phi_S$ (Departments give more high grades than are deserved)

$$V(\psi|S,c) = \max_{\psi'} \left\{ \begin{array}{ll} \phi_S \sum_k E_w \left[\sum_{t=0}^{\tau_h} \beta^t w_{ic(k:n)}(A|\psi) + \sum_{t=\tau_h+1}^{T} \beta^t w^g_{hic(k:n)} \right] & (1) \\ +(\psi + \eta - \phi_S) \sum_k E_w \left[\sum_{t=0}^{\tau_h} \beta^t w_{ic(k:n)}(A|\psi) + \sum_{t=\tau_h+1}^{T} \beta^t w_{lic(k:n)} \right] & (2) \\ +(1-(\psi+\eta)) \sum_k E_w \left[\sum_{t=0}^{T} \beta^t w_{lic(k:n)} \right] & (3) \\ +\beta E_{c'|c}(\pi_{SS} V(\psi'|S,c') + \beta \pi_{SS'} V(\psi'|S',c')) & \end{array} \right\}$$

(1): expected lifetime payoff for a high skill individual who is given high grades

(2): expected lifetime payoff for a low skill individual who is given high grades

(3): expected lifetime payoff for a low skill individual who is given low grades

Note that, for order statistics,

$$\sum_{k=1}^{n} E(x_{[k:n]}) = E\left(\sum_{k=1}^{n} x_{[k:n]} \right) = E(\sum_{i=1}^{n} x_i) = nE(x_i)$$

This significantly simplifies the value function. I evaluate the sums over t as well, and find

$$V(\psi|S,c) = \max_{\psi'} \left\{ \begin{array}{l} n\phi_S \left[\frac{1-\beta^{\tau_h+1}}{1-\beta} w_c(A|\psi) + \frac{\beta^{\tau_h+2}-\beta^{T+1}}{1-\beta} \mu^g_{hc} \right] \\ +n(\psi+\eta-\phi_S) \left[\frac{1-\beta^{\tau_h+1}}{1-\beta} w_c(A|\psi) + \frac{\beta^{\tau_h+2}-\beta^{T+1}}{1-\beta} \mu_{lc} \right] \\ +n(1-(\psi+\eta)) \left[\frac{1-\beta^{T+1}}{1-\beta} \mu_{lc} \right] + \beta E_{c'|c}(\pi_{SS} V(\psi'|S,c') + \beta \pi_{SS'} V(\psi'|S',c')) \end{array} \right\}$$

We then consider the alternative case.

Case II: $\psi \leq \phi_S$ (Departments give correct or too few high marks–already simplified)

$$V(\psi|S,c) = \max_{\psi'} \left\{ \begin{array}{ll} n(\psi+\eta)\left[\frac{1-\beta^{\tau_h+1}}{1-\beta} w_c(A|\psi) + \frac{\beta^{\tau_h+2}-\beta^{T+1}}{1-\beta}\mu^g_{hc}\right] & (1) \\ +n(\psi_S-(\phi+\eta))\left[\frac{1-\beta^{\tau_l+1}}{1-\beta}\mu_{lc} + \frac{\beta^{\tau_l+2}-\beta^{T+1}}{1-\beta}\mu^g_{hc}\right] & (2) \\ +n(1-\phi_S)\left[\frac{1-\beta^{T+1}}{1-\beta}\mu_{lc}\right] & (3) \\ +\beta E_{c'|c}(\pi_{SS}V(\psi'|S,c') + \beta\pi_{SS'}V(\psi'|S',c')) & \end{array} \right\}$$

(1): expected lifetime payoff for a high skill individual who is given high grades
(2): expected lifetime payoff for a low skill individual who is given high grades
(3): expected lifetime payoff for a low skill individual who is given low grades

3.3.2 Incentives

An inspection of these functions suggests the counteracting incentives for the colleges. For example, when $\psi \geq \phi_S$, the only parts of the objective function that the universities can affect are

$$n\frac{(\psi+\eta)(1-\beta^{\tau_h+1})}{1-\beta}\left(w_c(A|\psi)-\mu_{lc}\right) + \beta E_{c'|c}\left[\pi_{SS}V(\psi'|S,c') + \beta\pi_{SS',c'}V(\psi'|S',c')\right]$$

Given an assumption that $w(A|\psi)$ and $w'(A|\psi)$ decrease with ψ (which is to say, the wage that high skill firms pay for new graduates decreases as grade inflation increases, for now and the future), then increasing ψ (increases in grade inflation) has ambiguous effects:

$$n\frac{1-\beta^{\tau_h+1}}{1-\beta}\left[w_c(A|\psi)-\mu_{lc}+(\psi+\eta)\frac{\partial w_c(A|\psi)}{\partial\psi}\right] + \beta\left[\pi_{SS}\frac{\partial}{\partial\psi}E(V(\psi'|S,c')) + \pi_{SS'}\frac{\partial}{\partial\psi}E(V(\psi'|S',c'))\right]$$

$w_c(A|\psi) - \mu_{lc}$ is always positive; it is the wage premium given to workers in the skilled firms. Universities get this extra benefit by being able to put more of their workers in these institutions, at least until the workers are discovered to be low quality (the high workers were all already given high marks, so that changing ψ further only gives a temporary boost). This is the short term incentive to inflate grades, to get second tier students in good positions.
$(\psi+\eta)\frac{\partial w_c(A|\psi)}{\partial\psi}$ is negative, and measures the decrease in the wage premium because the firms are suspicious of the number of high marks given. They are uncertain whether it is because we are in a good state of the world or if it is pure inflation. $\pi_{SS}\frac{\partial}{\partial\psi}E_{c'|c}[V(\psi'|S,c')] + \pi_{SS'}\frac{\partial}{\partial\psi}E_{c'|c}[V(\psi'|S',c')]$ is likewise the future decrease in the wage premium, by the college losing credibility when it gives high marks by going over where it should have been.

