

$$\text{GPA}_{i,j,t,T} = (\alpha + \phi_i) + \rho \text{Female} + \beta \text{PS} + \lambda_1 \text{RC} + \lambda_2 \text{RC}^2 + \psi \text{GAI}_i + \sum_{j=1}^{12} \omega_j \text{AP}_j + \sum_{t=2}^{16} \{ \gamma_t S_t + \phi_t (S_t \cdot \text{GAI}_i) \} + \sum_{T=2}^{22} \theta_T \cdot C_T + \sum_{T=2}^{22} \sum_{j=1}^{12} \delta_{j,T} (C_T \cdot \text{AP}_j) + e_{i,j,t,T}$$

$$\frac{\partial(\text{GPA}_{i,j,t,T})}{\partial(C_T)} = \hat{\theta}_T + \sum_{j=1}^{12} \hat{\delta}_{j,T} (\text{AP}_j) \quad \text{and} \quad \frac{\partial(\text{GPA}_{i,j,t,T})}{\partial(\text{GAI}_i)} = \frac{1}{\sigma_{\text{GAI}}} \left\{ \psi + \sum_{t=2}^{16} \phi_t \cdot S_t \right\}$$

$$\frac{\partial(\text{GPA}_{i,j,t,T})}{\partial(S_t)} = \gamma_t + \phi_t \left\{ \frac{\text{GAI}_i - \overline{\text{GAI}}}{\sigma_{\text{GAI}}} \right\} = \gamma_t + \phi_t \cdot Z_{\text{GAI}}$$

$$\text{GAI}_i^* > \left\{ \frac{\hat{\gamma}_t \cdot \sigma_{\text{GAI}}}{\hat{\phi}_t} + \overline{\text{GAI}} \right\} \Rightarrow Z_{\text{GAI}}^* > \frac{\hat{\gamma}_t}{\hat{\phi}_t}, \quad \forall t = 2, \dots, 16.$$

RESEARCH ARTICLE

Measuring grade inflation and grade divergence accounting for student quality

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RESEARCH ARTICLE

Measuring grade inflation and grade divergence accounting for student quality

Horacio Matos-Díaz^{1*}

Abstract: This study uses a rich longitudinal data-set of 13,202 full-time students belonging to 11 cohorts over 22 consecutive semesters (Fall 1995 to Spring 2006) to model the determinants of the grade inflation rates prevailing at the University of Puerto Rico at Bayamón. The following new interesting findings are reported: (1) Estimated rates vary significantly among and within the academic programs, implying grade divergence, depending on the time reference used: cohort time dummies or semesters since admission to the institution. (2) The rates are significantly related to the proportions of female students, students who switch from their original academic programs, and students from private schools. (3) Results suggest that, under determinate circumstances, average and low-quality students consider higher grades as normal goods; conversely, high-quality students consider them as inferior goods.

Keywords: grade inflation index, GPA, student quality, random and fixed effects models

JEL classifications: C23, I20, I21

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Horacio Matos-Díaz obtained his PhD in Economics from Kansas State University in 2000. He is a professor of Economics at the University of Puerto Rico at Bayamón (UPR-Bayamón), where he has taught and conducted research during the last 36 years. His main interests are in the field of the economics of education.

RESEARCH GROUP OVERVIEW

This paper is closely related to three of his previously published research papers, which dealt, respectively, with the relationship between SET ratings and expected grade, accounting for students' risk aversion; with the ability of test scores and other proxies of academic potential to predict student GPA, after correcting for sample selection; and with issues related to reductions in academic standards and lenient grading, and their relationship with the SET process, using random-effects ordered probability models. His most recent research project (which can be considered a logical continuation of this study) seeks to determine the possible effects of the new admission policy adopted by the UPR system regarding both its objective of promoting equity in the student body composition and as a measure of academic aptitude capable of predicting student success.

PUBLIC INTEREST STATEMENT

There is grade inflation when student's grades tend to increase without a concomitant increase in their quality or achievement over an extended period of time. In this scenario, current students receive the same grades as past students, but with lower academic requirements and significantly less learning. This problem is even greater when grades tend to increase while students' quality tends to decrease over time, which would imply that grading does not reflect that decrease in quality. Evidence from this study shows that the estimated grade inflation rates at the UPR Bayamón are directly related to the proportion of female students and of students who shift academic programs, and indirectly related to the proportion of private school students. The rates vary significantly among and within academic programs over time. Evidence points to grade inflation mainly among average and below average-quality students.

1. Introduction

The phenomenon of grade inflation—the tendency of student grade point average (GPA) to increase without a concomitant increase in achievement—has been observed and widely studied since the 1970s (Hu, 2005; Johnes, 2004; Johnson, 2003). Rosovsky and Hartley (2002) discuss several explanations offered for grade inflation, including student evaluation of teaching (SET) ratings. Students' grades serve several purposes (Sabot & Wakeman-Linn, 1991). They send signals to the labor market and to graduate schools about the quality of university graduates and provide information to the students about their achievement levels, progress, and academic success. To the extent that it deviates from these traditional purposes, the university grading system lessens the value society attributes to higher education.

According to the leniency hypothesis (Gump, 2007), faculty members can buy higher SET ratings, recruit more students, or even become more popular, by relaxing their academic standards through leniency grading. McKenzie and Staaf (1974), McKenzie (1975), and Lichty, Vose, and Peterson (1978) have developed economic models that rationalize this conjecture and its relationship to grade inflation. Recent models in this tradition include Kanagaretnam, Mathieu, and Thevaranjan (2003) and Love and Kotchen (2010). Following the general guidelines of those models, a series of papers have studied the relationship between SET ratings and students' known or expected grades (EG) using different methods, including OLS (Dilts, 1983), 2SLS (Krautmann & Sander, 1999; Nelson & Lynch, 1984; Seiver, 1983), 3SLS (Zangenehzadeh, 1988), as well as fixed-effects models (Isely & Singh, 2005; McPherson, 2006). The majority of these studies do not properly model the phenomenon of grade inflation. Normally, authors present statistical evidence in favor of (or against) the interdependence between the SET and EG that leads them to infer or conclude that there is or there is not grade inflation. It should be emphasized that a relationship between EG and SET would provide a plausible explanation for high grades, but not for grade inflation which refers to an upward time trend in grades.

