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Estimating the effects of partial withdrawals on GPA through time: Evidence from the University of Puerto Rico

Horacio Matos-Díaz

Department of Business Administration, University of Puerto Rico at Bayamón, Bayamón, Puerto Rico 00959-1919

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In loving memory of my beloved son Horacio Matos-De Jesús (March 12, 1983–December 20, 2009)

Abstract

Although a direct relationship among partial withdrawals (*Ws*), GPA and grade inflation (GI) is suggested in prior research, this study demonstrates just the opposite. Evidence from a detailed panel-data comprising 34,426 sections offered in the UPR-Bayamón during 36 consecutive terms demonstrates that (1) traditional GI and the GI attributable to *Ws* run in opposite directions; (2) unobserved faculty heterogeneity, academic fields, as well as courses and academic environment characteristics exert strong and significant effects on both GPA and the GI attributable to *Ws* and (3) student evaluations of teaching are inversely and significantly related to *Ws* and to the GI attributable to them.

JEL classifications: **C**23; **I**20; **I**21

Keywords: Partial withdrawals; Grade inflation; Student evaluations of teaching; Puerto Rico; Random- and fixed-effects models

1. Introduction

The purpose of this study is to empirically test the arguments invoked to attribute a direct relationship between partial withdrawals (*Ws*) and student grade point average (GPA), as it is assumed in extant literature (hereafter "the conventional explanation"). The conventional explanation has been taken for granted and used to explain grade inflation (GI) at different US universities without a direct statistical testing.[1] For the conventional explanation to hold, two conditions should be required. First, cross-sections or time-series data depicting clearly the direct relationship between *Ws* and GPA should be gathered. Second, the conjecture that *Ws* cause GI would be sustained only if the increases in GPA, which could be attributable to *Ws*, could be isolated and might exhibit an upward temporal tendency. Otherwise, the conjecture should be rejected. None of the previous studies have accomplished these aforementioned conditions. Conversely, this study satisfies both requirements and demonstrates that GPA and GI inversely vary with *Ws*. To this end, a detailed panel-data comprising 34,426 sections offered in the University of Puerto Rico at Bayamón (UPR-Bayamón) during

E-mail address: horacio.matos1@upr.edu

[1] Refer to Hoyt and Reed (1976), Mc Spirit and Jones (1999), Rosovsky and Hartley (2002) and Oglive and Jelavic (2013).

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36 consecutive terms, from fall 1995 to spring 2013, is used. The contextualization of these contradictory relationships would have policy implications for students, universities and society. In order to put this issue in perspective, it would be necessary to discuss the phenomenon of GI, as well as the arguments developed to justify the conventional explanation, which will be discussed in the following sections.

Furthermore, this paper aims to uncover and estimate the impact of *Ws* on GPA at section level and the *Ws* effect on the GI prevailing at the UPR-Bayamón. It contributes to the literature by (1) using a unique longitudinal data-set containing detailed information of all sections offered in UPR-Bayamón during 18 consecutive academic years; (2) uncovering and measuring the effects of *Ws* on GPA and GI; (3) showing that traditional GI and GI attributable to *Ws* run in opposite directions; (4) analyzing the impact of unobserved faculty heterogeneity on GPA and the GI attributable to *Ws* and (5) measuring the effects of student evaluations of teaching (SET) on GPA.

The remainder of the paper is organized as follows: Section 2 is devoted to a brief discussion of GI, as well as inaccuracies of the conventional explanations offered for the relationship between *Ws* and GPA and proposes a new index to measure their relationship more accurately. Section 3 is devoted to the discussion of data and the statistical model to be estimated. Section 4 discusses the empirical results. Finally, Section 5 presents a summary and the conclusions.

2. Grade inflation in a nutshell

Research on GI has been ongoing for over 50 years (Oglive and Jelavic, 2013). The idea behind the concept is very simple: in order for GI to hold, it would be necessary to document a significant upward temporal tendency of GPA without a concomitant increase in academic achievement, other things equal.[2] This trend has been widely documented (Johnson, 2003; Johnes, 2004; Hu, 2005). Rosovsky and Hartley (2002) discuss several explanations for GI, including SET, as well as liberal changes in university withdrawal polices, among others.[3] In the economics literature, the phenomenon of GI has been strongly associated with SET processes, which have been adopted by practically all institutions of higher education across the United States.

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 and Tullock (1975), McKenzie (1975), Lichty et al. (1978), Kanagaretnam et al. (2003) and Love and Matthew (2010) have developed theoretical economic models that rationalize this conjecture and its relationship to GI. Following the general guidelines of those models, a series of studies have analyzed the statistical relationships between SET ratings and students' known or expected grades (EG) using different econometric methods.[4] Normally, researchers present statistical evidence in favor of (or against) the interdependence between the SET and EG that leads them to infer that there is or there is not GI. It should be emphasized that a relationship between EG and SET would provide a plausible explanation for high grades, but not for GI which, as stated, refers to an upward temporal trend in grades.

Several empirical studies estimate GI rates at different universities. Jewel et al. (2013), using data from the University of North Texas, report significant variations in GI rates over two decades. They attribute these variations to characteristics of academic departments, university-level factors or instructor-specific characteristics. Grove and Wasserman (2004) report significant GI rates over the life-cycle pattern of collegiate GPAs of five consecutive cohorts at a large US private university. Sabot and Wakeman-Linn (1991) analyze the problems of GI as well as those 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 US universities and find that grades tend to increase, but with marked differences among departments implying 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

[2] In order to measure GI accurately, it is necessary to control for student quality, as well as technological changes embodied in faculty members and the university academic facilities.

[3] They discuss seven possible explanations: 1) the sixties and the Vietnam War; 2) response to student diversity; 3) new curricular and grading policies; 4) SET; 5) students as consumers; 6) watering down content and 7) the role of adjunct professors. For details, refer to Rosovsky and Hartley (2002) and the references cited therein.

[4] The methods used include *OLS* (Dilts, 1983), 2*SLS* (Krautmann and Sander, 1999; Nelson and Lynch, 1984; Seiver, 1983), 3*SLS* (Zangenehzadeh, 1988), as well as fixed-effects models (Isely and Singh, 2005; McPherson, 2006).

grading as well as their relationship with the SET process at 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 adjusting their academic standards in order to increase students' EG and by promoting the academic conditions that would transform pessimistic relative EG into optimistic ones. In a recent study, Matos-Díaz (2014) confirms that such strategies have led to a decrease in academic standards at UPR-Bayamón, giving rise to both GI and grade divergence.

Much of the preceding research has been devoted to examining the relationship between SET and GI. Overlooked in the literature, however, is the relationship between GI and other possible explanations for the phenomenon offered by Rosovsky and Hartley (2002); particularly, the role of *Ws*. According to the conventional explanation, *Ws* give students the opportunity to drop from those courses in which their expected grades are too low and thus allow them to avoid decreases in their GPA. If so, increases in GPA should be expected to the extent that universities relax or democratize their *Ws* policies.

2.1. Ws, GPA and GI: what is wrong with the conventional explanation?

Ws can increase students' time until graduation and the total cost of the degree. Moreover, they could predict or signal total withdrawals and attrition from college, inducing a decrease in college graduation rates. For some researchers (e.g., Zwick and Sklar, 2005), the best criterion to measure an institution's academic success is, precisely, the proportion of students that complete their degrees in the allotted time. In this context, low graduation rates have a negative impact on institutions' rankings and, consequently, on their ability to attract students with greater academic potential. Moreover, student attrition represents a fiscal cost to institutions in terms of lost revenues from tuition, room and board and alumni donations (Schuh, 2005; Raisman, 2013). Attrition also constitutes a problem for society in general by reducing availability of college-educated workers in the labor market (Bound et al., 2007). It also has a negative impact in terms of lower tax receipts for federal and state governments (Schneider and Yin, 2011). Although these considerations are beyond the scope of this research, they illustrate how important it is to model the determinants of *Ws* and their impact on GPA and GI, which are, precisely, important components of this paper.

