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MODELING COLLEGE GRADUATION GPA: DO GENDER AND HIGH-SCHOOL TYPE REALLY MATTER?

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Modeling college graduation GPA: Do gender and high-school type really matter?

...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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Abstract

This study models the graduation grade point average (GGPA) of 2,407 graduates of the University of Puerto Rico at Bayamón from 1995-96 to 2000-01. Empirical evidence shows that: (a) female and public school students obtain significantly higher GGPAs and exhibit advantages when compared to male and private school students, (b) the probability of accessing a determined boundary in the distribution of GGPAs is significantly and nonlinearly related to the admission policy, (c) GGPAs exhibit an uptrend that varies inversely and significantly with graduates' quality, and (d) the probability of being in the lower bounds of the GGPAs distribution increases to the extent that graduates exceed graduation required time.

Keywords: admission policy, graduation lags, ordered probability models, maximum likelihood methods, quantile regression

JEL Classification: **I-**20, **I**-21, **C-**25

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1. Introduction

Many studies contend that the best criterion to measure a university's academic success is the proportion of students that graduate with a bachelor's degree within a defined time period (Zwick and Sklar 2005). In this context, one of the most compelling issues faced by universities is establishing admission policy criteria that allow them to limit entry to students who are most likely to complete their degree in the allotted time. The value of such an approach depends on the ability of the indicator used to predict student outcomes. Prior research shows that United States students' grades in college are significantly related to proxies of academic aptitude. Students with high scores on admission tests tend to obtain both higher grades (Park and Kerr 1990; Cohn et al. 2004) and a higher overall grade point average (GPA) (Betts and Morell 1999; Freeman 1999; Grove and Wasserman 2004; Rothstein 2004; Horowitz and Spector 2005). Similarly, college grades correlate positively with high-school GPA (HSGPA) (Noble 1991; Betts andMorell 1999; Rothstein 2004; Cohn et al. 2004). Some studies also suggest that females tend to earn higher grades than males in college (Leppel 1984; Betts and Morell 1999; Grove and Wasserman 2004).

Although there is a vast literature on determinants of college GPA, relatively few studies have focused on the determinants of college graduation GPA (GGPA). This study aims to fill this gap by modeling the GGPA of graduates of the associate and bachelor's degree programs at the University of Puerto Rico at Bayamón (UPR-Bayamón) for the six consecutive cohorts of students admitted during the 1995-96 to 2005-06 period. The paper addresses the following questions: Do students from public schools obtain significantly higher GGPAs and exhibit advantages relative to students from private ones? To what extent are academic outcomes affected by gender? How is the likelihood of accessing a determined maximum or minimum boundary in the distribution of the GGPAs affected by the admission policy? How does the GGPA vary in relation to the quality of graduates over the temporal trend of new incoming classes? What are the academic consequences of exceeding the minimum required time for graduation and which academic program do graduates come from? The answers to these questions might have policy implications for university admission guidelines in particular and for education policies in general.

To develop the model to address these questions, the original sample had to be truncated since a minimum period of time is required for students to complete all graduation requirements. The criterion used was that at least 12 semesters had passed since the last class to be studied was admitted to the UPR-Bayamón. A total of 8,258 new incoming students were admitted to the Institution during the time of the study. From this total, 420 graduated with an associate degree, 1,912 graduated with a baccalaureate's degree, and 75 obtained both degrees. Consequently, the final sample of the study was comprised of 2,407 observations.

This study contributes to the literature by (1) utilizing a rich data-set that describes in detail each graduate from the UPR-Bayamón belonging to six consecutive cohorts, (2) combining historical data with results from three different econometric models that allow evaluating the findings' robustness, (3) including a new variable related to the graduation lag or time required to complete graduation requirements, which allows comparing the academic performance of graduates by gender, academic programs and high school type throughout the GGPAs distribution, and (4) analyzing the possibility of grade inflation in the GGPAs distribution.

The University 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. Approximately, 99% of the students are Puerto Rican. The admission criterion at the UPR is based on the General Admission Index (GAI) of each applicant, which is the weighted mean of the HSGPA (50%) and the scores in the verbal aptitude (25%) and mathematical aptitude (25%) sections of the College Entrance Examination Board (CEEB) test. The GAI plays a crucial role not only in determining admission to the different campuses of the UPR, but also to particular programs. Throughout this article, the GAI will be utilized as the best available proxy of the graduates' quality.