There are several exceptions to this pattern. For example, Jewel, McPherson, and Tieslau (2013), using data from the University of North Texas, report significant grade inflation rates over two decades. They attribute these variations to characteristics of academic departments, university-level factors or instructor-specific characteristics. Grove and Wasserman (2004) reported significant grade inflation rates over the life-cycle pattern of collegiate GPA of five consecutive cohorts at a large USA private university. Sabot and Wakeman-Linn (1991) analyze the problems of grade inflation as well as of grade divergence. They present comparative evidence on the average academic grades given from 1962/1963 to 1985/1986 by the different departments of seven USA universities and find that grades tend to increase, but with marked differences among the departments, which implies grade divergence. The issue of grade divergence is analyzed in detail by Freeman (1999) and Achen and Courant (2009).

Matos-Díaz (2012) analyzes the issues of reductions in academic standards and lenient grading as well as their relationship with the SET process at the University of Puerto Rico at Bayamón (UPR-Bayamón). Results suggest that faculty members might be able to increase enrollment in their courses, get better SET ratings, and/or improve their teaching schedules by (1) adjusting their academic standards in order to increase students' EG and (2) promoting the academic conditions that would transform pessimistic relative EG into optimistic ones. The author suggests the possibility that such strategies probably lead to a decrease in academic standards and grade inflation at UPR-Bayamón.

This study uses the student as the proper unit of analysis in order to model the phenomena of grade inflation and grade divergence over two different time references: cohort time dummies and semesters since admission to UPR-Bayamón (hereafter "time reference 1 and 2", respectively). To estimate grade inflation accurately, it is necessary to account for student quality. Because student quality is proxied by the general admission index (GAI), which is a time-invariant variable, the grade inflation index (GII) cannot be defined at the student level. Thus, its estimation will require

transforming panel data into highly aggregated historical data. The aggregation of data over each time reference generates two sets (1 and 2) of 22 and 16 sub-samples, respectively. The partition of each set by academic programs produces two different restricted panels (panel 1 and 2) of 286 and 179 sub-samples, respectively.

This paper contributes to the literature in several ways. First, it uses a rich panel data of 13,202 full-time students (12 or more credits per semester) belonging to 11 consecutive cohorts that entered UPR-Bayamón from 1995–1996 to 2005–2006. Students were classified into 13 different academic programs and were tracked every semester until each one left the institution. Second, this is the first paper using two different time references in order to accurately estimate grade inflation and grade divergence. Third, the GII, accounting for student quality, is defined and its behavior through academic programs over both time references is analyzed using two-way fixed-effects models. Both models account for academic programs' unobserved heterogeneity while controlling for other student characteristics. Grade divergence and grade inflation are captured in the estimated cross-sections and period fixed-effects coefficients, respectively. Thus, this is the first paper in the field able to directly measure the determinants of the GII at such econometric accuracy and specificity levels. Finally, results from the unrestricted panel are consistent with and tend to confirm the historical growth paths of the GPA, GAI, and GII variables over both time references.

The remainder of the paper is organized as follows: Section 2 deals with the data and the models to be estimated, while Section 3 presents the results. A summary providing some conclusions closes the paper.

2. Data-set and Models

2.1. UPR-Bayamón and Its Admission Criterion

The UPR-Bayamón is an autonomous unit of the University of Puerto Rico system (UPR). Accredited by the Middle States Association of Colleges and Secondary Schools, the institution offers associate and bachelor's degrees, as well as articulated transfer programs to the Río Piedras, Mayagüez and Medical Sciences campuses. In the fall of 2006, total enrollment at UPR-Bayamón was 4,565, including 3,737 full-time students. The admission policy at the UPR is based on the GAI of each applicant, which is the weighted mean of the high school GPA (50%) and the scores in the verbal aptitude (25%) and mathematical aptitude (25%) sections of the College Entrance Examination Board test. The GAI plays a critical role, not only for admission to the different campuses of the UPR, but also for admittance to particular programs. Thus, it is used as the best available proxy of student quality.

2.2. The Unrestricted Panel

This study uses a rich longitudinal data-set that describes in detail every one of the 13,202 students belonging to the 11 cohorts that entered UPR-Bayamón from 1995–1996 to 2005–2006. The following variables are available for each student: GAI; school of origin code; gender; age; academic program to which the student is admitted; registered semester credit-hours (RC); and GPA. A set of 22 time dummies (C_T , $1 \leq T \leq 22$), which are included to capture time trend effects, identify the entry cohort to which each student belongs, as well as the corresponding semester. Hence, odd numbers designate fall semesters, while even ones designate spring semesters. For example, C_8 designates all spring semesters for students in cohort 4, while C_7 designates all fall semesters.

To track each student throughout time reference 2, a second set of 16 time dummies was defined, indicating the number of semesters since admission to UPR-Bayamón. For a few of the students in the sample this number is greater than 16, so they were grouped into the following single category: 16 or more semesters. The variable is defined as S_t , where $1 \leq t \leq 16$. Dummies are used to control for academic programs (13), high school of origin and student's gender. Table 1 describes all the variables used in the study.