Why should *Ws*, GPA and GI move in the same direction? The conventional explanation for this relationship runs as follows. According to students' criteria, the likelihood to withdraw from a course is directly related to its intrinsic difficulty level. Based on their performance on quizzes, presentations, papers, partial examinations and other academic activities, students form expectations of their probabilities to pass or fail the course. Those who are confident that they will pass, or obtain the grade they want, will complete the course, while those who are not will withdraw. If the deadline for *Ws* is scheduled too early in the term, students will have to decide whether to remain in, or to drop courses with great uncertainty since the information gathered by that time may not be sufficient to make accurate predictions. Therefore, it is likely that, based on their actual academic performance, many students wrongly decide to drop the course. Such an uncertainty would tend to diminish to the extent that deadlines for *Ws* are scheduled closer to the end of the term. By that time, each student should have enough academic information to make an accurate decision. Thus, students might use the new academic information to withdraw exclusively from those courses in which they are failing or that threaten their GPA. Therefore, *Ws* would allow cleaning each section by separating academically lagging students, who will withdraw, from those who will remain in the course. In such cases, students who drop will not experience the expected decrease in their GPA and the overall GPA of the students who remain in the course will increase. Hence, the GPA of both groups, i.e. of those who drop and of those who remain in the course, will increase by the liberalization of the *Ws* policies, other things equal.

Arguments very close to the conventional explanation have been invoked in order to understand GI at particular US institutions, such as Kansas State University (Hoyt and Reed, 1976) and Eastern Kentucky University (Mc Spirit and Jones, 1999). A similar argument is also implicit in Rosovsky and Hartley's (2002) third explanation for GI, regarding new curricular and grading policies. Recently, Oglive and Jelavic (2013) have retaken the discussion of this issue. However, this explanation is wrong since GPA and *Ws* inversely vary.

The conventional explanation predicts a direct relationship between *Ws* and the GPA of both students who withdraw from a course and of those who remain in it. An unobservability problem makes this prediction wrong in both instances. That is, by the end of a term one can observe the effect of students' decision only on the GPA of those who completed the course, but one cannot know how those who withdrew would have performed if they had not done so. To shed light on this issue, consider the definitions included in expressions (1)–(4):

$$(GPA_i|Ws) = \text{GPA of student } i \text{ after dropping}, \tag{1}$$

$$(GPA_i|\underline{Ws}) = \text{GPA if student } i \text{ had not dropped}, \tag{2}$$

$$\left(\overline{GPA}_j|Ws\right) = \text{overall GPA of students in section } j \text{ after their classmates have dropped}, \tag{3}$$

$$\left(\overline{GPA}_j|\underline{Ws}\right) = \text{overall GPA of section } j \text{ if none of the students had dropped}. \tag{4}$$

It should be expected that Eqs. (1) > (2) and (3) > (4). If so, the net benefit arising from *Ws* could be measured using expressions (5) and (6):

$$(GPA_i|Ws) - (GPA_i|\underline{Ws}), \tag{5}$$

$$\left(\overline{GPA}_j|Ws\right) - \left(\overline{GPA}_j|\underline{Ws}\right). \tag{6}$$

However, only the first terms of expressions (5) and (6) are observable. Unless the second terms are computed, it would not be possible to uncover the relationship among *Ws*, GPA and GI at both the student and section levels, respectively. None of the published studies until now have undertaken such a task. Therefore, even though the conventional explanation appears to be intuitive and convincing, it is based on anecdotal evidence and lacks empirical and theoretical content.[5] This study aims to fill such a gap.

A caveat is in order here. To replicate the suggested method at student-section level (expression (5)), the dimensions of the data matrix should be increased substantially in order to accommodate the academic records of the students enrolled in each one of the 34,426 sections analyzed, as well as the covariates defining their characteristics. A panel at such specificity levels is unavailable. Thus, this study uses the section as the unit of analysis. Nevertheless, suppose that student-section is the unit of analysis instead of the section and let $PWs \in [0, 1)$ be the proportion of *Ws* observed at section *j* or in the academic record of student *i*. By the end of a term, only the integers $\{0, 1, 2, 3, 4\}$ corresponding to letter grades $\{F, D, C, B, A\}$, for each course completed by student *i*, or {W} for each one withdrew (missing), will be observed. Thus, GPA is not defined and maximum likelihood methods, such as ordered probit or ordered logit, should be used to model the probability of each letter grade. Correcting for selectivity in such cases might be a challenge (Heckman, 1979).

As indicated above, *Ws* directly vary with the intrinsic difficulty of the course, according to students' criteria. In the limit, when course difficulty approaches zero, the average GPA approaches its maximum (implying grade compression) and *PWs* will tend toward zero. Conversely, in courses with greater difficulty, *Ws* will also increase and the GPA observed by the end of the term will be significantly lower than that observed in less difficult courses. Therefore, *Ws* and GPA should move in opposite directions.

In order to make the second term of expression (6) operational and measurable, it is supposed that, without the option of *Ws*, the most likely academic outcome would be that students fail the course. It could be possible that some students decide to withdraw for reasons not directly related to the course's inherent difficulty, such as economic adversities, personal problems, illnesses, etc. But even in such cases, one might expect that failing the course would be the most likely academic outcome had they decided to remain in the course under such circumstances. Otherwise, why should they withdraw from the course?

Hence, in order to account for and make expression (4) observable and tractable, the following modification is suggested:

$$\left(\overline{GPA}_j|\underline{Ws}\right) = \left\{\frac{(As\cdot 4 + Bs\cdot 3 + Cs\cdot 2 + Ds\cdot 1 + (Fs + Ws)\cdot 0)}{(As + Bs + Cs + Ds + Fs + Ws)}\right\}. \tag{4.1}$$

[5] In the first place, evidence from this study clearly demonstrates that at both the section and student levels, *Ws* and GPA move in opposite directions. Moreover, even if they directly vary, such as wrongly suggested by the conventional explanation; it should be mentioned that after *Ws*, the quality of the students who remain in the section would increase. If student quality increases, then GPAs should also increase. Therefore, labeling such a direct relationship as GI would be inaccurate.

After plugging Eq. (4.1) into Eq. (6), the maximum increment in the GPA of section j that could be attributable to Ws might be measured using the index proposed in expression (7). GI attributable to Ws would be documented to the extent that the index would increase over time.

$$y_j^{Ws} = \left(\overline{GPA_j}|Ws\right) - \left(\overline{GPA_j}|\underline{Ws}\right) \Rightarrow y_j^{Ws} \begin{cases} = 0 & \text{if} \quad Ws = 0 \\ > 0 & \text{if} \quad Ws \geq 1 \end{cases}. \tag{7}$$

Thus, three working hypotheses arise from this study. (1) Contrary to prior studies, an inverse and significant relationship between Ws and the GPA observed in each section by the end of the term is predicted. (2) Under specific circumstances, Ws really account for a significant proportion of the increment in the GPAs observed at the section level. Moreover, their effect could be modeled using the proposed index $\left(y_j^{Ws}\right)$, which would be predicted to significantly vary with the courses, institutional academic environment and faculty characteristics. (3) The time trends of traditional GI and the increases in GPA attributable to Ws, measured through y_j^{Ws}, would move in opposite directions.