3.4 Graduate School Decision

Now we allow students to choose for graduate school. This will both change their observables (and so ordering) as well as their cohort. Graduate school takes one period. A high skill individual i with pre-graduate school rank k will choose to attend graduate school if and only if

$$E_{w'}\left[\sum_{t=1}^{\tau_h+1}\beta^t w_{ic(\tilde{k}:n)}(A|\psi)+\sum_{t=\tau_h+2}^{T}\beta^t w^g_{hic(\tilde{k}:n)}\right]-\kappa_t > E_w\left[\sum_{t=0}^{\tau_h}\beta^t w_{ic(k:n)}(A|\psi)+\sum_{t=\tau_h+1}^{T}\beta^t w^g_{hic(k:n)}\right] \tag{1}$$

κ_t represents the direct cost of graduate school, and is known. $\tilde{k}$ is the adjusted ranking given the student now has graduate school completed. The first expectation is taken over the expected next period distribution of wages, as given by the expectation of c', the future cohort.

Let γ_k be an indicator for the sign of (1); in other words,

$$\gamma_k^1 = 1\left(E_{w'}\left[\sum_{t=1}^{\tau_h+1}\beta^t w_{ic(\tilde{k}:n)}(A|\psi)+\sum_{t=\tau_h+2}^{T}\beta^t w^g_{hic(\tilde{k}:n)}\right]-\kappa_t > E_w\left[\sum_{t=0}^{\tau_h}\beta^t w_{ic(k:n)}(A|\psi)+\sum_{t=\tau_h+1}^{T}\beta^t w^g_{hic(k:n)}\right]\right)$$

γ_k^2 and γ_k^3, for low skill students given high marks and low skill students given low marks respectively, are similarly defined.

3.4.1 Value Functions

Case I: $\psi > \phi_S$ (Departments give more high grades than are deserved)

$$V(\psi|S,c) = \max_{\psi'} \left\{ \begin{array}{lr} \phi_S \sum_k (1-\gamma_k^1) E_w \left[\sum_{t=0}^{\tau_h} \beta^t w_{ic(k:n)}(A|\psi) + \sum_{t=\tau_h+1}^{T} \beta^t w^g_{hic(k:n)} \right] & (1) \\ +\phi_S \sum_{\tilde{k}} \gamma_k^1 E_{w'} \left[\sum_{t=1}^{\tau_h+1} \beta^t w_{ic(\tilde{k}:n)}(A|\psi) + \sum_{t=\tau_h+2}^{T} \beta^t w^g_{hic(\tilde{k}:n)} \right] & (1*) \\ +(\psi+\eta-\phi_S) \sum_k (1-\gamma_k^2) E_w \left[\sum_{t=0}^{\tau_h} \beta^t w_{ic(k:n)}(A|\psi) + \sum_{t=\tau_h+1}^{T} \beta^t w_{lic(k:n)} \right] & (2) \\ +(\psi+\eta-\phi_S) \sum_{\tilde{k}} \gamma_k^2 E_{w'} \left[\sum_{t=1}^{\tau_h+1} \beta^t w_{ic(\tilde{k}:n)}(A|\psi) + \sum_{t=\tau_h+2}^{T} \beta^t w_{lic(\tilde{k}:n)} \right] & (2*) \\ +(1-(\psi+\eta)) \sum_k (1-\gamma_k^3) E_w \left[\sum_{t=0}^{T} \beta^t w_{lic(k:n)} \right] & (3) \\ +(1-(\psi+\eta)) \sum_{\tilde{k}} \gamma_k^3 E_{w'} \left[\sum_{t=1}^{T} \beta^t w_{lic(\tilde{k}:n)} \right] & (3*) \\ +\beta E_{c'|c}(\pi_{SS} V(\psi'|S,c') + \beta \pi_{SS'} V(\psi'|S',c')) & \end{array} \right\}$$

(1): exp. lifetime payoff for a high skill individual with high grades, no graduate degree
(1*): exp. lifetime payoff for a high skill individual with high grades, graduate degree
(2): exp. lifetime payoff for a low skill individual with high grades, no graduate degree
(2*): exp. lifetime payoff for a low skill individual with high grades, graduate degree
(3): exp. lifetime payoff for a low skill individual with low grades, no graduate degree
(3*): exp. lifetime payoff for a low skill individual with low grades, graduate degree

Now, the cohort includes individuals who have completed a graduate degree, and so the rankings depend on the past choices, shape the development of c–but not completely, as one graduate program does not determine the entire cohort of the labor market that a graduate is entering.

3.4.2 Incentives

What happens to the number of people pursuing graduate school, ceteris paribus, with an increase in mean grade awarded? To answer this, we examine the indicator function. We want to examine, in essence, $\partial/\partial\psi(Pr(\gamma_k = 1))$.

Consider a student with high skill and high marks. The only elements inside the expectation that are affected, ceteris paribus, by grade inflation are the expected payoffs before type is learned. For grade inflation to cause more high skilled workers to get masters degree as a direct result, it must hold that

$$\begin{aligned}
\frac{\partial}{\partial \psi}\left\{E_{w'}\left[\sum_{t=1}^{\tau_h+1}\beta^t w_{ic(\tilde{k}:n)}(A|\psi)\right]-E_w\left[\sum_{t=0}^{\tau_h}\beta^t w_{ic(k:n)}(A|\psi)\right]\right\}>0 \\
\Leftrightarrow \left(\frac{1-\beta^{\tau_h+1}}{1-\beta}\right)\frac{\partial}{\partial \psi}\left\{\beta E_{w'}\left[w_{ic(\tilde{k}:n)}(A|\psi)\right]-E_w\left[w_{ic(k:n)}(A|\psi)\right]\right\}>0 \\
\Leftrightarrow \frac{\partial}{\partial \psi}\left\{\beta E_{w'}\left[w_{ic(\tilde{k}:n)}(A|\psi)\right]-E_w\left[w_{ic(k:n)}(A|\psi)\right]\right\}>0 \qquad (2)
\end{aligned}$$

To know when this happens, we can first consider how the distribution of $w_{ic}(A|\psi)$ are changed, and from this conclude how the order statistics are affected. $w_{ic}(A|\psi)$ is normally distributed, as it is the sum of two normally distributed random variables (with weights determined by the model). As a normal distribution, it is defined completely by its mean and its variance.