Table 1. Descriptive Statistics of the Unrestricted Sample

Dummy variables							
Var.	Mean	Var.	Mean	Var.	Mean	Var.	Mean
Accounting	.0696 (.2544)	S ₁	.1854 (.3886)	S ₁₆	.0025 (.0496)	C ₁₅	.0471 (.2119)
Business	.1585 (.3652)	S ₂	.1576 (.3643)	C ₁	.0603 (.238)	C ₁₆	.0371 (.1889)
Computer Sciences	.0869 (.2817)	S ₃	.147 (.3541)	C ₂	.0502 (.2184)	C ₁₇	.0391 (.1938)
Education	.1046 (.306)	S ₄	.1217 (.3269)	C ₃	.0652 (.2469)	C ₁₈	.03 (.1706)
Electronics	.0821 (.2745)	S ₅	.0973 (.2963)	C ₄	.0549 (.2278)	C ₁₉	.0339 (.18)
Engineering Technologies	.0351 (.1841)	S ₆	.078 (.2682)	C ₅	.0576 (.2329)	C ₂₀	.0231 (.1502)
Engineering Transfers	.0446 (.2065)	S ₇	.0661 (.2485)	C ₆	.0489 (.2157)	C ₂₁	.0266 (.1609)
Humanities	.0312 (.2065)	S ₈	.0547 (.2273)	C ₇	.0661 (.2485)	C ₂₂	.0129 (.1129)
Materials Management	.038 (.1911)	S ₉	.0402 (.1963)	C ₈	.0547 (.2273)		
Natural Sciences	.1422 (.3492)	S ₁₀	.0234 (.1512)	C ₉	.0402 (.1963)		
Office Systems	.0846 (.2783)	S ₁₁	.0121 (.1093)	C ₁₀	.0488 (.2155)		
Physical Education	.0662 (.2486)	S ₁₂	.007 (.0835)	C ₁₁	.055 (.2281)		
Social Sciences	.0565 (.2309)	S ₁₃	.0037 (.0037)	C ₁₂	.0461 (.2098)		
Female	.5793 (.4937)	S ₁₄	.0021 (.0021)	C ₁₃	.0517 (.2213)		
PS	.4546 (.4979)	S ₁₅	.0014 (.0374)	C ₁₄	.0422 (.201)		
Continuous variables							
Var.	Mean	SD	Max	Min			
GPA	2.74	.5956	4.00	.00			
GAI	285.66	35.5	385	137			
RC	15.14	2.09	21	12			
RC-square	233.68	64.15	441	144			

Notes: For all dummies, standard deviations (SD) are reported in parentheses, Max = 1 and Min = 0; Var. = variables.

2.3. The Restricted Panels

From each sub-sample of sets 1 and 2, the arithmetic means of the GPA, GAI, and GII variables are computed. Means are indexed to identify their time reference and, in the case of the restricted panels 1 and 2, their academic program. To document grade inflation, it is necessary to present evidence showing a self-sustained increase in GPA over time without a concomitant increase in student achievement or academic ability. However, neither achievement nor academic ability is observable. To overcome this data limitation, the GAI is used as the best available proxy of student's academic ability, achievement or quality.

Given that GPA and GAI variables are expressed in different metrics, it was necessary to normalize both of them. This was done by dividing each value in the series by its first one, generating their respective time reference growth rates. It should be expected that GPA vary directly and strongly with GAI. In the limit case, where they vary directly proportional, the series would mimic each other and their ratio would always be equal to one. If GPA tends to grow over time while GAI remains constant, then it could be conjectured that academic standards have diminished, providing the bases for grade inflation. Thus, current students receive the same grades as past students, but with less

academic requirements, a lesser amount of content, and significantly less learning. The problem of grade inflation would be even greater if GPA tends to increase while GAI tends to decrease over time, because in such a case grading did not decrease in order to account for less qualified students. These considerations give rise to the following operational definition:

$$\text{GII} = \frac{\text{NGPA}}{\text{NGAI}} \quad (1)$$

The “N” in front of the terms stands for normalized. If $\text{GII} > 1$, then evidence will point to grade inflation which could be consistent with diminishing academic standards over time. Grade deflation will be documented whenever $\text{GII} < 1$; that is, when GPA tends to decrease even when GAI is constant or increasing over time. Finally, $\text{GII} = 1$ would imply neither grade inflation nor grade deflation.

2.4. Models to be Estimated

The following two-way fixed-effects models will be estimated using data from the restricted panels 1 and 2, respectively.

$$\text{GII}_{j,T} = (w + a_j + d_T) + b_1 \Pi_F + b_2 \Pi_{PS} + b_3 \Pi_{\Delta AP} + e_{j,T} \quad (2)$$

$$\text{GII}_{j,t} = (c + g_j + h_t) + z_1 \Pi_F + z_2 \Pi_{PS} + z_3 \Pi_{\Delta AP} + v_{j,t} \quad (3)$$

Subscript j ($j = 1, \dots, 13$) indexes the academic programs, while subscripts T and t index the cohort time dummies and semesters since admission to UPR-Bayamón, respectively ($T = 1, \dots, 22$ and $t = 1, \dots, 16$). Finally, w and c are the overall intercepts, while $e_{j,T}$ and $v_{j,t}$ are the composite error terms.

Both models share the following covariates: proportion of female students (Π_F), proportion of students from private schools (Π_{PS}), and proportion of students who switched from their original academic programs ($\Pi_{\Delta AP}$). Some data facts related to these three proportions should be emphasized. For example, in those academic programs with low mathematics requirements such as Education, Physical Education, Humanities, Social Sciences, and Office Systems, the proportions of female students and private school students are 80 and 39%, respectively. On the other hand, in those academic programs with higher mathematics requirements and possibly greater inherent difficulty of content, such as Engineering Transfers, Electronics, and Computer Sciences, the respective proportions are 18 and 43%. Finally, for the whole sample, the proportion of students who switched from their original academic program is only 4.4%. However, 10% of the students enrolled in Social Sciences came from other programs by means of transfers.

Given these data, it is reasonable to assume that if students self-sorting by academic programs in such a way that Π_F is greater in programs of low mathematics and difficulty contents, then it should be expected that \hat{b}_1 and \hat{z}_1 be positive and significant. On the other hand, if Π_{PS} is greater in programs of high mathematics and difficulty contents, then both estimated coefficients \hat{b}_2 and \hat{z}_2 should be negative and significant.¹ Lastly, if students transfer from more demanding programs to less demanding ones looking for better grades with less academic effort, the estimated coefficients \hat{b}_3 and \hat{z}_3 should be positive and significant. Thus, it should be expected that the GII would respond significantly to changes in those three proportions across both time references.