3. Data and empirical model

3.1. Data description

The UPR-Bayamón is an autonomous unit of the UPR system. Accredited by the Middle States Association of Colleges and Secondary Schools, it 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 2013, total enrollment at UPR-Bayamón was 5,075, including 4,305 full-time students.

As stated earlier, this study uses a detailed panel-data comprising 34,426 sections (hereafter the "whole sample") offered in the UPR-Bayamón from 1995 to 2013. For each one, the following variables are available: enrollment; instructor who taught the course; letter grade distribution (As, Bs, Cs, Ds, Fs and Ws); GPA; variance of the GPA distribution; adjusted GPA (AGPA); effect of Ws on GPA $\left(y_j^{Ws}\right)$ and academic fields (21 dummies). Dummies control for academic schedule (weekdays and hours) and for summer terms. For each faculty member in the sample, the following time-varying variables are available: age; experience (semesters teaching at the institution); academic rank; degree and tenure status. Dummies control for instructor's gender and whether or not SET were conducted in the section. A semi-continuous variable $T_T \in [1, 36]$ identifying semester/year is included to capture time trend (structural change) effects.[6] Appendix A describes the variables used.

To estimate the proposed index $\left(y_j^{Ws}\right)$, the analysis should be restricted to the set of 24,956 sections where $Ws > 0$ (sub-sample 1). All 9,470 sections of the complementary set where $Ws = 0$ were excluded (sub-sample 2). The GPAs of sub-sample 1 should be adjusted using expression (4.1).

3.2. Model to be estimated

The preceding discussion suggests that the increase in GPA (potential GI) attributable to the Ws observed in section j of the course taught by professor p is modeled as:

$$y_{jp}^{Ws} = \left(\alpha_0 + \alpha_p\right) + \sum_{k=2}^{21} \beta_k AF_k + \phi T_T + \delta Female + \gamma Tenure + \psi SET + \boldsymbol{\lambda} \mathbf{X}_{jp} + \varepsilon_{jp} \tag{8}$$

AF_k = academic fields, T_T = time trend, X_{jp} = a vector of control variables and ε_{jp} = composite error term. Unobservable faculty heterogeneity $\left(\text{UFH} = \alpha_p\right)$ is modeled as both fixed- and random-effects. Academic field specific-effects can be accounted for using their estimated coefficients ($\hat{\beta}_k$). The estimated coefficients $\hat{\delta}$, $\hat{\gamma}$ and $\hat{\psi}$ control for gender, tenure and SET specific-effects, respectively. Control variables include faculty rank, age, degree and experience; weekdays and time of the course; section size and summer session.

[6] Sections offered during summers are counted as part of fall sessions.

To hold the hypothesis that GI could be attributable to *Ws*, $\hat{\phi}$ should be positive and significant. If, looking for better SET ratings, faculty members reduce their academic standards through leniency grading, it should be expected that *Ws* tend to decrease in all courses under SET. If so, $\hat{\psi}$ should be negative and significant. If compared to males, females are easy (tough) graders, then $\hat{\delta}$ should be negative (positive) and significant. It can be conjectured that, compared to tenured faculty, non-tenured will be more responsive to student demands for leniency grading. If so, $\hat{\gamma}$ should be negative and significant. Finally, it should be expected that the vector of estimated $\hat{\lambda}$ coefficients be significant, but their signs might move in either direction.

4. Results and discussion

4.1. Stylized facts of Ws

This section discusses results from the whole sample of 34,426 sections offered in the UPR-Bayamón from 1995 to 2013, reported in Appendices B and C. According to Appendix B, during the 36 terms studied, the ratio of *Ws* to total enrollment was 11.19%. This ratio decreased over time, from 13.21% in the fall 1995 term to 8.58% in the spring 2013 term. During the same period, GPA increased from 2.54 to 2.78. Thus, evidence is consistent with GI; however, the proportion that could be attributable to *Ws* decreased over time. This result points to diminishing academic standards, since course difficulty and *Ws* move in the same direction.

Appendix C reports several important facts of *Ws* by academic fields. The service departments responsible for offering the highest number of sections were English (3,483), Mathematics (3,262), Humanities (2,583) and Spanish (2,582). The *PWs* in mathematics courses was the greatest (30%), while the respective proportions in the English, Humanities and Spanish courses were 7.9%, 7.3% and 5.28%. Two other service programs exhibiting high *PWs* were Economics & Statistics (16.98%) and Chemistry (15.56%). The last column of Appendix C transforms *Ws* into equivalent sections by academic field. This was done by dividing each *Ws* value by the average section size of the respective academic field. The total *Ws* (89,160) observed during the period would require offering 3,798 equivalent sections in order to satisfy future demand.

In order to gauge the economic and academic consequences entailed by *Ws*, it will be necessary to estimate their costs. If the equivalent sections were offered by part-time faculty and were paid through the mechanism of additional compensations ($2,000 per section), then their lower-bound monetary cost would be around $7.6 million. However, their true cost might be significantly higher. The 3,798 equivalent sections are greater than the total sections offered by service departments such as English (3,483) and Mathematics (3,262) and greater than all the sections offered jointly by six different programs.[7] That is, *Ws* entail a waste of resources greater than the whole budget assigned to and spent by such programs during 18 consecutive years. This is, indeed, a significant waste of scarce resources.

4.2. On the temporal relationship among Ws, GPA and GI

The last three columns of Appendix B report the distributions of GPAs and y^{Ws} by term. GPAs in column D belong to the whole sample, while those in column E belong to sub-sample 1. Both series exhibit an increasing tendency across time consistent with GI. Each GPA in D is greater than its counterpart in E. On the other hand, y^{Ws} diminishes over time, indicating the decreasing contribution of *Ws* to AGPA. Such a decreasing tendency is clearly depicted in Fig. 1.

In order to isolate the relationship between *Ws* and GI, three different scenarios are considered: the whole sample and sub-samples 1 and 2. From each sample, and for each of the 36 terms studied, the average GPA is computed. The three series are plotted in Fig. 2. Each exhibits an increasing tendency over time (GI). However, sub-sample 2 ($Ws = 0$) exhibits the highest GPA by term, ranging from 2.97 to 3.13. Conversely, sub-sample 1 ($Ws > 0$) exhibits the lowest GPA by term, ranging from 2.41 to 2.60. Just in the middle lies the whole sample, in which case GPA by term ranges from 2.54 to 2.78. Therefore, contrary to what is predicted by the conventional explanation, Fig. 2 clearly demonstrates that *Ws* and GPA move in opposite directions. Furthermore, for the whole sample, the partial correlation coefficient between *Ws* and GPA is −0.53. The coefficient is equal to −0.49 for sub-sample 1. Both estimated coefficients are highly

[7] The programs are Marketing (661), Materials Management (186), Finance (706), Engineering Transfers (414), Chemistry (926) and Economics & Statistics (835), for a total of 3,728 sections.