The minimum GAI required for each program varies throughout time depending on changes in enrollment. Given its weight in the admission process, it would be expected that the GAI plays a similar role as a predictor of academic success throughout each student's academic career. If so, it would be expected that the institutional academic success would increase throughout time to the extent to which newly admitted incoming classes satisfy this criterion. However, the evidence discussed in the next section is at odds with such a conjecture.

According to Bowen et al. (2009), there are marked differences in the proportion of students that graduate with a bachelor's degree in or before six years. For example, the graduation rates for classes that began their studies in 1999 vary between 66% and 84%, as well as 45% and 61%,[1] depending on the universities considered. Likewise, for a group of 540 state

[1] Refer to Tables 1.1 to 1.3 on pages 11-13 of the cited text, for details.

universities whose academic offerings are focused on undergraduate and master's degree programs, the rates vary between 35% and 56%. At the end of the 2005-06 academic year the respective graduation rates of the six UPR-Bayamón classes studied were: 28.50; 25.14; 30.10; 29.94; 30.81; and 25.62 percent. Therefore, the highest graduation rate observed in this study (31%) is lower than the lower rate (35%) of the state institutions studied by Bowen et al. (2009).

Given that only 28.24% of the students considered in this study reached the expected goal of graduation, the analysis of the determinants of their GGPA acquires particular relevance. With this aim, the rest of the study is organized as follows: The second section discusses the data-set and the specification of the statistical models and the third section discusses the results, the article ends with a summary and the study conclusions.

2. Information and statistical procedures

For each of the students admitted to the UPR-Bayamón, the following data are available: GAI, high school code, gender, academic program to which she/he was admitted, academic program which he/she graduated from, HSGPA, and the UPR-Bayamón GGPA. To identify the temporal trend (T_T) of the six classes considered in this study, six dummies, whose reference group is the first class of the 1995-96 period, are defined. In addition, a time variable measuring the graduation lag in terms of the semesters exceeding the minimum time required for graduation is defined ($-1 \le t^* \le 16$). The academic programs (AP) are identified with eleven dummies, whose reference group is: Other Academic Programs.[2] Dummies also identify the graduate's gender and school of origin, the respective reference groups are male and public. Table 1 describes the variables utilized in the study.

<<Place Table 1 here>>

The statistical models

Two different approaches are utilized to model the GGPA. The first one uses linear models such as *OLS* and quantile regression to estimate Models 1 and 2, reported in Table 5, as well as the five models included in Table 6, respectively. Model 1 (Table 5) uses a dummy variable to identify the high school of origin (private = 1) while Model 2 utilizes 223 dummies to identify each of the UPR-Bayamón graduate's high school of origin. The equation to be estimated is specified as follows:

[2] This cluster is comprised by graduates from social sciences, engineering transfers and health sciences.

(1) $$GGPA_i = \alpha + \delta(Female) + \rho(PHS) + \lambda(Associate) + \gamma GAI_i + \sum_{j=1}^{10}\left(\theta_j \cdot AP_j\right) + \sum_{t=1}^{9}\left(\phi_t \cdot t^*\right) + \sum_{T=2}^{6}\left\{\psi_T \cdot T_T + \beta_T\left(GAI_i \cdot T_T\right)\right\} + \mu_i$$

It is assumed that the disturbances (μ_i) are normally distributed.

The second approach utilizes maximum likelihood models (ordered probit) to compute the probability with which a student may obtain access to a determined bound of the GGPA distribution, including the possibility of graduating with honors (Model 3, Table 5). For this purpose, a partition of the GGPA is made and five different rankings are defined, three of which are closely related to the institutional criteria used when granting honors at graduation. Let us consider the dummies of expression (2):

(2) $$\begin{cases} y_0 = 1 & \text{if GGPA} \leq 2.49, \\ y_1 = 1 & \text{if } 2.50 \leq \text{GGPA} \leq 2.99, \\ y_2 = 1 & \text{if } 3.00 \leq \text{GGPA} \leq 3.32, \\ y_3 = 1 & \text{if } 3.33 \leq \text{GGPA} \leq 3.74, \\ y_4 = 1 & \text{if GGPA} \geq 3.75, \end{cases}$$

According to the UPR-Bayamón Academic Senate Certification No. 11 (1988-89), *Cum Laude*; *Magna Cum Laude*; and *Summa Cum Laude* are granted to graduates whose GGPA are 3.00-3.32; 3.33-3.99; and 4.00 points, respectively. Therefore, y_0 and y_1 define the inferior bounds of the GGPA distribution for which there are no academic honors. Furthermore, y_2 corresponds with *Cum Laude*, while y_3 and y_4 define the higher bounds of the distribution and coincide with *Magna Cum Laude*.