In order for grade divergence to hold, it will be necessary to observe significant differences in the GII across academic programs. If so, grade divergence can be captured in the estimated

cross-section fixed-effects coefficients ($\hat{\alpha}_j$ and $\hat{\beta}_j$). On the other hand, grade inflation across both time references can be captured in differences in the estimated period fixed-effects coefficients (\hat{d}_T and \hat{h}_t).

Model 4 is specified using GPA as the dependent variable and GAI as a covariate because it is a time-invariant variable at student level. The model controls for student's gender (female=1), school of origin (private=1), RC and academic programs (Social Sciences=reference group). Unobservable student heterogeneity (φ_i) is modeled as random-effects.²

$$\begin{aligned} \text{GPA}_{ij,t,T} = & (\alpha + \varphi_i) + \rho \text{Female} + \beta \text{PS} + \lambda_1 \text{RC} + \lambda_2 \text{RC}^2 + \psi \text{GAI}_i \\ & + \sum_{j=1}^{12} \omega_j \text{AP}_j + \sum_{t=2}^{16} \{ \gamma_t S_t + \phi_t (S_t \cdot \text{GAI}_i) \} + \sum_{T=2}^{22} \theta_T \cdot C_T + \sum_{T=2}^{22} \sum_{j=1}^{12} \delta_{j,T} \{ C_T \cdot \text{AP}_j \} + e_{ij,t,T} \end{aligned} \quad (4)$$

3. Results and Discussion

3.1. Grade Inflation and Grade Divergence: Historical Data Reports

Average time growth rates of GPA, GAI, and GII normalized variables, estimated from sub-sample sets 1 and 2, are reported in Figures 1 and 2. Compared to the base year, GAI exhibits an increasing path over time reference 1 (except for cohort 2),³ reaching its maximum growth rate (5.95%) at C_{20} . However, GAI behaves quite differently throughout time reference 2. It increases until S_4 , driven by the attrition of low-quality students during their first semesters at the institution. Between S_4 and S_8 , GAI decreases because many high-quality students transfer to other UPR campuses or obtain their associate degrees, although it remains above the unitary threshold. Finally, GAI decreases after S_8 and goes below the unitary threshold because the best students complete their bachelor's degree and leave the institution. Only the lower quality students remain in campus. This behavior explains the "life-cycle"⁴ pattern of GPA over time reference 2, which in turn will explain the inverted U-shape exhibited by the variable over time reference 1.

Along time reference 1, GPA is always over the unitary threshold (except at C_3) until C_{18} , reaching its maximum growth rate (7.3%) at C_{14} . Then, it decreases and is underneath the unitary threshold at three times (C_{19} , C_{21} , and C_{22}). That is, GPA increases, reaches its absolute maximum, and then decreases. To explain such an inverted U-shape, it is necessary first to analyze the behavior of GPA over time reference 2. Over it, GPA exhibits a similar inverted U-shape. It increases, reaching its maximum growth rate (13.8%) at S_8 ; then, it decreases and reaches its minimum growth rate (5.3%) at S_{14} . However, it is always above the unitary threshold. To the right of S_8 , GPA is decreasing because only the lower quality students of each cohort remain in the sample.

Students of cohorts 8, 9, 10, and 11 remain in the sample at the most 4, 3, 2, and 1 years, respectively. Thus, the maximum number of semesters since admission (S_t) of cohort 8 students is 8 ($S_t \leq S_8$), 6 for cohort 9 students ($S_t \leq S_6$), 4 for cohort 10 students ($S_t \leq S_4$), and only 2 for cohort 11 students ($S_t \leq S_2$). Therefore, students of cohorts 8–11 should be to the left of S_8 , S_6 , S_4 , and S_2 , respectively, and exhibit lower GPAs along time reference 2, which is equivalent to reversing movements from S_8 to the origin. Hence, the GPA decreasing pattern to the right of S_8 over time reference 2 explains its decreasing pattern to the right of C_{14} through time reference 1. That is to say, movements to the right of C_{14} over time reference 1 correspond to movements to the origin from the left of S_8 over time reference 2. In such a direction, GPA decreases over time. Consequently, to the right of C_{14} , GPA tends to diminish because of insufficient time reference 2 sub-sample observations. Thus, the life-cycle pattern of GPA over time reference 2 explains the inverted U-shape of GPA over time reference 1, particularly, its decreasing portion to the right of C_{14} .

Figures 1 and 2 describe the behavior of the GII along both time references. The index is always over the unitary threshold until C_{14} and reaches its maximum rate (5.32%) at C_4 . Based on the points discussed in the prior paragraph, it is misleading to analyze the behavior of the index to the right of C_{14} . That is, if cohorts 8–11 would have been in the sample during longer periods, the behavior of GPA would be different from the exhibited pattern. Therefore, evidence shows that the 14 sub-samples drawn from the first seven cohorts admitted to UPR-Bayamón (1995–1996 to 2001–2002) exhibit grade inflation. The eight sub-samples drawn from the last four cohorts (2002–2003 to 2005–2006), do not have enough time reference 2 observations to accurately estimate the index.

The behavior of the GII is quite different along time reference 2. It increases and reaches its maximum rate (13.3%) at S_8 . Then, it decreases and reaches its minimum rate (8.7%) twice: at S_{12} and S_{13} . Therefore, irrespective of the time reference used, the evidence points to the same conclusion: the existence of grade inflation. However, the magnitude of the phenomenon will depend on the time reference used. It is not argued here that one reference is better than the other; both complement each other. Hence, the growth pattern of GPA along time reference 1 cannot be explained without knowing the corresponding pattern over time reference 2. This last point has seemingly been ignored in the mainstream literature.

Using data from restricted panels 1 and 2, the GII was computed by academic program and plotted graphically over time reference 1 and 2. There are marked differences in the index's value among academic programs, implying grade divergence, as well as along both time references, implying grade inflation. The pattern displayed is very similar to the one depicted in Figure 1.⁵

3.2. The Two-way Fixed-effects Models

The estimated regression coefficients of Equation 2 are reported in Table 2. The three coefficients (\hat{b}_1 , \hat{b}_2 , and \hat{b}_3) behave as conjectured. Each one exhibits the expected sign and is significant. For example, other things being equal, increments of 10 percentage points (pp) in Π_F will increase the GII by 1.17 pp. However, if such increase were in Π_{PS} , the GII will decrease by .71 pp. Likewise, if it

Figure 1. Growth path of GPA, GAI and GII over time reference 1.