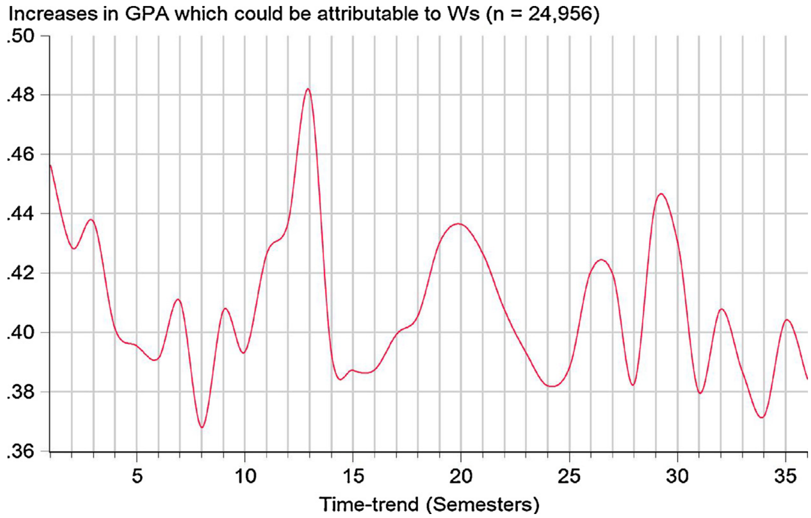

Fig. 1. Time path of y^{Ws} at UPR-Bayamón.

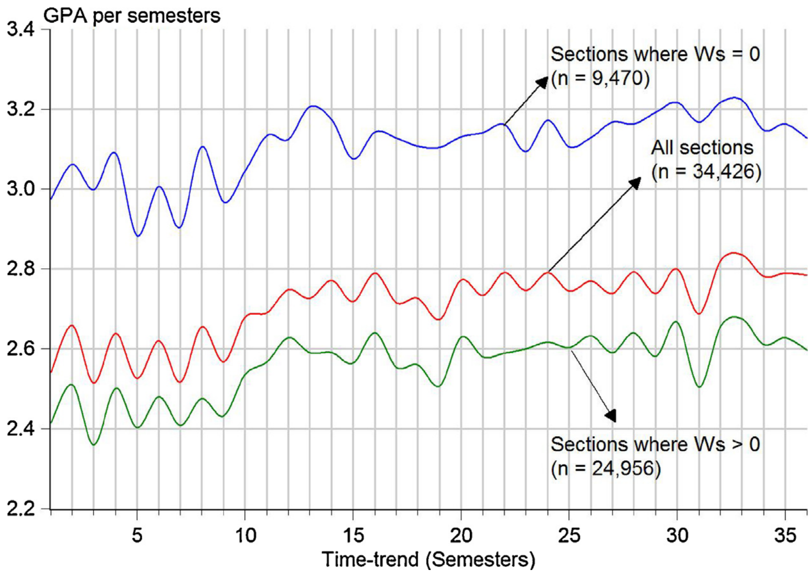

Fig. 2. GPA through time under different scenarios at UPR-Bayamón.

significant at conventional levels. Thus, empirical evidence does not allow for rejecting the first working hypothesis formulated: *Ws* and GPA move in opposite directions over time.

The inverse relationship between *Ws* and GPA documented at the section level gives rise to a counterfeit conjecture. If the unobservability issue discussed in Section 2.1 is ignored, one might be tempted to think that the decreases in the GPA observed after the increases in *Ws* occur because, on average, the students who withdraw are academically better than those who remain in the course. Evidence from a panel data used in prior studies at UPR-Bayamón, where the student was the unit of analysis, shows that *Ws* are highly concentrated in the lower-bounds of the GPA distribution. However, at the higher-bounds, they are practically inexistent. Therefore, the reported inverse relationship holds also at student level.[8]

[8] For data details, refer to Matos-Díaz (2014).

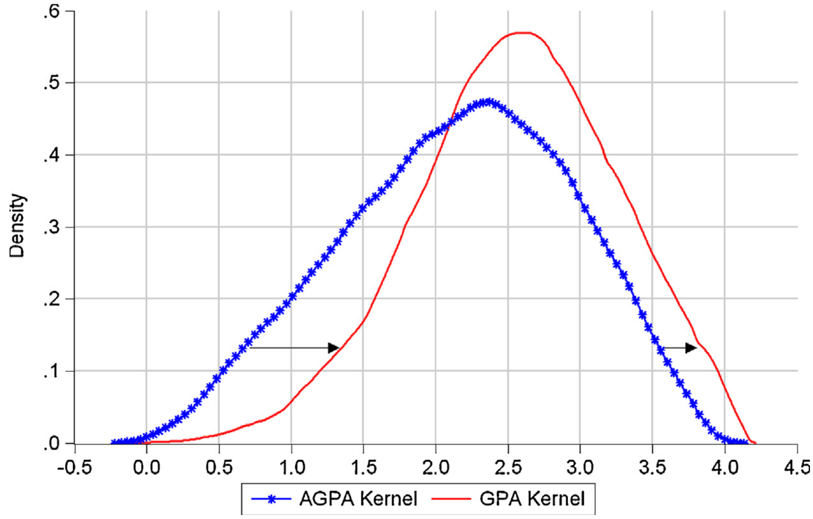

Fig. 3. AGPA $\left(\overline{GPA}|\underline{Ws}\right)$ and GPA $\left(\overline{GPA}|Ws\right)$ Kernel distributions at UPR-Bayamón.

Consequently, one should explore the specific circumstances under which *Ws* and GPA would move in the same direction. To shed light on this issue, the GPAs of sub-sample 1 were adjusted according to expression (4.1). The series of values of AGPA and GPA are plotted in Fig. 3. As mentioned earlier, the AGPA is constructed under the assumption that all the students who withdraw do remain in the course and receive a final letter grade of "*F*." As expected, the AGPA Kernel lies to the left of the GPA Kernel. At section level, the difference between GPA and AGPA is equivalent to the index proposed in expression (7). Thus, *Ws* have the effect of shifting the unobservable AGPA distribution to the right as shown by the arrows, causing GI. Only under such specific circumstances will *Ws* and GPA move in the same direction and the GI attributable to them could be estimated. Hence, the second working hypothesis formulated in Section 2.1 should not be rejected. However, none of the prior published studies have made such estimations. Therefore, the conventional explanation for the relationship among *Ws*, GPA and GI is wrong.

4.3. Predicting the increase in GPA attributable to Ws: y_{jp}^{Ws}

Four different versions of model (8) were estimated and their coefficients are reported in Table 1. UFH was modeled as both random- and fixed-effects. However, according to the Hausman test, the fixed-effects model is preferable to that of random-effects.[9] Thus, the random-effect estimates (Model 2) are included only for comparison purposes, while the discussion is based on the fixed-effects estimated coefficients (Model 4).[10] Two other specifications (Models 1 and 3) are included in Table 1. Model 1 reports the panel least squares (PLS) estimates using all the covariates in order to compare them with the random-effects model. On the other hand, Model 3 uses the same method, but deletes the time-invariant covariates (female and biology) to establish a comparison with the fixed-effects model. For all models, standard errors corrected for heteroskedasticity and contemporaneous correlation are reported in parentheses.[11]

The academic fields exert strong and significant effects on y_{jp}^{Ws}. For instance, 85% and 95% of the respective estimated $\hat{\beta}_k$ coefficients of Models 1 and 3 are significant. However, when UFH is accounted for using fixed-effects in Model 4, only 4 programs retain their significance.[12] The superiority of UFH over academic field is evident when the adjusted *R*-squares of Models 3 and 4 are compared. This coefficient increases from 0.19 (Model 3) to 0.3 (Model

[9] The assumption of no correlation between the error term $\left(\varepsilon_{jp}\right)$ and the explanatory variables is rejected at the 0.0000 significant level.
[10] It should be mentioned that the fixed-effects model is unable to provide estimates of time-invariant covariates such as female and biology.
[11] See EViews (2009, 649), for details.
[12] The programs are Accounting; Economics & Statistics; Finance and Mathematics, which is only marginally significant.

Table 1
Uncovering the effects of *Ws* on GPA.