Using the expression (2), the ordered variable y_i^G, where superscript '*G*' stands for graduated, is defined in expression (3):[3]

(3) $$y_i^G = \{0 \text{ if } y_0 = 1;\ 1 \text{ if } y_1 = 1;\ 2 \text{ if } y_2 = 1;\ 3 \text{ if } y_3 = 1;\ 4 \text{ if } y_4 = 1\}$$

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[3] The variable is operationally defined as follows: $y_i^G = \sum_{k=0}^{4}\left(\mathbf{y}_k \cdot k\right)$.

The observed value y_i^G is modeled through the latent unobservable variable y_i^{G*}, which is assumed linearly dependent on the same vector of covariates utilized in Models 1 and 2.[4] The model to be estimated is specified in the expression (4):

(4) $$y_i^{G*} = \mathbf{X}_i^T \boldsymbol{\beta} + \varepsilon_i$$

The disturbance terms (ε_i) are assumed to be normally distributed (zero mean and unit variance), with cumulative and density distributions denoted by $\Phi(\cdot)$ and $\phi(\cdot)$, respectively. The estimated coefficients ($\hat{\beta}_j$) of this model should be carefully analyzed since, in contrast to the linear model cases, they do not correspond to the marginal effects of the covariates.[5] Nevertheless, at the ends of the ranking the direction of the marginal effects of a variable is determined by the sign of its coefficient ($\hat{\beta}_j$). Hence, $P\left(y_i^G = 0\right)$ varies inversely, while $P\left(y_i^G = 4\right)$ varies directly with the sign of $\hat{\beta}_j$. In the other rankings it is not possible to determine the sign of the marginal effect a priori. It is solely determinable through computations of the corresponding partial derivatives or by simulations.

3. Results and Discussion

Graduates' performance by gender, high school type and academic programs

Tables 2 and 3 compare the graduates' performance by academic programs, gender and high school of origin. Utilizing the admission policy (GAI) as proxy for student quality, Table 2 shows that compared to females, male graduates start college with an advantage of one point. However, it disappears when graduates are compared along academic programs. Females start college with higher GAIs than males in eight out of eleven programs. Females' greater advantage is shown in Electronics (25 points). Males exhibit advantages in three programs only: Physical Education (3 points), Other Programs (3 points), and Office Systems (16 points, but only one male graduated from this program).

The females' advantage increases while in college, and they graduate with GPAs greater than those of males. Overall, females' GGPA is 16 points greater than those obtained by males (p-value < 0.0000). Their advantage is even greater when compared among

[4]The observed values of y_i^G are determined from y_i^{G*} according to the rule described in EViews 7, User Guide II, (2009): pp. 267-273.
[5] See Greene (2012), for details.

academic programs since they exhibit greater GGPAs in ten out of eleven programs. Only in Biology their advantage is reversed, but the difference that favors males is merely one point.

Figure 1 provides added perspective on gender by showing student differences at the beginning of college, as well as at the time of graduation. The figure plots the kernel density functions of HSGPA and GGPA separately for males and females. The females' advantage is clearly depicted in both distributions. According to prior studies of U.S. student performance (Bridgeman et al. 2000; Cohn et al. 2004; Rothstein 2004), females tend to earn higher grades in high school, whereas males tend to do better on admission tests. On the other hand, Mau and Lynn (2001) report that males obtain significantly higher scores on admission tests, but females obtain significantly higher college grades. The findings of this study are at odds with those results since females performed better than males on HSGGPA, GAI, and on GGPA. An explanation for the causes of females' advantages is beyond the scope of this research. However, there is a growing literature in the fields of sociology and psychology, which deal with such important issues (Buchmann and DiPrete 2006; Sackett et al. 2009; Furnham et al. 2013). Finally, compared to males, females also exhibit advantages in terms of graduation lags. Overall, their average lag is 2.94 semesters, while males' value is 3.43 semesters. Females perform better than males in eight out of eleven programs. Therefore, females start college with higher admission scores, graduate from college with better grades and complete their degrees faster than males.