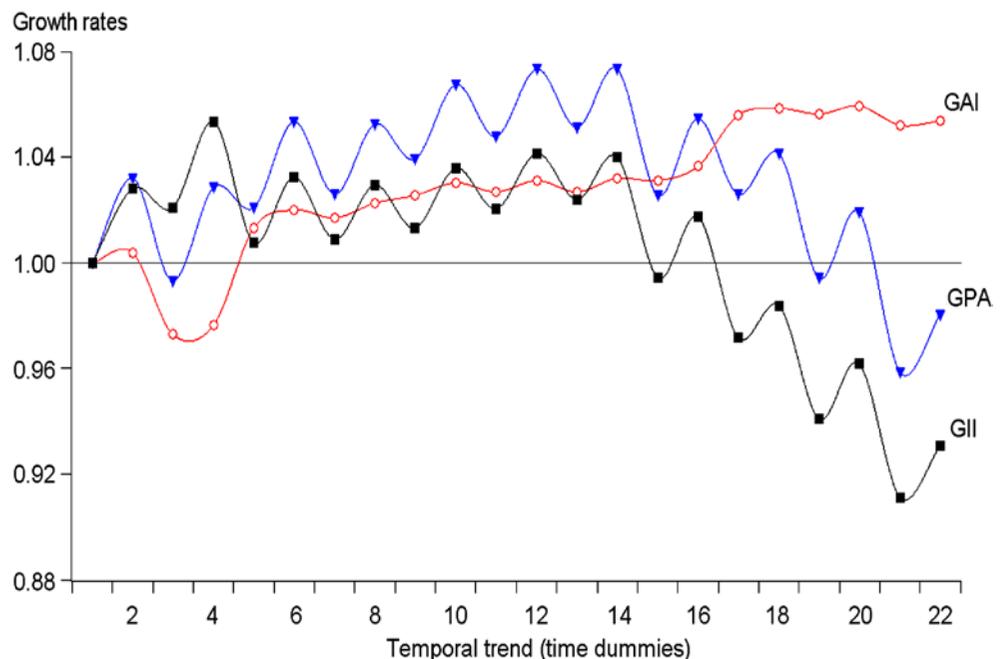


Table 2. Determinants of the GII over Time Reference 1

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	.963647	.023308	41.34385	.0000
Female proportion	.117387	.031638	3.710350	.0003
Private school proportion	-.071322	.028021	-2.545303	.0115
Program changes proportion	.205531	.093536	2.197356	.0289
Effects specification				
Cross-section fixed (dummy variables)				
Period fixed (dummy variables)				
Programs (cross-section)	Effects		Cohorts (period)	Effect
Accounting (P1)	-.005679		1	-.003481
Business (P2)	.002176		2	.022445
Computer Sciences (P3)	.040068		3	.003024
Education (P4)	-.042190		4	.039450
Electronics (P5)	.018397		5	.006265
Engineering Technologies (P6)	.059958		6	.034250
Engineering Transfers (P7)	.050898		7	.003572
Humanities (P8)	-.040849		8	.027355
Materials Management (P9)	.006099		9	.008505
Natural Sciences (P10)	-.030212		10	.031523
Office Systems (P11)	-.081544		11	.019521
Physical Education (P12)	-.011394		12	.041329
Social Sciences (P13)	.034273		13	.017762
			14	.037162
			15	-.010151
			16	.008715
			17	-.028437
			18	-.017366
			19	-.059153
			20	-.027253
			21	-.090354
			22	-.064682

Notes: The standard errors of the fixed-effects coefficients are not reported because, for estimation purposes, EViews treats them as nuisance parameters. Periods included: 22; cross-sections included: 13; total panel (balanced); observations: 286; R-square = .74.

were in $\Pi_{\Delta AP}$, then the GII will increase by 2.06 pp. Table 2 also reports the estimated cross-section and period fixed-effects. They were submitted to three different statistical tests to determine the significance of the cross-section, the period and all of the effects jointly. The three null hypotheses of statistical insignificance were rejected through the *F* and Chi-square tests (p -value = .0000).⁶

The distribution of signs and values of the estimated cross-section effects ($\hat{\alpha}_j$) induces changes in the overall intercept of Equation 2, which in turn implies that the grade inflation rates will vary significantly among the academic programs. On the other hand, 13 out of the first 14 estimated period effects ($\hat{\delta}_T$) are positive, while seven out of the last eight are negative. Given that the intercept of the equation ($\hat{w} \approx .96$) is 4 pp beneath the unitary threshold, such a result is in accordance with the

growth pattern exhibited by the GII as reported in Figure 1: it increases from the origin until C_{14} and then decreases. These results show that the GII varies significantly across academic programs, implying grade divergence. In the same way, it varies over time reference 1, implying grade inflation.