Variables	Model 1	Model 2	Model 3	Model 4
Constant	0.2751** (0.0119)	0.2687** (0.0213)	0.3643** (0.0108)	−0.0342 (0.1449)
Accounting	0.1886** (0.0095)	0.1806** (0.0218)	0.117** (0.0093)	0.2472** (0.0546)
Biology	0.1474** (0.0095)	0.1179** (0.0205)		
Chemistry	0.1842** (0.0087)	0.1529** (0.0206)	0.116** (0.008)	−0.1204 (0.2146)
Computer Sciences	0.1301** (0.0093)	0.1145** (0.0205)	0.0537** (0.0082)	−0.0087 (0.08)
Economics & Statistics	0.2398** (0.0135)	0.1018** (0.0193)	0.1681** (0.0125)	0.1013** (0.0235)
Education	0.0277** (0.0084)	0.0003 (0.0160)	−0.0378** (0.0075)	−0.0127 (0.0525)
Electronic	0.1519** (0.0109)	0.1581** (0.0267)	0.0734** (0.0099)	0.0695 (0.0795)
Engineering Technologies	0.1094** (0.011)	0.1016** (0.022)	0.0345** (0.0104)	0.0257 (0.0679)
Engineering Transfers	0.1219** (0.017)	0.1234** (0.0265)	0.0432** (0.0166)	0.0413 (0.0691)
English	0.0344** (0.0072)	0.0054 (0.0149)	−0.0335** (0.006)	0.0513 (0.0804)
Finance	0.0302** (0.011)	0.0062 (0.0216)	−0.0374** (0.0105)	0.0749* (0.038)
Humanities	0.0332** (0.0067)	0.0349* (0.0159)	−0.0375** (0.0059)	−0.0702 (0.1033)
Management	−0.001 (0.0084)	−0.0142 (0.0154)	−0.0684** (0.0079)	0.0422 (0.0322)
Marketing	−0.1047** (0.0081)	−0.0897** (0.0194)	−0.1721** (0.0076)	−0.0098 (0.0408)
Materials Management	0.0042 (0.0191)	0.0049 (0.0277)	−0.0724** (0.0188)	−0.0634 (0.0693)
Mathematics	0.3088** (0.0084)	0.268** (0.0206)	0.2360** (0.0075)	0.1343† (0.0752)
Physical Education	−0.013 (0.0085)	−0.0204 (0.0165)	−0.0891** (0.0072)	−0.0417 (0.0524)
Physics	0.1328** (0.0122)	0.1368** (0.0255)	0.0535** (0.0115)	0.0253 (0.085)
Office Systems	0.0696** (0.01)	0.0622** (0.0255)	0.0002 (0.0093)	0.0412 (0.1097)
Spanish	−0.0211** (0.0068)	−0.05** (0.0148)	−0.0884** (0.0057)	−0.1234 (0.1072)
Assistant Professor	0.0159** (0.0057)	−0.0014 (0.0066)	0.0206** (0.0057)	−0.0069 (0.0071)
Associate Professor	0.0253** (0.0062)	0.0129 (0.0084)	0.0287** (0.0063)	0.0054 (0.0098)
Professor	0.0631** (0.0068)	0.0427** (0.0107)	0.0694** (0.0069)	0.0308* (0.0132)
Doctorate	−0.0193** (0.0043)	0.0026 (0.0074)	−0.0202** (0.0043)	0.0087 (0.0094)
Female	0.0119** (0.0036)	0.0152† (0.0089)		
Professor's Age	1.07E − 05 (0.0002)	0.0006 (0.0004)	−0.0003 (0.0002)	0.0103** (0.0037)
Professor's experience	−0.0007** (0.0003)	−0.0007 (0.0004)	−0.0006* (0.0003)	−0.0015† (0.0009)
Tenure	0.0150** (0.0057)	0.0092 (0.007)	0.0136* (0.0057)	0.0044 (0.0078)
Class size 1	0.0692** (0.0053)	0.0544** (0.0052)	0.0684** (0.0053)	0.0506** (0.0053)
Class size 3	−0.0437** (0.0038)	−0.0264** (0.0036)	−0.0502** (0.0039)	−0.0228** (0.0036)
Morning	−0.0046 (0.0036)	−0.0074* (0.0035)	−0.0036 (0.0036)	−0.007* (0.0036)
Night	−0.0476** (0.0069)	−0.0271** (0.007)	−0.0503** (0.007)	−0.0234** (0.0073)
Summer	−0.1611** (0.0168)	−0.174** (0.0159)	−0.1562** (0.0169)	−0.1727** (0.0162)
SET	−0.0186** (0.0049)	−0.0168** (0.0048)	−0.019** (0.0049)	−0.0172** (0.0049)
Five days a week (MTWTF)	0.0276** (0.0075)	0.0271** (0.0076)	0.0295** (0.0075)	0.0276** (0.008)
Monday & Wednesday (M&W)	0.0225** (0.0046)	0.0173** (0.0046)	0.0227** (0.0046)	0.0162** (0.0046)
Tuesday & Thursday (T&T)	0.0227** (0.0042)	0.0171** (0.0042)	0.0223** (0.0042)	0.0162** (0.0043)
Time trend	−8.31E − 05 (0.0002)	−2.91E − 05 (0.0004)	−0.0001 (0.0002)	−0.0037† (0.0021)
Random- or fixed-effects?	No, PLS	Yes, R–E	No, PLS	Yes, F–E
Adjusted *R*-square	0.1937	0.0453	0.1856	0.2959
Cross-sections	851	851	851	851
Total panel observations	24,935	24,935	24,935	24,935

Notes: †, *, ** statistically significant at the 10, 5 and 1 percent levels (two-tailed test), respectively. PLS = panel least squares. For all models, standard errors (in parentheses) are corrected for heteroskedasticity and contemporaneous correlation.

4), representing an increment of 58% in the total variation explained by the model. Therefore, UFH is responsible for and explain a large proportion of the total variation observed around y_{jp}^{Ws}.[13]

The significance of faculty characteristics such as rank, degree, gender, age, tenure and experience depends on the specification of the model. When UFH is accounted for (Model 4), only the covariates professor and age are significant and positive; meanwhile, experience is negative, but only marginally significant. Compared to sections taught by

[13] The null hypothesis stating that the fixed-effects are redundant should be rejected. The estimated cross-section F and Chi-square statistics are 5.59 and 4,492.81, respectively. Both statistics are significant at 0.0000 levels. For technical details, refer to EViews (2009, 672–674).

instructors, the presence of a professor increases the expected y_{jp}^{Ws} by 0.04 points. On the other hand, y_{jp}^{Ws} increases by 0.01 points per year of aging and decreases by 0.0015 points per additional semester of experience.

The covariates that define the section characteristics, such as class size, hour and weekdays, as well as summer and SET are robust to model specifications. All of them are significant and sign consistent, except the covariate morning (Model 3). Compared to the reference group (17–29 students per section), y_{jp}^{Ws} increases by 0.05 points in smaller sections and decreases by 0.02 points in greater ones. Thus, *Ws* and class size move in opposite directions. On the other hand, compared to sections offered in the afternoon, the expected y_{jp}^{Ws} decreases by 0.01 or 0.02, depending whether or not it is offered in the morning or at night, respectively. Thus, *Ws* are higher in sections offered in the afternoon. There is a direct and significant relationship between y_{jp}^{Ws} and the days the course is offered. Compared to the reference group, in courses offered every day (Monday–Friday), y_{jp}^{Ws} increases by 0.03 points. It increases by 0.02 points if the course is offered on Mondays and Wednesdays or Tuesdays and Thursdays.

Apparently, more difficult courses are organized in small sections, scheduled at determinate days and hours and offered by tough-grading faculty, all of which tend to increase *Ws* inducing increments on y_{jp}^{Ws}.