<<Place Tables 2-3, and Figure 1 here>>

Table 3 shows that on average private schools students start college with admission scores greater than those obtained by public schools students (two points). Nevertheless, in seven out of eleven programs, public school students start college with admission scores greater than those exhibited by private school ones. Furthermore, in five out of these seven programs, public school students' GGPAs are greater than those obtained by their counterparts from private schools. Private school students perform better than students from public schools only in terms of the graduation lag. On average, their lag is 2.89 semesters while the lag exhibited by public school students is 3.31 semesters. However, public school students exhibit shorter graduation lags in three programs (Education, Physical Education and Other Programs). Thus, there is no guaranty for parents that the expensive private schools will provide their children with the kind of education that will allow them to outperform students from free public schools in college. The reasons for choosing private schools will be discussed below.

Table 4 compares the GGPA by academic programs at different points and intervals of the graduation lags distribution. A total of 237 (9.85%) students completed the graduation requirements in or before the allotted time ($-1 \leq t^{*} \leq 0$). A second cluster comprised by 303 (12.59%) and 657 (27.3%) students exhibits graduation lags of one and two semesters, respectively. As it should be expected, these three groups of graduates obtained the highest GGPAs. On the other hand, a total of 825 (34.28%) students exhibit graduation lags between three and five semesters, inclusive. Finally, 329 (13.67%) and 56 (2.33%) graduates needed six to eight, and nine or more semesters in order to complete their degrees, respectively. As expected, graduates belonging to these last three clusters obtained the lowest GGPAs. Finally, females constitute the great majority of the graduates who finish their degrees in the allotted time (72%) or whose graduation lags are of one (66%) or two semesters (62%). Thus, two important findings come from Table 4: (a) GGPAs vary inversely with graduation lags, and (b) the existence of graduation lags is obvious and persistent across all the programs, but its incidence is significantly less among females.

<<Place Table 4 here>>

OLS models

Columns one and two of Table 5, display the estimated regression coefficients of Model 1. Graduates from the Engineering Technologies, Electronics, and Materials Management are at disadvantage. Other things being equal, the GGPA expected by a graduate from one of these programs is 0.44, 0.29, and 0.25 points less than the one expected by a graduate from the reference group, respectively. These penalties may be associated with the academic rigor displayed by the faculty or with the inherent difficulty of the curricula. Everything else being equal, the females' expected GGPA is significantly greater than that expected from males. The difference varies between 0.0664 and 0.0753 points. Likewise, the bachelor's degree graduates' expected GGPA is 0.14 points less than the one expected from the associate's degree graduates. This is a relatively high penalty, but the inherent difficulty of these programs' curricula is significantly greater than that of the associate programs.

The linear nature of Models 1 and 2 imply that the marginal effect of such explanatory variables like school of origin, graduate's quality (GAI), as well as student's gender is uniform throughout the distribution of the GGPAs, independently of the bounds where it is evaluated. This aspect will be discussed in the next section, and analyzed in light of the highly nonlinear ordered probability model, which allows for capturing the effect of all these considerations.

The GGPA expected from private school graduates is 0.02 points less than the one expected by public school ones. This result is in accordance with Horowitz and Spector (2005). In their study of the determinants of GPA at Ball State University, they report an insignificant private high school coefficient. They do find a significant religious school coefficient of 0.055, but its effect disappears through time in college. The effect the schools of origin have on the UPR-Bayamón graduates' GGPA is emphasized even more when it is controlled for each of them, for it is found that 223 are statistically significant (Model 2). Such a result implies that the inclusion of those schools incorporate into the analysis other elements of valuable information in the socio-economic conditions that frame the environment from which the graduates come. The evidence suggests that its effect on the academic performance of the graduates is significant and long-lasting, even many years after admission to the UPR-Bayamón.

<<Place Table 5 here>>

It was conjectured that, given the weight of the GAI in the admission process, it should play a significant role as a predictor of graduates' academic success. To shed light on the matter, the coefficient of elasticity of the GGPA with respect to the GAI is computed. Its equation is included in the expression (5):

$$(5) \qquad \varepsilon_{\mathrm{GGPA}_i \to \mathrm{GAI}_i} = \frac{\partial(\mathrm{GGPA}_i)}{\partial(\mathrm{GAI}_i)} \frac{\overline{\mathrm{GAI}}}{\overline{\mathrm{GGPA}}} = \frac{\overline{\mathrm{GAI}}}{\overline{\mathrm{GGPA}}} \left\{ \frac{\hat{\gamma} + \sum_{T=2}^{6} \left(\hat{\beta}_T \cdot T_T \right)}{\sigma_{GAI}} \right\}$$