First, consider what happens to the mean with the change. Assume that there is no change in the cohort, so that we can represent $E(w^g_{hic}) = \mu^g$ (suppressing the h). Consider the case of interest: $\phi_S/\psi < 1$ (when there is already some grade inflation). Note that σ_F is unaffected in the period that the students are deciding by the inflation in that period. I first consider someone who has a k above the median. Then, the original mean is

$$E(w_{ic}(A|\psi_1)) = \left(\sigma_F\frac{\phi_F}{\psi_1}+(1-\sigma_F)\frac{\phi_U}{\psi_1}\right)\mu^g - \left(\sigma_F\left(1-\frac{\phi_F}{\psi_1}\right)+(1-\sigma_F)\left(1-\frac{\phi_U}{\psi_1}\right)\right)\mu^m$$

The inflation from ψ_1 to ψ_2 would mean that the change in mean is the difference in that quantity. This encompasses both meanings of grade inflation that we might be concerned with (giving undeserved high marks, or giving more undeserved high marks than before). It can be shown that the difference in means is given by

$$E(w_{ic}(A|\psi_2)) - E(w_{ic}(A|\psi_1)) = \left(\frac{1}{\psi_2}-\frac{1}{\psi_1}\right)(\sigma_F\phi_F+(1-\sigma_F)\phi_u)(\mu^g+\mu^m)$$

The first term is always negative, because $\psi_1 < \psi_2$. The second term is just positive terms, and the third term is positive (expected wages are always positive). Therefore, the product is negative, which means that grade inflation causes expected wages in that period to drop for students with high marks. This is as was earlier established, and denotes the expectations by firms of lower quality workers in the mix–the short term penalty for grade inflation.

We are concerned with how the order statistic changes with the grade inflation though. Given we know that the mean decreases, if the variance remains constant, then the order statistics decrease by the same amount, and Inequality 2 is negative, so that there is no increase in the expected proportion of students pursuing graduate degrees. If the variance decreases, then the same conditions hold, now even more strongly (as there is a larger decrease if they get a graduate degree). So the only possible case when grade inflation would cause graduate school to be more attractive is when the variance increases. In that case, with a decreasing mean, the marginal student with k might be better off pursuing graduate school. The uncertainty is driven by the additional fact that, looking at 2, we need to combat the β that takes into account that earnings are pushed back a year for graduate students.

Under which cases does the variance increase and make is possible? Using similar methods, it can be shown that the change in variance when grading level inflates from ψ_1 to ψ_2 can be expressed as

$$2\left[\left(\frac{1}{\psi_2^2}-\frac{1}{\psi_1^2}\right)(\sigma_F\phi_F+(1-\sigma_F)\phi_u)^2-\left(\frac{1}{\psi_2}-\frac{1}{\psi_1}\right)(\sigma_F\phi_F+(1-\sigma_F)\phi_u)\right]>0 \qquad (3)$$

More algebra shows that a sufficient condition for Inequality 3 to hold is that

$$\frac{\psi_1+\psi_2}{\psi_1\psi_2}>\sigma_F\phi_F+(1-\sigma_F)\phi_U \qquad (4)$$

Because of the β in Inequalty 2, this is a necessary but not sufficient condition for there to be increased graduation enrollment as a result of grade inflation. Condition 4 will always hold, as the right side is bounded above by one, while the left side is bounded below by 2. Given that the β needs to be overcome as well though, it is useful to consider conditions that make Condition 4 hold more "strongly", so as to make the deflated implication of the inequality still be positive, implying a change from not attending to attending graduate school.

First, if β is larger, it is more likely for the change to be large enough to induce graduate school for some, as they will not mind postponing wages a year to attend graduate school. Second, if ψ_1 is very low, then it is easy to get movement from any ψ_2 (as ψ_1 approaches zero, the left side goes to ∞). An intuition here is that we have not imposed the penalty for grade inflation yet (the firms have not learned), so that the jump causes firms to believe that there is a bumper crop of high quality students. Given that, and the assumption that the cohort next period is the same, you want to improve your ranking, given you are going to be identified anyways. Third, the higher the proportion of high quality students in either state of the world, the less likely people will change. The most likely changes happen when few people are actually high quality, and there had been low inflation. Then, more inflation will increase the expected payout. Fourth, if there is an asymmetry in beliefs, such that in a world where ϕ_F is large, σ_F is small (in the favorable state of the world, there are a lot of high quality students, but firms believe there are not many), this will increase the probability as well.

The same result holds for any student whose k is below the median that has $\tilde{k}$ above the median (as is likely, especially if the number of graduate students is relatively low).

The important result is that there seem to be conditions in the model under which grade inflation will increase the probability of change, so as to differentiate themselves more. Whether they make this change depends on how close some individuals are to the margin of switching, so that the increase induced by grade inflation switches the sign of Inequality 2. The uncertainty from grade inflation can cause the wage distribution before type is learned to grow in variance. In that case, the best strategy for some individuals is to improve in the rankings, even if it means missing a year and paying a fixed cost.

3.5 Estimation

Overall identification of the policy function will come from exogenous changes in the wages. Then, given department characteristics, including the current level of grades given, one sees the reaction of the departments in grading policy. This movement is exogenous, and as far as we believe that departments change their grading decisions in response to labor markets, we will be able to identify the policy functions in different states.