There is a strong, negative and significant effect exerted by summer covariate on y_{jp}^{Ws} in all models. After accounted for UFH (Model 4), y_{jp}^{Ws} decreases by 0.17 points if the course was offered during summer. Other things equal, *Ws* diminish dramatically in summer sessions. This result becomes more pertinent when it takes into account that, for sub-sample 1, mathematics courses (259) represented 75% of all summer courses (346). According to student performance, mathematics courses are, precisely, the most difficult ones. Their overall GPA and *PWs* in fall and spring terms are 1.69 and 32%, respectively. However, the respective figures for summer sessions are 2.16 and 14%. Thus, GPA increases by 28%, while *PWs* decreases by 56% if the course is taught in summer. These numbers explain succinctly why mathematics summer courses are so popular among students and why the Mathematics Department's market share of the summer offer is as high as 75%. Given that course inherent difficulty remains equal, no matter the session, there are only two possible explanations (1) students take fewer courses in the summer and therefore can concentrate on a particular course more intensively and/or (2) faculty members grade more leniently, relaxing academic standards possibly to prevent competition for teaching assignments.

To empirically test the leniency hypothesis, attention is placed on the SET estimated coefficient ($\hat{\psi}$). According to this conjecture, faculty members will be able to get better SET ratings if they reduce academic standards and course difficulty levels through leniency grading. Such a symbiotic relationship between students and faculty has been proposed in the literature for a long time without direct statistical testing.[14] If so, it should be expected that in courses where SET = 1, difficulty level diminishes, GPA increases and *Ws* decrease. However, in order for GI to hold under the conventional explanation, it should require an increase in *Ws*, which will happen when SET = 0 instead of SET = 1. Therefore, contrary to what is predicted by the conventional explanation, SET = 1 will induce an increase in GPA and a decrease on y_{jp}^{Ws}.

The SET estimated coefficient ($\hat{\psi} = -0.02$) is significant, implying that *Ws* diminish whenever SET = 1, inducing decreases of 0.02 points on y_{jp}^{Ws}. Thus, according to students' criteria, inherent difficulty significantly decreases just for the simple reason that the course is under SET. This result confirms the symbiotic relationship conjectured in the leniency hypothesis. However, this hypothesis had not been submitted to direct statistical testing before the present study.

To test whether GI could be attributable to *Ws*, the analysis needs to focus on the estimated time trend coefficient. After accounting for UFH (Model 4), y_{jp}^{Ws} decreases over time, since the coefficient ($\hat{\phi} = -0.0037$) is marginally significant. Such a tendency is consistent with the behavior exhibited by the index in Fig. 1, as well as the time path of *Ws* in Appendix B. When Model 4 was re-specified and estimated using time dummies in order to capture the effects of time-varying coefficients, only five of them were significant (14%). However, such specification allows a replication of the pattern of signs which is very consistent with the temporal tendency of y_{jp}^{Ws}, as depicted in Fig. 1.[15] Therefore, y_{jp}^{Ws} tends to decrease over time, implying grade deflation attributable to *Ws* at UPR-Bayamón. However, during the same period, evidence demonstrates the existence of traditional GI. Therefore, the third working hypothesis formulated in Section 2.1 should not be rejected.

[14] For some relevant studies in the field, refer to footnote 4.

[15] Results are available upon request.

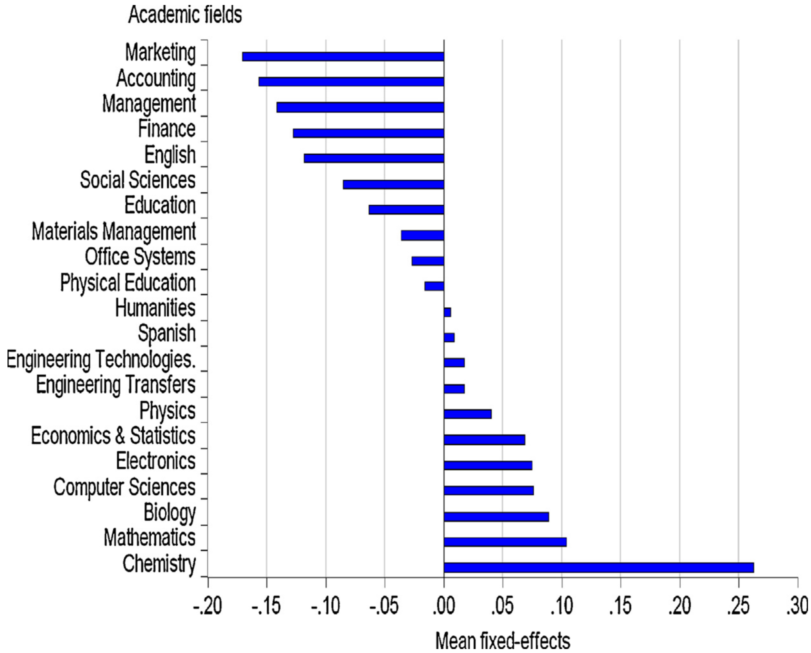

Fig. 4. Faculty mean fixed-effects by academic fields.

According to Models 1 and 3, academic fields exert a significant effect on y_{jp}^{Ws}. Even after accounting for UFH in Model 4, Accounting, Economics & Statistics, Finance and Mathematics programs continue to be significant. The other programs lose their significance because of the strong effect exerted by UFH. To clearly demonstrate the impact exerted by UFH on *Ws* and y_{jp}^{Ws}, Fig. 4 displays the faculty mean fixed-effects by academic fields. Even though the sum of total effects is zero, within each academic field it could be positive or negative. Thus, the programs that show the lowest *PWs* and the higher GPA, also exhibit the lowest faculty mean fixed-effects and vice versa. For instance, Marketing *PWs*, GPA and faculty mean fixed-effects are $\{2.72\%;\ 3.09 \text{ and } -0.17\}$. The respective triplets of the Chemistry and Mathematics programs are $\{15.56\%;\ 2.25 \text{ and } 0.26\}$ and $\{30.18\%;\ 1.69 \text{ and } 0.1\}$. Thus, tough- and easy-grader faculties are not randomly distributed among programs and even within the same program such a distribution may vary significantly. Programs lying to the left of the middle point at the abscissa (0.00) consist principally of easy-grader faculty, while those to its right are constituted principally by tough-graders. Therefore, to a great extent, the GPA and *Ws* divergence observed among academic programs is explained by their UFH effects, which range from −0.17 points in Marketing to 0.26 points in Chemistry.

5. Summary

Using a rich panel containing detailed information of the 34,426 sections of all courses offered during 18 consecutive academic years, this study sought to estimate the effects of *Ws* on GPA at the UPR-Bayamón. Empirical evidence does not allow rejecting the three hypotheses formulated, given that, as conjectured (1) *Ws* and GPAs move in opposite directions at both section and student levels; (2) the index designed to capture the effects of *Ws* on GPA $\left(y_{jp}^{Ws}\right)$ exhibits an excellent statistical fitting and is very sensitive to changes in the courses, institutional environment and faculty characteristics and (3) the time trends of GI and the increases in GPA attributable to *Ws* move in opposite directions.

Thus, over the 36 terms analyzed, evidence points to a self-sustained upward temporal tendency in GPAs accompanied by a downward temporal one in *Ws*. Therefore, the existence of traditional GI is demonstrated, but the proportion that could be attributable to *Ws* decreases over time. Given that GPAs inversely vary, while *Ws* directly vary with courses' inherent difficulty, these time paths signal an institutional academic environment characterized by diminishing standards. In such a context, evidence clearly demonstrates that UFH and the SET process exert strong and significant effects.