The main effect $\left(\hat{\gamma} = 0.1847\right)$ is positive and significant, which is consistent with the prior conjecture. However, the interaction coefficients $\left(\hat{\beta}_T\right)$ are all negative, implying that their relative importance as predictors of academic success tends to decrease throughout the temporal trend of entering cohorts.[6]

The exercise described in the above paragraph lacks the limitations inherent to the linear nature of Models 1 and 2. According to Model 1, increases of 1 standard deviation in the GAI (graduates quality proxy) are associated with increases of 0.18 points in the expected GGPA, whether the prediction is made starting from the lower or higher bounds of the distribution. It is assumed that the marginal effect of the variable is the same throughout the entire distribution. Such a condition could be very restrictive and questionable.

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[6] In Model 1, 2 of the estimated interaction coefficients $\left(\hat{\beta}_T\right)$ are insignificant. Nevertheless, a Wald Test rejects the null hypothesis which states that the five coefficients are simultaneously equal to zero, at any specified confidence level.

Quantile models[7]

The estimated quantile regression coefficients reported in Table 6 will shed light on the issue of nonlinearities. In order to compare the coefficients of models 1 and 2 (Table 5) and models 1-5 (Table 6), all seven models were estimated utilizing the same set of covariates. Table 6 reports the quantile regression coefficients estimated at different percentile points: 0.15, 0.25, 0.5, 0.75, and 0.85. For space limitations, only a few of the covariates included in Table 5 are reported in Table 6. The private high school variable is significant only in the neighborhood of the percentiles 75 and 85. Its signs and estimated coefficient values are consistent with prior results reported in Table 5. On the other hand, female and GAI covariates are highly significant and nonlinear. Other things being equal, the GGPA expected by females is significantly greater than that expected by males. The difference varies from 0.052 to 0.077, depending on the percentile utilized as reference. Once again, the estimated coefficients are very similar to those reported in Table 5; however, they allow for capturing the nonlinearities of the variable throughout the grades' distribution.

At percentile 15 and for the first cohort's graduates, an increment of 1 standard deviation in GAI will increase the expected GGPA by 0.14 points. The value of the estimated coefficient changes along the distribution depending on the percentile of reference and reaches its maximum (0.203) at the percentile 75. A high proportion (88%) of the estimated interaction coefficients $\left(\hat{\beta}_T\right)$ is negative, which implies that the effect of GAI on GGPA tends to decrease across time. Nevertheless, only 32% of them are significantly different from zero.

<<Place Table 6 here>>

Maximum likelihood models

To overcome the linear model limitations, this section re-evaluates the results of some of the relations discussed utilizing an ordered probability model. The fact that females and public school graduates exhibit higher GGPAs than those obtained by males and private school graduates was documented previously. Econometrics results from *OLS*, quantile and probit models demonstrate the robustness of such empirical findings. Nevertheless, based only on these statistical results, their adequacy could be questioned. For example, one could conjecture the existence of a self-sorting process by gender, school of origin, the quality of students (GAI) and the inherent difficulty of the courses included in the curricula of the selected academic programs. If it were the case that the males (females) from private (public) schools of

[7] The standard reference in this field is Koenker (2005).

greater quality applied mainly for admission in more (less) competitive programs and of greater (less) inherent difficulty, such as the Engineering Transfer, Biology, Electronics, Computer Sciences or Accounting, then the most probable results would be those reported by the statistical models.

The estimated coefficients of Model 3 (Table 5) provide a simple mechanism for verifying this self-sorting conjecture's adequacy. It should be emphasized that the marginal effect of dummy variables (gender, high school type, and academic programs) over the probability that the GGPA will lie in any of the five rankings of the distribution should be estimated through simulations since their qualitative character lessens the validity of the computation of partial derivatives. Utilizing the coefficients of Model 3 (Table 5) and the sub-routine "Make a Model" supported by EViews package, the expected GGPA was computed using different scenarios. Each scenario considers the effect of gender, academic programs, and GAI. These simulations categorically confirm that the probability of performance in the upper (lower) bounds of the GGPA distribution demonstrated by females, as well as that by public school graduates is greater than that demonstrated by males and graduates from private schools, respectively.[8] The estimated differences by gender and by school of origin are significant, ranging upwards of seven to nine percentage points (pp). When simulating the effects of the different academic programs and for the different values of the GAI, it is demonstrated that the results are robust and invariant to the inherent difficulty of the curricular content of the academic program of graduation, as well as to the quality of the graduates. Also, the differences by gender are invariant to the nature of the school of origin and vice versa.[9] These results are at odds with the prior self-sorting conjecture.[10]