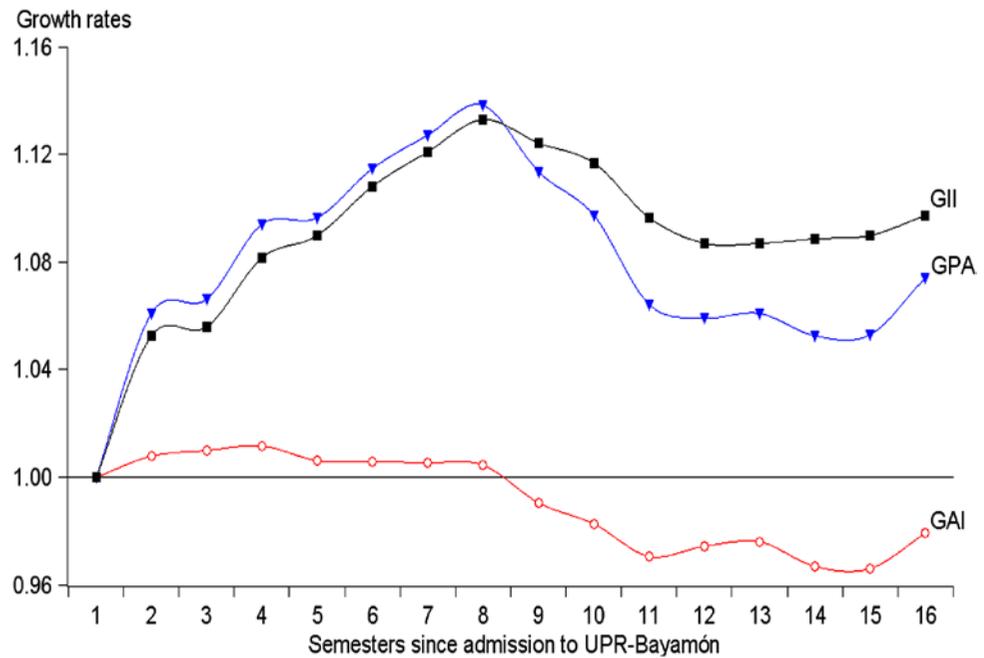
The estimated regression coefficients, cross-section and period fixed-effects of Equation 3 are reported in Table 3. The coefficients \hat{Z}_1 , \hat{Z}_2 , and \hat{Z}_3 exhibit the expected sign, but only \hat{Z}_1 is significant. Other things being equal, increments of 10 pp in Π_F will increase the GII by 1.2 pp. The null hypotheses about the effects' insignificance were rejected through the F and Chi-square tests (p -value = .0000). The distribution of signs and values of the estimated cross-section effects (\hat{g}_j) implies that the rates vary across the academic programs, which is consistent with grade divergence. The overall intercept of Equation 3 ($\hat{C} \approx 1.04$) is 4 pp above the unitary threshold. So, the distribution of signs and values of the estimated period effects (\hat{h}_t) imparts an inverted U-shape to the GII over time reference 2, similar to the curvature depicted in Figure 2.⁷ Accordingly, the statistical results are consistent with and provide analytical support to the story told by the historical data reported in Figures 1 and 2. Hence, in order to have a good grasp of the magnitude and scope of the grade inflation and grade divergence phenomena, their analysis should have to consider not only the distribution of grades among academic programs, but also their path over both time references.

Table 3. Determinants of the GII over Time Reference 2

Variable	Coefficient	Std. Error	t-Statistic	Prob.
Constant	1.036490	.028400	36.49591	.0000
Female proportion	.120986	.040928	2.956095	.0036
Private school proportion	-.048557	.032106	-1.512395	.1326
Program changes proportion	.015553	.120995	.128547	.8979
Effects specification				
Cross-section fixed (dummy variables)				
Period fixed (dummy variables)				
Programs (cross-section)	Effects	Semesters (period)		Effects
P1	-.065928	1		-.080349
P2	-.005637	2		-.029051
P3	.075258	3		-.027754
P4	-.027072	4		-.003901
P5	.054562	5		-.003031
P6	.080556	6		.013712
P7	-.029746	7		.005020
P8	-.059835	8		.030095
P9	.066833	9		.020489
P10	.009494	10		.023374
P11	-.073785	11		-.007577
P12	.039965	12		.007047
P13	-.064663	13		-.008977
		14		-.006116
		15		.024200
		16		.034586

Notes: The standard errors of the fixed-effects coefficients are not reported because, for estimation purposes, EViews treats them as nuisance parameters. Periods included: 16; cross-sections included: 13; total panel (unbalanced) observations: 179; R-square = .74.

Figure 2. Growth path of GPA, GAI and GII over time reference 2.



3.3. The Unrestricted Panel

The estimated regression coefficients of Equation 4 are reported in Table 4. The statistical fit of the model is excellent. The impact of the academic programs on GPA is measured by their estimated main and time dummies interaction effects coefficients: $\hat{\omega}_j$ and $\hat{\delta}_{j,T}$, respectively. Their respective proportions of significant coefficients are 42 and 68%. Females and students from private schools have advantages over their counterparts. The GPA expected by a female is .22 points greater than the expected by a male; while the expected by students from private schools is .019 points greater than the expected by students from public schools. There is a significant and concave relationship ($\hat{\lambda}_1 > 0$ and $\hat{\lambda}_2 < 0$) between GPA and the RC variable, which is standardized. GPA reaches its absolute maximum at $RC \approx 18$ credit-hours.

In order to detect grade inflation and grade divergence, the attention is centered on the estimated main effects coefficients of the time dummies ($\hat{\theta}_T$) and their interactions effects with the academic programs ($\hat{\delta}_{j,T}$), which are captured into the following 21 partial derivatives ($T=2, \dots, 22$):

$$\frac{\partial(GPA_{ij,t,T})}{\partial(C_T)} = \hat{\theta}_T + \sum_{j=1}^{12} \hat{\delta}_{j,T}(AP_j) \tag{5}$$

Sixty seven percent of $\hat{\theta}_T$ coefficients are significant. The first 15, which belong to the sub-samples drawn from the first eight entering cohorts are positive, implying GPAs greater than the GPA of the reference group ($C_1 =$ fall semesters of cohort 1). On the other hand, three of the last six, which belong to the last three entering cohorts, are negative, implying GPAs lesser than the GPA of the reference group. The pattern of signs of these main effects is in accordance with the historical data reported in Figure 1: grade inflation for almost all sub-samples drawn from the first seven cohorts. Sixty eight percent of the interaction effects ($\hat{\delta}_{j,T}$) are significant. They allow for the possibility of capturing the instances in which GPA changes among and within the academic programs throughout time reference 1. Thus, the estimated interaction coefficients ($\hat{\delta}_{j,T}$) allow to measure grade divergence across different academic programs along time reference 1.