On the other hand, even though *Ws* decrease over time, they entail a high institutional cost greater than the whole budget assigned to and spent by academic programs such as Mathematics and English over 18 consecutive years.

The significance of faculty characteristics such as rank, degree, gender, age, tenure and experience depends on the specification of the model. When UFH is accounted for, only the covariates professor and age are significant. On the other hand, the covariates that define the section characteristics (class size, hour and weekdays) are robust to model specifications. Almost all of them are significant and sign consistent. Hence, evidence points to the conclusion that more difficult courses are organized in small sections, scheduled at determinate days and hours and offered by tough-grading faculty, all of which tend to increase *Ws* and thus induce increments on y_{jp}^{Ws}.

Summer covariate exerts a strong, negative and significant effect on y_{jp}^{Ws} in all estimated models. After accounting for UFH, y_{jp}^{Ws} decreases by 0.17 points if the course was offered during summer session, implying a significant reduction in *Ws*. Evidence confirms the student-faculty symbiotic relationship predicted by the leniency hypothesis, since the SET estimated coefficient ($\hat{\psi} = -0.02$) is significant. However, before this study, this relationship had not been submitted to direct statistical testing.

Academic fields and UFH exert strong and significant effects on y_{jp}^{Ws} and *Ws*. The programs that show the lowest *PWs* and the higher GPA also exhibit the lowest faculty mean fixed-effects and vice versa. Thus, tough- and easy-grader faculty members are not randomly distributed among programs and even within the same program such a distribution may vary significantly. Therefore, to a great extent, the GPA and *Ws* divergence observed among academic programs is explained by their UFH effects.

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Appendix A. Sample statistics.

Dummy variables

Variable	Mean	Variable	Mean	Variable	Mean
Accounting	0.0519 (0.2219)	Marketing	0.0129 (0.1129)	Doctorate	0.234 (0.4234)
Biology	0.05 (0.218)	Materials Management	0.0049 (0.0695)	Tenure	0.7067 (0.4553)
Chemistry	0.0335 (0.1799)	Mathematics	0.1269 (0.3329)	Class size 1	0.163 (0.3694)
Computer Sciences	0.066 (0.2484)	Physical Education	0.0412 (0.1986)	Class size 3	0.2775 (0.4478)
Economics & Statistics	0.0299 (0.1702)	Physics	0.0295 (0.1693)	Morning	0.5413 (0.4983)
Education	0.0554 (0.2287)	Office Systems	0.0432 (0.2034)	Night	0.0923 (0.2894)
Electronic	0.0563 (0.2305)	Social Sciences	0.057 (0.2318)	Summer	0.0139 (0.1169)
Engineering Technologies	0.0291 (0.168)	Spanish	0.0679 (0.2516)	SET	0.1148 (0.3188)
Engineering Transfers	0.0113 (0.1057)	Female	0.5362 (0.4987)	Monday–Friday	0.0153 (0.1228)
English	0.1021 (0.3027)	Instructor	0.328 (0.4695)	Monday & Wednesday	0.306 (0.4608)
Finance	0.0182 (0.1335)	Assistant	0.219 (0.4136)	Tuesday & Thursday	0.3684 (0.4824)
Humanities	0.0767 (0.2661)	Associate	0.2187 (0.4134)		
Management	0.0362 (0.1868)	Professor	0.2269 (0.4188)		

Continuous variables					
Variable	Description	Mean	Std. dev.	Min	Max
Age	Professor's age (years)	47.34	9.34	23	74
Experience	Professor's experience (semesters)	13.99	10.78	1	50
Trend	Time-trend (semesters)	18.04	10.42	1	36
y_j^{Ws}	Increase in GPA attributable to Ws	0.4092	0.2681	0	3.09
$\left(\overline{GPA}\vert Ws\right)$	Grade point average	2.55	0.6933	0	4
$\left(\overline{GPA}\vert \underline{Ws}\right)$	Adjusted grade point average	2.15	0.7999	0	3.91

Note: For all dummies, standard deviations are reported in parentheses, max = 1 and min = 0.

Appendix B. Stylized facts of *Ws* by terms.

Academic year	Enrollment (A)	Sections (B)	S. size (A/B)	*Ws* (C)	% of *Ws* (C/A)	GPA (D)	GPA (E)	y^{Ws}
95/96: F	21,534	914	24	2,845	13.21	2.54	2.42	0.46
95/96: S	19,719	868	23	2,348	11.91	2.66	2.51	0.43
96/97: F	25,010	1,037	24	3,440	13.75	2.51	2.36	0.44
96/97: S	21,948	902	24	2,611	11.90	2.64	2.50	0.41
97/98: F	25,193	1,024	25	2,936	11.65	2.53	2.40	0.40
97/98: S	23,901	1,009	24	2,601	10.88	2.62	2.48	0.39
98/99: F	25,541	1,040	25	3,167	12.40	2.52	2.41	0.41
98/99: S	24,423	1,043	23	2,489	10.19	2.65	2.47	0.37
99/00: F	25,189	1,020	25	2,846	11.30	2.57	2.43	0.41
99/00: S	24,063	1,003	24	2,603	10.82	2.68	2.53	0.39
00/01: F	24,797	1,051	24	3,094	12.48	2.69	2.57	0.43
00/01: S	23,745	1,024	23	2,945	12.40	2.75	2.63	0.44
01/02: F	24,808	1,038	24	3,606	14.54	2.73	2.59	0.48
01/02: S	24,128	1,034	23	2,425	10.05	2.77	2.59	0.39
02/03: F	23,116	973	24	2,311	10.00	2.72	2.56	0.39
02/03: S	21,605	933	23	2,046	9.47	2.79	2.64	0.39
03/04: F	22,279	946	24	2,427	10.90	2.71	2.55	0.40
03/04: S	20,456	899	23	2,055	10.05	2.73	2.56	0.40
04/05: F	20,976	940	22	2,555	12.18	2.67	2.51	0.43
04/05: S	18,964	875	22	2,227	11.74	2.77	2.63	0.44
05/06: F	19,909	902	22	2,391	12.01	2.73	2.58	0.43
05/06: S	17,929	835	21	1,705	9.51	2.79	2.59	0.41
06/07: F	20,015	909	22	2,171	10.85	2.75	2.60	0.39
06/07: S	18,010	829	22	1,680	9.33	2.79	2.62	0.38
07/08: F	21,369	937	23	2,304	10.78	2.74	2.60	0.39
07/08: S	20,400	925	22	2,280	11.18	2.77	2.63	0.42
08/09: F	22,232	959	23	2,676	12.04	2.74	2.59	0.42
08/09: S	19,866	887	22	1,947	9.80	2.79	2.64	0.38
09/10: F	23,329	999	23	2,921	12.52	2.74	2.58	0.44
09/10: S	21,329	922	23	2,518	11.81	2.80	2.67	0.43
10/11: F	22,516	961	23	2,399	10.65	2.69	2.50	0.38
10/11: S	20,817	927	22	2,100	10.09	2.82	2.65	0.41
11/12: F	22,765	977	23	2,321	10.20	2.83	2.67	0.39
11/12: S	21,490	970	22	1,924	8.95	2.78	2.61	0.37
12/13: F	23,100	1,000	23	2,497	10.81	2.79	2.63	0.40
12/13: S	20,386	914	22	1,749	8.58	2.78	2.60	0.38
Total	796,857	34,426	23	89,160	11.19%			
Sample size (SS) = 34,426							SS = 24,956	

Notes: "F" and "S" stand for fall and spring semesters, respectively, y^{WS} = increase in GPA attributable to *Ws*.