While it seems a good case can be made for the policy function's identification, it is more difficult to argue for identification of the different signalling costs. Can we separately identify the short term cost to high quality students, the short term benefit to low quality students, and the long term cost to departments reputation? The short term costs could only be identified with the appropriate firm level data, as detailed in Section 4.1. With that, you would see the variation of different departments in the same market (or the same department at different times), at the same level of grade inflation. Variation would should how different levels of grade inflation, controlling for other covariates through the model, would affect the initial wages of the workers. You can compare this against the low-skill sector wages at the same time to see how the low quality students with high marks (seen in the data) are benefitted. The short term cost to high quality students would be the lowered initial wages, comparing them against departments that did not inflate in the same circumstances.

As for the long term reputation cost, you could see how firms change their reactions (in initial wages, conditional on a given wage) to grade inflation to a given department over time, and this should offer the necessary traction for identification.

Conditional on having the data, the model would be solved through maximum likelihood. There are various ways to construct this. One possible example is the following: in the first stage, to find the true distribution of wages, perform period by period maximum likelihoods to recover the normal distribution parameters. In the model, assume that departments engage an AR(1) process on the parameters.

Then, set up a likelihood function as follows:

$$L_{itm}(\Theta|\Omega, w_{mt}, \psi_{itm}) = \prod_{d=1}^{D} Pr\left(\psi_{itm} = \psi_d | w_{mt}, \Theta, \Omega\right)^{1(\psi_{itm}=\psi_d)}$$

Where i indexes the department, m indexes the labor market that the department is competing in, and t the time they are at. Therefore, ψ_{itm} is the amount of high marks that department i in field m gives at time t. d is the chosen discretization of high marks, and D is the set (say, for example, 0,0.1,0.2,...,0.9,1). Θ represents the parameters to be estimated, which include $\tau_h, \tau_l, \Pi, \phi_F, \phi_U$, and the AR(1) parameters association with the wage expectations. Ω the set of parameters estimated or established outside of the likelihood function (β and the set of μ's and σ's). Finally, w_{mt} is the wage distribution observed in market m at time t, which also influences their decisions.

$Pr\left(\psi_{itm} = \psi_d | w_{mt}, \Theta, \Omega\right)$ is simulated from solving the value functions using contraction mapping, finding the policy functions given the stochastic elements and the decisions they make conditional on the parameter constellation, and solving for these probabilities.

Therefore, the entire likelihood is given by

$$L(\Theta|\Omega, w, \psi) = \prod_{i=1}^{I}\prod_{t=1}^{T}\prod_{m=1}^{M} L_{itm}(\Theta|\Omega, w_{mt}, \psi_{itm})$$

Then solve this likelihood function using Maximum Simulated Likelihood (to account for the stochastic elements you would need to simulate).

4 Further Development

4.1 Data Requirements

In order to estimate the model as I have constructed it so far, I would need more data than I currently have. Most importantly, to uncover how the firms are learning (and thus the feedback to how the departments choose grading), I would need labor market outcomes of these specific students. I would need to see how the wages differ based on different levels of grade inflation, and, if possible, the contracting agreements over time (length of contracts, contracts after, etc.). I am currently pursuing data on this front from business schools and law schools. From the conversations I have had, these departments do keep track of their graduates and their employment after. However, I have so far been unable to convince any program to share this private data with me.

To estimate the model with graduate enrollment, I would need to know the decisions of undergraduates whether to attend graduate school or not. The UCLA data has graduate program enrollments, but not the decision of undergraduates whether to attend or not. The only people that could be tracked are those that do both their undergraduate and graduate work at UCLA, a biased sample of those who do graduate work overall. Data that can be used here might come from the National Longitudinal Study of Youth (NLSY) or High School and Beyond (HSB). These sources have information about grades received and decisions regarding college, as well as labor market outcomes. The problem here is knowing the grading distributions that their grades come from, and seeing variation over time for a given institution to be able to tease out the reputation effects. If data could be acquired in some other setting, that would be more powerful.

Also, it would be helpful to get data from other universities as well, so that competing departments could more directly be compared. At this point, I will have to assume that departments in related fields compete with each other.

4.2 Remodeling

Not having the necessary additional data discussed in Section 4.1, I now look at how I can remodel the problem so as to make it tractable with the data that I currently do have. I will at this point only outline the kind of model that I will create.

One of the main problems is the lack of wage outcome data. Therefore, the next version will not attempt to model the firms' side. The labor market will be assumed thick and unaffected in expectation by the grading policy of a single department (no reputation). In that case, expectations can be constructed off of Current Population Survey each year. This representative sample can construct what people in similar industries make. Then, this can be used to determine what changes in the labor market does to grading strategy.

With this change, the only dynamic (punishment via reputation) is eliminated. Therefore, for the next version of the model, I will simplify it to be a static model. Departments face the problem of choosing grades so as to accomplish two things. First, it is to attract the proper student base (as they see it), which might explain why smaller departments have the higher mean grades. Second, they choose grades so as to optimize their matches of students into the labor market. This retains the short term costs and benefits to grade inflation; changes in expected wages could potentially change either of these.

While simplifying the firm side, the remodeling will complicate the student side. Students will now choose the departments endogenously, so as to maximize their personal future expected lifetime wages.

I will use quantile regression to standardize grades through SAT scores, as earlier described. I will also want the model to account for competition and student expectations. Perhaps this can be obtained through NLSY or HSB, to derive what the overall expectations of grades from the overall average grade in the nation. This would imply that the model is really interested in deviations from some moving (increasing) norm.