The simulations mechanism was used to isolate the quality of the graduates based on their probability of performance in the different bounds of the GGPA distribution. The results of the simulations are reported in Table 7. In this exercise, graduates are assumed to have completed their bachelor's degree in the allotted time ($t^* < 1$) and belong to the first class of the studied period (T_1), while all other variables were evaluated at their reference group or mean values. An increase of 1 standard deviation in the GAI will increase the probability of the expected performance in the higher bounds of the grade distribution (GGPA $\geq$ 3.75) by 25 pp, while decreases of equal magnitude will reduce this probability by 12 pp. Meanwhile, increases of 2 standard deviations will increase this probability by 45 pp, while decreases of equal

[8] In Model 3, Table 5, private school coefficient variable is not statistically different from zero.

[9] The simulations of the effect of the changes in the quality of the graduates utilizing deviants of one and two standard deviations from the mean of the GAI were done simultaneously in each of the academic programs considered.

[10] The simulation results are not reported, but they are available upon request.

magnitude would reduce it to practically zero. The probability of the GGPAs of the other four rankings varies inversely in relation to the quality of the graduates. Thus, the probability of performance in the lower bounds of the GGPAs distribution (GGPA ≤ 2.49) is reduced to 50% (from 0.02 to 0.01) if the quality of graduates increases in 1 standard deviation, while a decrease of such magnitude would have the effect of increasing this probability by 100% (from 0.02 to 0.04). Therefore, the magnitude and direction of the GGPA responses to the changes in the quality of graduates would depend on the relative position in the GGPA distribution where it is evaluated. The specificity of these results cannot be obtained with the linear models that were previously discussed.

GGPA behavior over the temporal trends

The three estimated models reported in Table 5, allow for the study of the GGPA's evolution on the two temporal tendencies utilized in the study: T_T and t^*. Models 1 and 2 allow for examining whether or not the evidence is consistent with the presence of inflation in the GGPAs distribution. Such a phenomenon would exist if the GGPA would tend to increase throughout time without a concomitant increase in the quality of graduates.[11] Hence, it was required that the partial derivative of expression (6) be positive:

$$(6) \qquad \frac{\partial(\mathrm{GGPA}_i)}{\partial T_T} = \hat{\psi}_T + \hat{\beta}_T \cdot \mathrm{GAI}_i$$

The estimated coefficients $\hat{\psi}_T$ are positive and significant (except $\hat{\psi}_2$), while all the interaction coefficients $\left(\hat{\beta}_T\right)$ are negative. The pattern of signs of the $\hat{\psi}_T$ coefficients is consistent with GGPA inflation, since they tend to increase over the temporal trend of the new incoming classes even after controlling for the quality of the graduates. This conclusion is reinforced given that the GAI variable is standardized. Therefore, the GGPA inflation is increased within the subset of graduates whose quality (GAI) is less than the mean. Thus, the GGPAs of the academically less advantaged students tend to increase faster than that of the more advantaged ones. If, with the aim of recruiting, retaining and/or graduating more students, the academic programs make the academic standards more flexible, then the most probable result would be GGPA inflation, particularly among those graduates who are academically less advantaged than the mean.

[11] For a literature review refer to Hu (2005), Johnes (2004) and Johnson (2003).

It is a different story when the temporal reference corresponds to the semesters in excess of the time required to complete the degree ($t^{*}=$ graduation lag). In the case of the linear Models 1 and 2 (Table 5), all the estimated coefficients $\left(\hat{\phi}_t\right)$ are negative and significant. This result implies that the decision to prolong studies at the UPR-Bayamón is not a good strategy since the GGPA tends to decrease as students exceed the minimum time required for graduation. It is unclear if the GGPA tends to diminish because the graduates exceed the minimum time required for graduation or if they delay the graduation date because they have not satisfied the minimum academic requirements necessary for graduation. To shed light on this point, the expected GGPA value was simulated in each of the rankings in Model 3 (Table 5) and the results are included in the graphs displayed in Figure 2. It is evident that only the probability of the GGPA of the lower bounds of the distribution tends to increase as the graduates exceed the required time for graduation. Therefore, graduation candidates will fall into the lower bounds of the GGPA distribution to the extent they exceed the minimum time required for graduation. These results come from Model 3 (Table 5), a highly nonlinear one.