Appendix C. Stylized facts of *Ws* by academic fields.

Academic fields	Enrollment (A)	Sections (B)	Section size (C = A/B)	*Ws* (D)	% of *Ws* (D/A)100	Equivalent sections (D/C)
Marketing	17,716	661	27	482	2.72%	18 (0.5%)
Physical Education	37,646	1,822	21	1,889	5.02	90 (2.37%)
Spanish	69,621	2,582	27	3,674	5.28	136 (3.58%)
Social Sciences	57,065	2,121	27	3,276	5.74	121 (3.19%)
Management	35,168	1,286	27	2,121	6.03	79 (2.08%)
Materials Management	4,450	186	24	296	6.65	12 (0.32%)
Education	48,358	2,168	22	3,249	6.72	148 (3.9%)
Finance	18,180	706	26	1,248	6.86	48 (1.26%)
Humanities	68,495	2,583	27	4,999	7.3	185 (4.87%)
English	85,359	3,483	25	6,740	7.9	270 (7.11%)
Office Systems	26,954	1,708	16	2,574	9.55	161 (4.24%)
Engineering Transfers	6,680	414	16	727	10.88	45 (1.18%)
Engineering Technologies	16,558	1,058	16	1,929	11.65	121 (3.19%)
Computers	42,008	2,266	19	4,968	11.83	261 (6.87%)
Physics	22,229	1,159	19	2,636	11.86	139 (3.66%)
Biology	36,516	1,532	24	4,561	12.49	190 (5.0%)
Electronics	32,796	2,090	16	4,404	13.43	275 (7.24%)
Accounting	35,954	1,576	23	5,188	14.43	226 (5.95%)
Chemistry	24,322	926	26	3,785	15.56	146 (3.84%)
Economics & Statistics	22,884	835	27	3,885	16.98	144 (3.79%)
Mathematics	87,895	3,262	27	26,529	30.18	983 (25.88%)
Total	796,854	34,424	23	89,160	11.19%	3,798 (100%)

References

Achen, A.C., Courant, P.N., 2009. What are grades made of? J. Econ. Perspect. 23, 77–92.

Bound, J., Lovenheim, M.F., Turner, S., 2007. Understanding the Decrease in College Completion Rates and the Increased Time to the Baccalaureate Degree. University of Michigan, Population Studies Center Research Report 07-626.

Dilts, D.A., 1983. A statistical interpretation of student evaluation feedback. J. Econ. Educ. 11, 10—15.

EViews7, 2009. User's Guide II. Quantitative Micro Software, Irvine, CA.

Freeman, D.G., 1999. Grade divergence as a market outcome. J. Econ. Educ. 30, 344—351.

Grove, W.A., Wasserman, T., 2004. The life-cycle pattern of collegiate GPA: longitudinal cohort analysis and grade inflation. J. Econ. Educ. 35, 162–174.

Gump, S.E., 2007. Student evaluation of teaching effectiveness and the leniency hypothesis: a literature review. Educ. Res. Q. 30, 55–68.

Heckman, James, 1979. Sample selection bias as a specification error. Econometrica 47, 153–161.

Hoyt, D., Reed, J., 1976. Grade inflation at KSU: Student and faculty perspectives. Research Report No. 36. June 1976. (ERIC Document Reproduction Service No. ED160018).

Hu, S., 2005. Beyond Grade Inflation: Grading Problems in Higher Education (ASHE Higher Education Report, vol. 30 (6. Jossey-Bass, Wiley, San Francisco.

Isely, P., Singh, H., 2005. Do higher grades lead to favorable students evaluations? J. Econ. Educ. 36, 29–42.

Jewel, R.T., McPherson, M.A., Tieslau, M.A., 2013. Whose fault is it? Assigning blame for grade inflation in higher education. Appl. Econ. 45, 1185–1200.

Johnes, G., 2004. Standards and grade inflation. In: Johnes, G., Johnes, J. (Eds.), International Handbook on the Economics of Education. Edward Elgar Publishing, Northampton, MA, pp. 462–483.

Johnson, V.E., 2003. Grade Inflation: A Crisis in College Education. Springer-Verlag, New York, NY.

Kanagaretnam, K., Mathieu, R., Thevaranjan, A., 2003. An economic analysis of the student evaluations: implications for universities. Manag. Decis. Econ. 24, 1–13.

Krautmann, A.C., Sander, W., 1999. Grades and student evaluations of teachers. Econ. Educ. Rev. 18, 59–63.

Lichty, R.W., Vose, D.A., Peterson, J.M., 1978. The economic effects of grade inflation on instructor evaluation: an alternative interpretation. J. Econ. Educ. 9, 3–11.

Love, D.A., Matthew, J.K., 2010. Grades, course evaluations, and academic incentives. East. Econ. J. 36, 151–163.

Matos-Díaz, H., 2012. Student evaluation of teaching, formulation of grade expectations, and instructor choice: explorations with random-effects ordered probability models. East. Econ. J. 38, 296–309.

Matos-Díaz, H., 2014. Measuring grade inflation and grade divergence accounting for student quality. Cogent Econ. Financ. 2, 1–16.

McKenzie, R.B., 1975. The economic effects of grade inflation on instructor evaluations: a theoretical approach. J. Econ. Educ. 2, 99–106.
McKenzie, R.B., Tullock, G., 1975. The New World of Economics: Explorations into the Human Experience. Richard D. Irwin, Inc, Illinois.
McKenzie, R.B., Staaf, R.J., 1974. An Economic Theory of Learning: Students Sovereignty and Academic Freedom. Blacksburg, VA, University Publications.
McPherson, M.A., 2006. Determinants of how students evaluate teachers. J. Econ. Educ. 37, 3–20.
Mc Spirit, S., Jones, K.E., 1999. Grade inflation rates among different ability students, controlling for other factors. Educ. Policy Anal. Arch. 7, 1–16.
Nelson, J.P., Lynch, K.A., 1984. Grade inflation, real income, simultaneity, and teaching evaluations. J. Econ. Educ. 15, 21–39.
Oglive, K., Jelavic, M., 2013. Grade inflation in the US higher educational environment: a faculty perception study. Int. J. Manag. Educ. 7, 406–416.
Raisman, N., 2013. The Cost of College Attrition at Four-Year Colleges and Universities. An Analysis of 1669 US Institutions, Policy Perspectives. The Educational Policy Institute, Virginia Beach, VA.
Rosovsky, H., Hartley, M., 2002. Evaluation and the Academy: Are We Doing the Right Thing? Grade Inflation and Letters of Recommendation. American Academy of Arts and Sciences, Cambridge, MA, pp. 1–25.
Sabot, R., Wakeman-Linn, J., 1991. Grade inflation and course choice. J. Econ. Perspect. 5, 159–170.
Seiver, D.A., 1983. Evaluations and grades: a simultaneous framework. J. Econ. Educ. 14, 32–38.
Schneider, M., Yin, L., 2011. The High Cost of Low Graduation Rates: How Much Does Dropping Out of College Really Cost? American Institutes for Research, Washington, DC.
Schuh, J.H., 2005. Finances and retention: trends and potential implications. In: Seidman, A. (Ed.), College Student Retention: Formula for Student Success. Praeger, Greenwich, CT, pp. 89–106.
Zangenehzadeh, H., 1988. Grade inflation: a way out. J. Econ. Educ. 19, 217–223.
Zwick, R., Sklar, J.C., 2005. Predicting college grades and degree completion using high school grades and SAT scores: the role of student ethnicity and first language. Am. Educ. Res. J. 42, 439–464.