5 Conclusion

Grade inflation is happening, both in the United States generally and in the sample, UCLA, specifically. However, grade inflation varies between departments. Hypothesizing that there are signaling costs to grade inflation, understanding grade inflation and its causes will help to grasp the situation in which these costs are realized. There is grade inflation, and related trends are found in the data that are important to understanding grade inflation and how it should be modeled. The model implies that grade inflation could induce some high skill students to change their decision from attending graduate school to not attending graduate school for signalling purposes. The model I create here is not estimable, given the current data. The next steps in the research are to rework the model under the suggestions in the paper and apply the UCLA data to uncover the research questions.

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Appendix I: Tables

Table 1: Summary Statistics

	Graduate Students	Undergraduate Classes
Number of Departments	137	137
Number of Class Enrollments	1,598,513	9,809,975
Number of Quarters	83	83
Mean Class Enrollments per Department	529.48	2924.86
Mean Grade Awarded	3.708	3.394
Mean Grade Awarded (1980-1985)	3.621	3.291
Mean Grade Awarded (2005-2008)	3.736	3.474
Proportion with Positive Coefficients	0.793	0.765
Mean Math SAT Score	627.47	608.11
Mean Verbal SAT Score	559.05	547

Table 2: Fixed Effect Panel Regression on Mean Grade Awarded and Proportion of A's (times 1000)

	Mean Grade Awarded		Proportion of 4.0s	
	Undergrad. Classes	Grad. Students	Undergrad. Classes	Grad. Students
Mean	0.3655	0.0747	0.5612	0.00119
Verbal SAT	(0.0699)***	(0.049)	(0.0518)***	(0.0431)
Mean	-0.0458	-0.1331	-0.2698	-0.0828
Math SAT	(0.0884)	(0.057)**	(0.0655)***	(0.0508)
Term	4.6891	4.8062	0.4096	6.1055
	(0.5149)***	(0.5093)***	(0.3819)	(0.4455)***

Table 3: Bottom 20 Mean Grade Awarded

	1980-1985			2005-2008	
Dept	Mean Grade Awarded	Num Enr	Dept	Mean Grade Awarded	Num Enr
CHEM	2.660	55360	LIFESCI	2.791	43562
ECON	2.694	54529	CHEM	2.868	106752
GEOG	2.704	26832	MATH	2.884	51680
MATH	2.739	77775	ECON	2.972	64306
PHYSICS	2.788	46880	MIC IMM	3.013	15940
HUMANIT	2.791	2888	PSYCH	3.048	107098
ANTHRO	2.819	17772	PHYSIOL	3.077	19026
BIOL	2.859	32160	GEOL	3.096	15358
POL SCI	2.889	30809	BIOL	3.099	15116
MIC IMM	2.891	5786	PHILOS	3.115	26532
PHILOS	2.909	13838	PHYSICS	3.133	63528
PSYCH	2.926	62816	GEOG	3.165	24592
SOCIOL	2.928	23323	SOCIOL	3.170	54200
ATMOSCI	2.934	2607	ANTHRO	3.174	31052
ENGR	2.952	70330	CLASSIC	3.185	11622
COMM ST	2.993	32953	LING	3.188	13356
GEOL	3.002	7516	EL ENGR	3.189	30718
ENGLISH	3.005	48738	AERO ST	3.199	18524
HIST	3.030	45191	NEURBIO	3.206	6790
LING	3.032	8337	COMPTNG	3.220	4346

Table 4: Top 20 Mean Grade Awarded

	1966-1980			2005-2008	
Dept	Mean Grade Awarded	Num Enr	Dept	Mean Grade Awarded	Num Enr
PSYCTRY	3.723	1067	EDUC	3.864	44424
EDUC	3.689	18511	BMEDPHY	3.845	1110
SOC WEL	3.641	7477	BIOMATH	3.792	1038
NURSING	3.628	7212	WLD ART	3.765	11326
ART ARC	3.574	12972	BIOSTAT	3.742	6956
MCH STR	3.545	1919	MUSIC	3.740	18346
WLD ART	3.500	9119	NURSING	3.733	17018
NR EAST	3.499	7018	S ASIAN	3.723	7192
THEATER	3.491	34578	URB PLN	3.716	8246
EL ENGR	3.488	1481	HNRS	3.711	7472
PUB HLT	3.474	19387	ETHNOMU	3.703	23444
AFR STD	3.472	1818	FILM TV	3.698	29456
LIB SER	3.410	4190	SOC WEL	3.695	12738
FLKLORE	3.408	2180	INF STD	3.692	7400
SLAVIC	3.395	3137	HLT SER	3.686	8752
MUSIC	3.394	31878	PUB HLT	3.683	7854
MGMT	3.378	56624	ART	3.666	10672
HNRS	3.356	2152	PHARM	3.663	1390
ART	3.348	25522	ENV HLT	3.642	2704
CED	3.306	2953	THEATER	3.621	26068

Appendix II: Figures

Figure 1: Grade Inflation by College: Rojstaczer (2009)

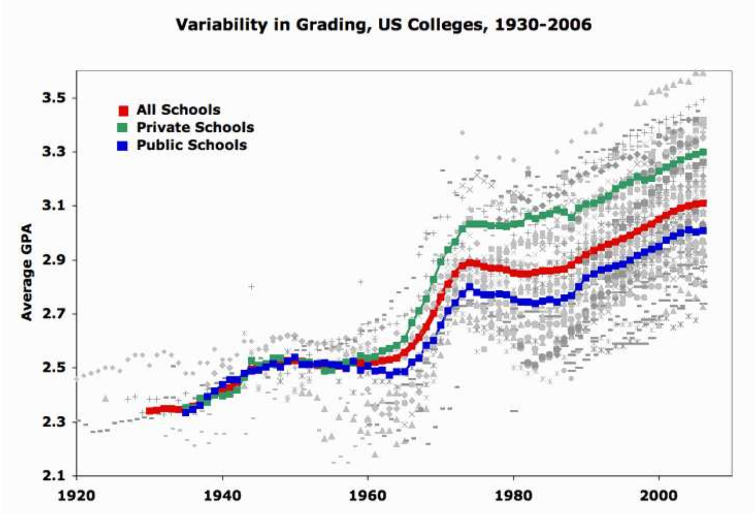


Figure 2: Attained Graduate Schooling (source: US Census)