Table 4. Predicting GPA at UPR-Bayamón: 1995–1996 to 2005–2006

IV	Coefficient	IV	Coefficient	IV	Coefficient	IV	Coefficient
Constant	2.36** (.0346)	S ₂	.0554** (.0143)	GAI × S ₅	-.0296** (.004)	C ₈	.0963* (.0455)
AP1	.1229** (.0399)	S ₃	.0226** (.0036)	GAI × S ₆	-.0341** (.0044)	C ₉	.1843** (.0467)
AP2	.1068** (.0363)	S ₄	.0523** (.0144)	GAI × S ₇	-.0352** (.0045)	C ₁₀	.1517* (.0492)
AP3	.004 (.0406)	S ₅	.0504** (.004)	GAI × S ₈	-.0365** (.0049)	C ₁₁	.1847** (.0464)
AP4	.0389 (.0402)	S ₆	.0747** (.0145)	GAI × S ₉	-.0482** (.0055)	C ₁₂	.1771** (.0487)
AP5	-.0092 (.0439)	S ₇	.0822** (.0045)	GAI × S ₁₀	-.054** (.0068)	C ₁₃	.2254** (.0482)
AP6	.0421 (.049)	S ₈	.1106** (.0147)	GAI × S ₁₁	-.0558** (.0086)	C ₁₄	.1808** (.051)
AP7	.0287 (.0461)	S ₉	.112** (.0055)	GAI × S ₁₂	-.0614** (.0113)	C ₁₅	.0342 (.0501)
AP8	.3235** (.0555)	S ₁₀	.1289** (.0154)	GAI × S ₁₃	-.0838** (.0157)	C ₁₆	.0136 (.0532)
AP9	.0635 (.0493)	S ₁₁	.1128** (.0091)	GAI × S ₁₄	-.0883** (.0221)	C ₁₇	.1456** (.052)
AP10	.0008 (.0348)	S ₁₂	.1273** (.0181)	GAI × S ₁₅	-.0568* (.0245)	C ₁₈	.1122* (.0541)
AP11	.1885** (.0452)	S ₁₃	.1500** (.0161)	GAI × S ₁₆	-.0704** (.019)	C ₁₉	-.0117 (.057)
AP12	.2243** (.046)	S ₁₄	.1325** (.0254)	C ₂	.0381 (.0312)	C ₂₀	-.0067 (.06)
Female	.2158** (.0101)	S ₁₅	.1155** (.026)	C ₃	.1714** (.0454)	C ₂₁	.1024 (.0651)
PS	.0189* (.0093)	S ₁₆	.1364** (.023)	C ₄	.1877** (.0479)	C ₂₂	-.0053 (.0764)
RC	.0141** (.0013)	GAI × S ₂	-.0217** (.0039)	C ₅	.1201** (.0458)		
(RC) ²	-.0024** (.0009)	GAI × S ₃	-.0211** (.0035)	C ₆	.1212** (.048)		
GAI	.3229** (.0057)	GAI × S ₄	-.0275** (.004)	C ₇	.1042** (.0426)		

Notes: Panel robust standard errors are in parentheses. The equation also controls for 252 interactions between academic programs and time dummies. IV=independent variables. R²=.17; cross-sections included: 13,066; total panel (unbalanced) observations: 70,085.

*Statistically significant at the 5% level.

**Statistically significant at the 1% level.

Let σ_{GAI} be the standard deviation of GAI distribution, then the following two partial derivatives warrant some explanation:

$$\frac{\partial(GPA_{ij,t,T})}{\partial(GAI_i)} = \frac{1}{\sigma_{GAI}} \left\{ \psi + \sum_{t=2}^{16} \phi_t \cdot S_t \right\} \quad (6)$$

$$\frac{\partial(GPA_{ij,t,T})}{\partial(S_t)} = \gamma_t + \phi_t \left\{ \frac{GAI_i - \overline{GAI}}{\sigma_{GAI}} \right\} = \gamma_t + \phi_t \cdot Z_{GAI} \quad (7)$$

Expression 6 describes the relationship between GPA and GAI (student quality) over time reference 2. The variables move in the same direction since the estimated main effect coefficient ($\hat{\psi}$) is positive

and significant. However, all the estimated interaction effects coefficients ($\hat{\phi}_t$) are negative and significant. This result implies that the official admission criterion used by the UPR-Bayamón predicts academic success better early on in the education, which is what would be expected if the contents of university education gradually shift from those of high school. This result is in accordance with predictive validity studies, which often find that the correlation between the admission policy and the outcome variable is higher the earlier in the education the outcome is measured.⁸

Expression 7 describes the behavior of GPA over time reference 2. All the estimated main effects coefficients ($\hat{\gamma}_t$) are positive and significant, but all the estimated interaction effects coefficients ($\hat{\phi}_t$) are negative and significant. So, the 15 partial derivatives have positive intercept and negative slope. For average-quality students ($\overline{\text{GAI}}$), the expression collapses to its intercept because the GAI variable is standardized. Hence, the slopes become positive and steeper, increasing the value of the derivatives in all cases in which student quality is less than average. Contrary to what would be expected, this result implies that the GPA of low-quality students ($\text{GAI}_i < \overline{\text{GAI}}$) tends to increase faster than the GPA of high-quality ones ($\text{GAI}_i > \overline{\text{GAI}}$) over time reference 2. How could this result be explained?

It has been argued that high-quality students face lower marginal costs because they learn faster than low-quality students and consequently incur in lower opportunity costs (Winkler, 1987). If so, the greater the student quality the lower the cost of acquiring higher grades. Subsequently, if there has been a reduction in academic standards and professors have become more lenient in grading, then the price of higher grades tends to decrease, inducing the two well-known substitution and income effects. It seems that, among low-quality students, the substitution effect dominates, providing them a greater incentive to move up along the distribution of grades at UPR-Bayamón. Thus, for average and low-quality students, this result implies grade inflation over time reference 2, which is consistent with the growth pattern of the GII in Figure 2.