<<Place Table 7 and Figure 2 here>>

Qualifications

The preceding analysis is based on several caveats. First, the information utilized comes from a single campus (UPR-Bayamón) and is limited to only six cohorts. Thus, the results reported in this study could not be generalized to the whole UPR system, even when the other campuses utilize the same admission criterion (GAI). On the other hand, there is a selectivity problem because only the academic performance of the successful students (the graduates) is observed. That is, the utilized sample does not represent all the students who were originally admitted to the UPR-Bayamón because by design all those who did not complete at least an associate degree were excluded.

Second, the respective proportions of students graduated from public and private high schools in Puerto Rico are, approximately, 80 and 20%. However, the odds of 8:2 favoring public high school graduates vanishes while in college since, representing only 20% of the high school graduates, private high school students occupy 45% of the new admissions granted by the UPR-Bayamón and constitute 54% of their graduates. Thus, a significant proportion of public high school graduates did not even consider the possibility to apply for college admission. These proportions raised serious equity and social justice considerations that should be studied in detail in future research projects.

Although it is true that the prior discussion throughout the paper has been highly influenced by the author's economic jargon and own opinions; it is not less true the fact that the conclusions derived from the collected, discussed and analyzed data have serious and evident implications and concerns across all fields of the social sciences. Its analysis should be the object of future research.

4. Summary

The objective of this study was to model the GGPA of the UPR-Bayamón graduates belonging to six classes admitted from 1995-96 to 2000-01. The GGPA expected by females is significantly greater than the one expected by males. This result is invariant with respect to the inherent difficulty of the academic program of graduation, the high school of origin, or the quality of the graduates. In addition, public high school graduates exhibit advantages in terms of the expected GGPA when compared to private school ones.

This result is counterintuitive, since it is very difficult to explain why parents would be willing to incur in usually fairly large expenses to finance their children's private education, even though this would mean putting them at a disadvantage in comparison to students of the free public school education system. Given its empirical nature, the question regarding how high the differences induced by private education should be to justify the investment expense made by parents has yet to be answered. Therefore, the existence of differences equal to zero or negative contrast with the rational assumption by parents whose children study in private high schools.

Such a result opens up an array of conjectures. A possible explanation would lie in that the parents identify other desirable attributes in private education not related to quality, relevance, quantity or the pertinence of knowledge added in students and/or how well students are prepared for university studies in selective institutions. Parents might be interested in exposing their children to particular educational settings where they would only share with classmates from a certain social or economic level.[12] Also, one should consider the possibility that many parents choose private education because of physical safety or institutional control over the conditions of the academic settings where their children study. Schools could also be chosen according to their orientation or religious preference, even when this would undermine the quality of the provided education. Perhaps parents have private information regarding the intellectual quality of their children and send them to private

[12] Unlike the United States, in which the academic quality and the social and economic level of public school students greatly varies according to the neighborhoods in which these schools are located, in Puerto Rico the great majority of students in private schools are from affluent or middles class families, while those of the lower middle and working class families constitute the majority of public school students.

schools because it is the only system where they would have a real probability of graduating. This suggests that there might be some self-selection issue here. For example, parents might have access to information that allows them to sort private schools according to admission requirements in order to maximize the probabilities of academic success for their children. These and other possible explanations should be the object of future studies.

The empirical evidence demonstrates that the GGPA is directly, significantly and highly nonlinearly related to the GAI. This index defines the official admission criterion of the UPR-Bayamón and constitutes the best proxy of the graduates' quality. Nevertheless, the nonlinear nature of the relationship implies that the effect of graduate's quality would depend on the distribution bounds of the GGPAs where they are evaluated. Therefore, it would be impossible to detect using linear models, as has been the norm in this type of study. Finally, upon analyzing the behavior of the GGPA on the two temporal references utilized in the study, the results obtained tend to complement each other. The GGPA exhibits an upward and significant tendency over the temporal trend of the new incoming classes consistent with the grade inflation phenomenon. However, the GGPA varies inversely with the graduate's quality (GAI). Such a result points to the possibility of reductions in the academic standards by the programs and departments with the aim of recruiting, retaining and graduating more students (Matos-Díaz 2012). Evidence documented in this study points to the conclusion that the probability of grades in the lower bounds of the GGPAs distribution increases to the extent that graduates exceed the time required for graduation.