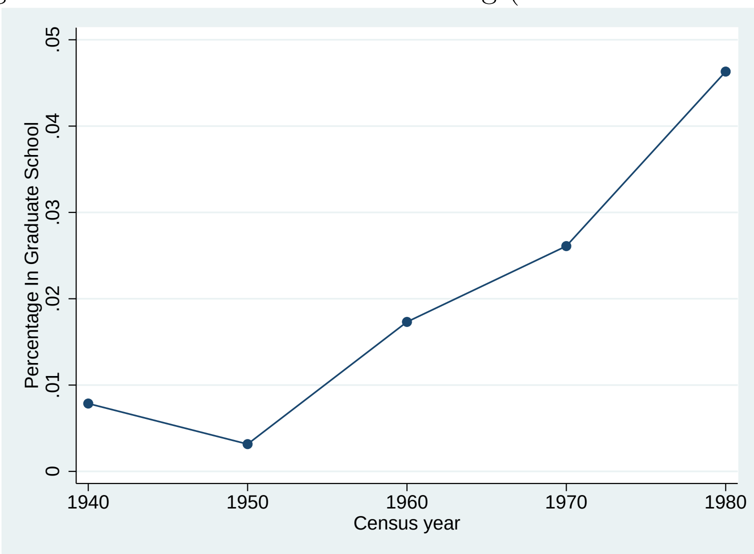
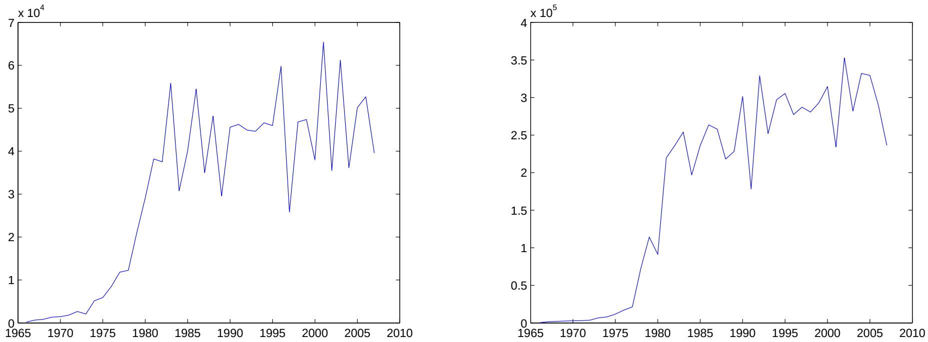
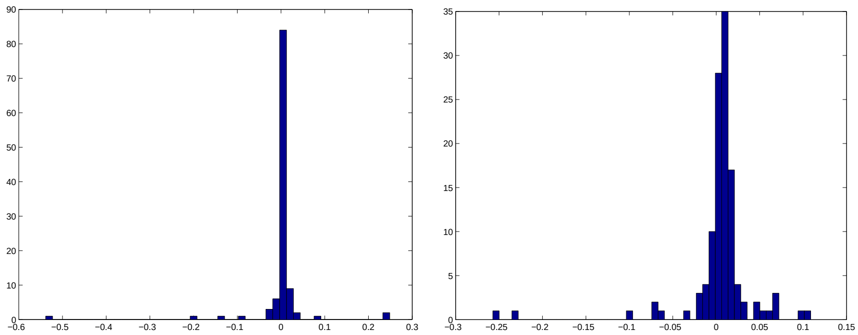


Figure 3: Number of Observations



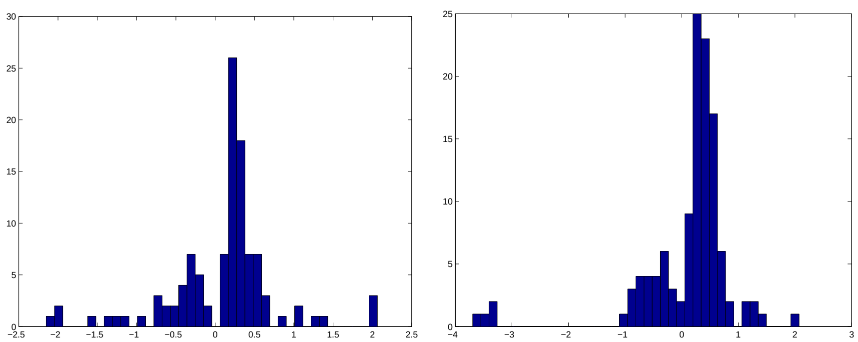
(a) Graduate Students (b) Undergraduate Classes

Figure 4: Mean Grade Awarded Time Trends



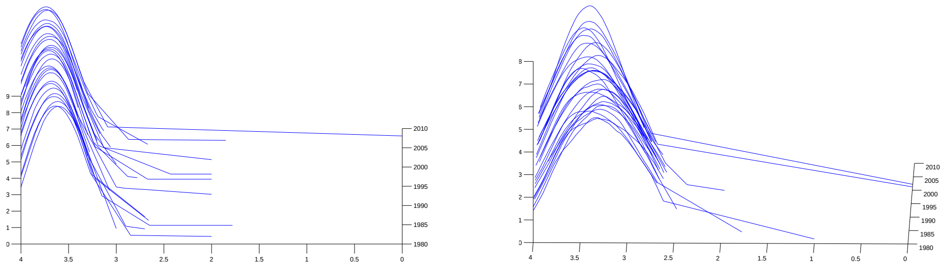
(a) Graduate Students (b) Undergraduate Classes