The implications of such a result are quite different in the case of high-quality students. Each partial derivative will become negative, implying grade deflation over time reference 2, whenever:

$$\text{GAI}_i^* > \left\{ \frac{\hat{\gamma} \cdot \sigma_{\text{GAI}}}{\hat{\phi}_t} + \overline{\text{GAI}} \right\} \Rightarrow Z_{\text{GAI}}^* > \frac{\hat{\gamma}_t}{\hat{\phi}_t}, \forall t = 2, \dots, 16. \quad (8)$$

The estimated threshold lies in the following range: $1.07 \leq \hat{Z}_{\text{GAI}}^* \leq 3.03$.⁹ That is, for those high-quality students whose GAI is at least $1.071\sigma_{\text{GAI}}$ greater than the mean, income effect dominates, inducing them to substitute higher grades for other activities such as more leisure hours, part- or full-time jobs, or simply, enjoying life doing whatever they want to do. Under such conditions, high-quality students would have been considering higher grades as inferior goods, since their consumption tends to diminish to the extent that faculty members decrease their market price through lenient grading. The conjecture of higher grades as inferior goods was formally deduced long ago by Lichty et al. (1978). It should be rigorously analyzed in future research projects using new data-sets from different universities.

4. Summary

This study uses a rich longitudinal data-set to analyze the relationship between student quality and grade inflation at UPR-Bayamón from 1995–1996 until 2005–2006. All full-time students belonging to the 11 entering cohorts are tracked during each semester until they leave the institution. Two different time references are used: cohort time dummies (time reference 1) and semesters since admission to UPR-Bayamón (time reference 2). The path of the normalized GPA, GAI, and GII variables is analyzed over both references. Along time reference 1, evidence shows grade inflation for almost all the 14 sub-samples drawn from the first seven cohorts admitted to UPR-Bayamón (1995–1996 to 2001–2002); while the eight sub-samples drawn from the last four ones (2002–2003 to 2005–2006), do not have sufficient information to accurately estimate the index. Grade inflation is

documented throughout time reference 2. The maximum and minimum rates are 13.3 and 8.7%, respectively. Therefore, conclusions about the presence and magnitude of grade inflation depend on the time reference used, a point that has been ignored by the mainstream economic literature.

Given that GAI (proxy of student quality) is a time-invariant variable, it is not possible to define the GII at student level. Notwithstanding, a statistical model was specified to estimate the determinants of GPA using GAI as a covariate. Controlling for unobservable student heterogeneity (random-effects), student's gender, high school of origin, enrolled credit-hours, student's quality and academic programs, the evidence is in accordance with the growth pattern exhibited by the GPA, GAI, and GII variables over the time references reported in Figures 1 and 2.

To analyze the behavior of the grade inflation rates among academic programs, sub-samples sets 1 and 2 were partitioned generating two restricted panels of 286 and 179 sub-samples, respectively. Evidence from two-way fixed-effects models shows that over both time references the estimated grade inflation rates are directly related to the proportions of female students and students who shift their original academic programs and indirectly related to the proportion of private school students. Furthermore, over time reference 1, the estimated coefficients of the three proportions are statistically significant. However, over time reference 2, only the coefficient of the female proportion is significant. Finally, the rates vary significantly among and within academic programs over both time references.

This relationship among students' characteristics and the phenomena of grade inflation and grade divergence could have serious academic and institutional policy implications. An overview of the data shows that there are six academic programs with higher GAIs: Engineering Transfers (335), Natural Sciences (310), Accounting (309), Computer Science (300), Business Administration (288), and Electronics (287). A second cluster comprises the seven programs with the lower GAIs: Social Sciences (279), Education (277), Materials Management (272), Humanities (264), Office Systems (260), Engineering Technologies (257), and Physical Education (250). The average GAI (student quality) of the whole sample is 286. Therefore, on average, the programs of the first (second) cluster comprise students whose quality is greater than (less than) the mean. On the other hand, the proportions of female and private high school students in the programs of the first and second clusters are (47 and 49%) and (70 and 40%), respectively.

Thus, the seven programs in the second cluster are predominantly constituted by below average-quality students, females (70%), and public school students (60%). The last two proportions are directly and significantly related to the GII over time reference 1. On the other hand, according to expression 7, evidence points to grade inflation along time reference 2 only among average and below average-quality students. So, on average, the incidence of grade inflation is concentrated among and within the seven programs of the second cluster. It seems that the faculty members and administrators of these programs have become aware of the powerful and persuasive incentive of grades and are using them as a mechanism in order to recruit, retain, and graduate more students. The impact of increasing lenient grading on the quality, relevance, and pertinence of the education received by students needs to be analyzed in future studies.

Dedication

In memory of my beloved son, Horacio Matos-De Jesús (March 12, 1983–December 20, 2009), whose too early, tragic and unexpected death truncated my plans of celebrating each day of his life until the end of mine.

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Notes

1. For details, refer to Davies and Guppy (1997), and Szafran (2001) and the references cited therein.
2. The presence of time-invariant covariates (female, private school and GAI) rules out the possibility of using the fixed-effects method.
3. For that academic year (1996–1997), the Central Admission Office of the UPR reduced the GAI in all units to increase total enrollment. However, the experiment was discarded the next academic year.
4. I have borrowed this name from Grove and Wasserman (2004).
5. Both sets of graphs are available upon request.
6. See EViews, User Guide II (2009, 672–674), for details.
7. Models 2 and 3 may have been estimated with $(n-1)$ dummies instead. However, under such specification, each dummy coefficient will be an estimate of $(\alpha_i - \alpha_{rg})$, where rg is the reference group. For example, the estimated fixed-effect of S_3 is .030095 and the corresponding effect of the reference group is $-.008977$; thus, the coefficient of the dummy 8 would be equal to: $.030095 - (-.008977) = .039072$. All other results will be unchanged. See Greene (2012, 359–370), for details.
8. This point was brought into my consideration by an anonymous reader to whom I am grateful.
9. The estimated values from $t=2$ until $t=16$ are: 2.55; 1.07; 1.90; 1.70; 2.19; 2.34; 3.03; 2.32; 2.39; 2.02; 2.07; 1.79; 1.50; 2.03; and 1.94; respectively.

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