Figure 5: Largest Mean Grade Awarded Changes



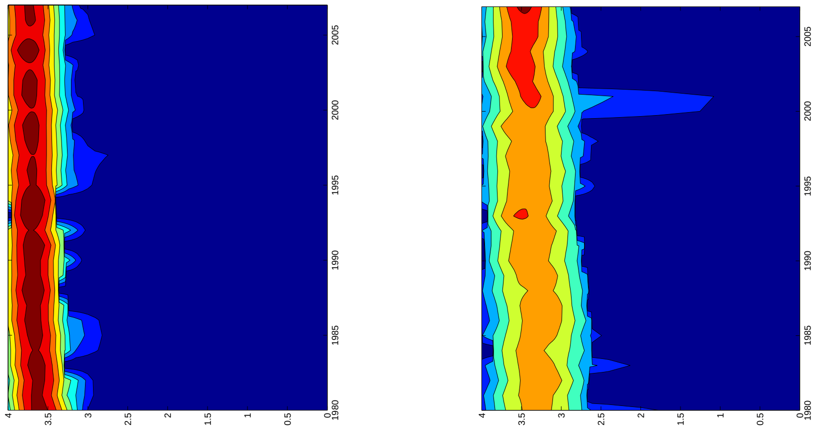
(a) Graduate Students (b) Undergraduate Classes

Figure 6: Marginal Mean Grade Awarded Distribution



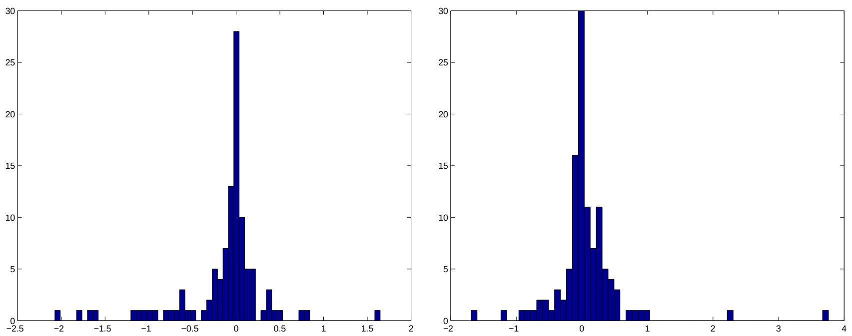
(a) Graduate Students (b) Undergraduate Classes

Figure 7: Contour of Joint Distribution, Mean Grade Awarded



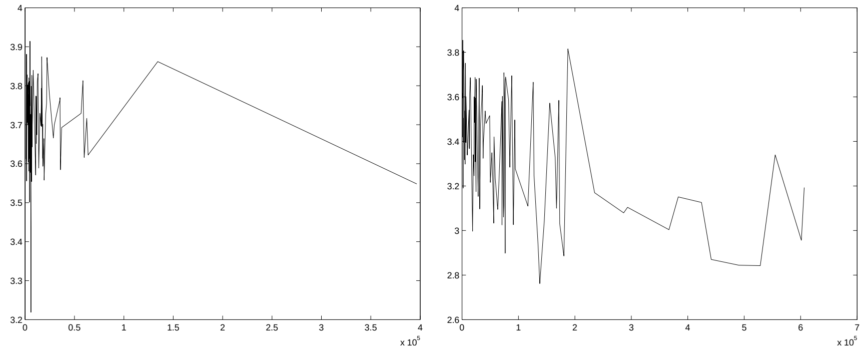
(a) Graduate Students (b) Undergraduate Classes

Figure 8: Class-Enrollments Per Dept. Time Trends



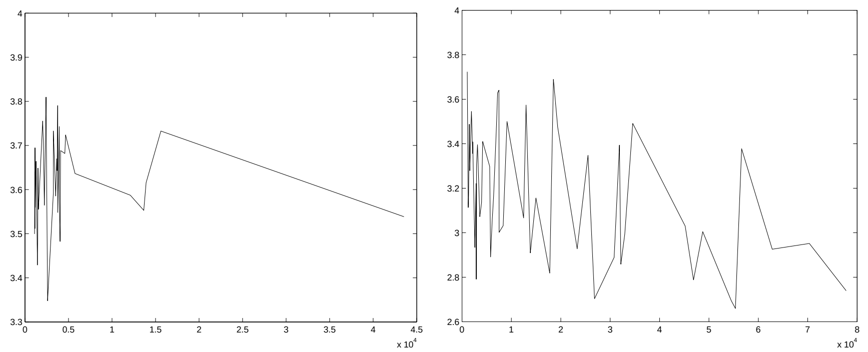
(a) Graduate Students (b) Undergraduate Classes

Figure 9: Class Enrollments vs Mean Grade Awarded

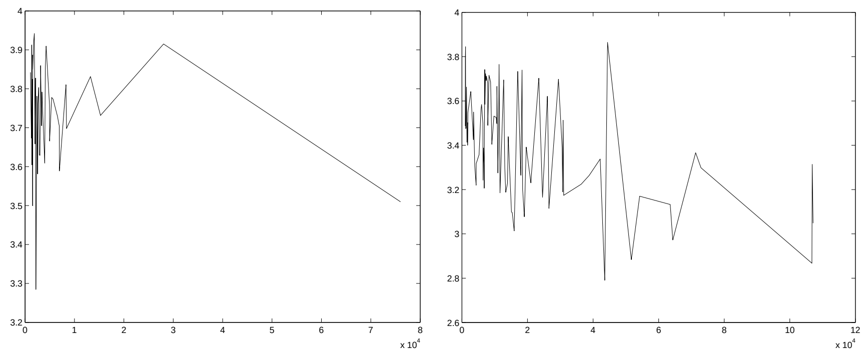


(a) Graduate Students (b) Undergraduate Classes

Figure 10: Class-Enrollments vs Mean Grade Awarded

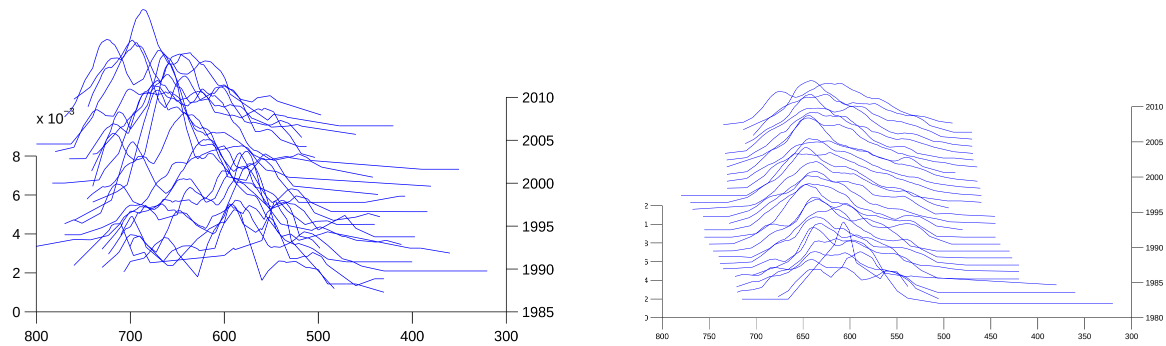


(a) Graduate Students (1980-1985) (b) Undergraduate Classes (1980-1985)



(c) Graduate Students (2005-2008) (d) Undergraduate Classes (2005-2008)

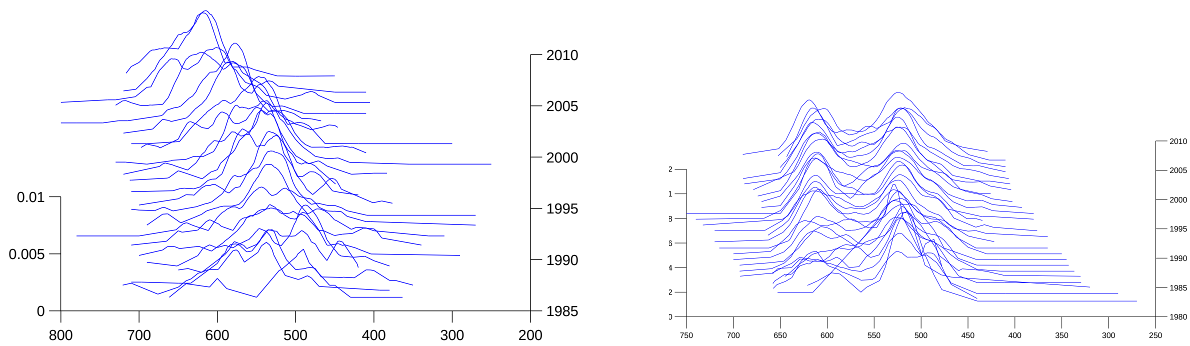
Figure 11: Marginal Distribution, SAT Verbal Scores



(a) Graduate Students

(b) Undergraduate Classes

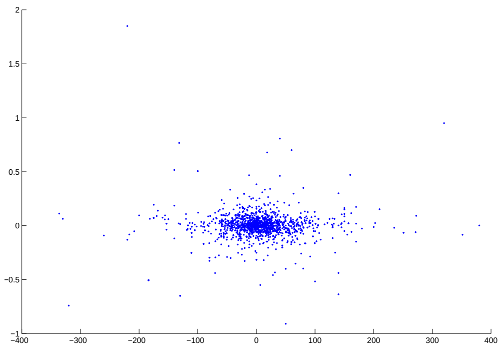
Figure 12: Marginal Distribution, SAT Math Scores



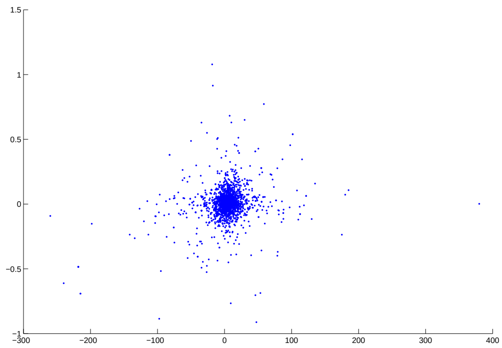
(a) Graduate Students

(b) Undergraduate Classes

Figure 13: Verbal SAT score first differences vs. Mean Grade Awarded first differences

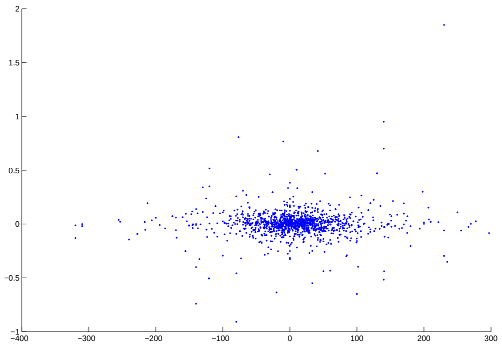


(a) Graduate Students

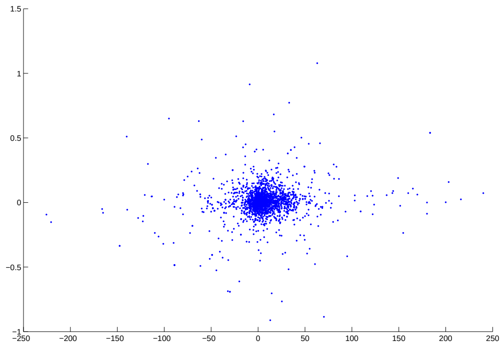


(b) Undergraduate Classes

Figure 14: Math SAT score first differences vs. Mean Grade Awarded first differences



(a) Graduate Students



(b) Undergraduate Classes