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Table 1: Variables description

Variable	Description	$\bar{X}$	σ	Máx.	Mín.
Accounting	1, if Accounting	0.1235	0.3291	1	0
Business	1, if Business	0.2328	0.4227	1	0
Computer	1, if Computer Science	0.0919	0.2889	1	0
Education	1, if Education	0.1120	0.3155	1	0
Electronics	1, if Electronics	0.0856	0.2798	1	0
Engineering	1, if Engineering Technologies	0.0292	0.1685	1	0
Material Mg.	1, if Materials Management	0.0261	0.1594	1	0
Biology	1, if Biology	0.0870	0.2819	1	0
Physical Ed.	1, Physical Education	0.0539	0.2259	1	0
Office Systems	1, if Office Systems	0.1082	0.3107	1	0
Other Programs	1, if Other Programs	0.0418	0.2001	1	0
Gender	1, if Female	0.6193	0.4856	1	0
High School	1, if Private HS	0.5383	0.4986	1	0
Bachelor	1, if Bachelor Degree	0.1698	0.3755	1	0
T_t	Temporal trend	3.3580	1.6696	11	1
T_1	1, if cohort is 1995-96	0.1795	0.3839	1	0
T_2	1, if cohort is 1996-97	0.1785	0.3830	1	0
T_3	1, if cohort is 1997-98	0.1740	0.3792	1	0
T_4	1, if cohort is 1998-99	0.1740	0.3792	1	0
T_5	1, if cohort is 1999-00	0.1604	0.3670	1	0
T_6	1, if cohort is 2000-01	0.1336	0.3402	1	0
GAI	UPR General Application Index	287.13	36.104	385	110
GGPA	Graduation Grade Point Average	3.06	0.3901	4.00	2.04
HSGPA	High School GGPA	3.37	0.4617	4.00	0.29
y_i^G	Ordered GGPAs	1.74	1.01	4	0
t^*	Graduation Lags (semesters)	3.11	2.29	16	-1
$t^* = 0$	1, if lag ≤ 0	0.0994	0.2993	1	0
$t^* = 1$	1, if lag = 1	0.1257	0.3316	1	0
$t^* = 2$	1, if lag = 2	0.2716	0.4449	1	0
$t^* = 3$	1, if lag = 3	0.1216	0.3269	1	0
$t^* = 4$	1, if lag = 4	0.1664	0.3725	1	0
$t^* = 5$	1, if lag = 5	0.0567	0.2313	1	0
$t^* = 6$	1, if lag = 6	0.0813	0.2734	1	0
$t^* = 7$	1, if lag = 7	0.0279	0.1648	1	0
$t^* = 8$	1, if lag = 8	0.0263	0.1600	1	0
$t^* = 9$	1, if lag ≥ 9	0.0230	0.1500	1	0

$\bar{X}$ = arithmetic mean; σ = standard deviation; Max. = maximum; Min. = minimum

Table 2: GAI, GGPA and graduation lags by gender and academic programs

	Females				Males			
Academic Programs	GAI	GGPA	$\overline{t}^*$	*n*	GAI	GGPA	$\overline{t}^*$	*n*
All Programs	287	3.11	2.94	1518	288	2.95	3.43	889
Accounting	307	3.28	2.93	187	306	3.17	2.86	91
Business	289	3.05	2.81	370	283	2.91	3.48	189
Computer	307	3.20	2.59	54	301	3.06	3.2	166
Education	277	3.17	3.19	265	267	2.77	7.75	4
Physical Education	250	3.01	2.88	64	253	2.96	2.93	61
Electronics	314	3.07	2.78	9	289	2.84	3.81	189
Engineering Technologies	284	2.77	4.54	13	265	2.68	3.65	55
Materials Management	282	2.87	3.35	26	270	2.77	4.55	44
Biology	306	3.12	2.67	165	301	3.13	2.67	55
Office Systems	268	2.99	2.87	279	284	2.90	3	1
Other Programs	296	3.21	3.37	86	299	3.17	3.35	34
				1518				889

Notes: *n* = sample size, $\overline{t}^* =$ average graduation lag (semesters).

Table 3: GAI, GGPA and graduation lags by high-school and academic programs

	Public High Schools				Private High Schools			
Academic Programs	GAI	GGPA	$\overline{t}^*$	*n*	GAI	GGPA	$\overline{t}^*$	*n*
All Programs	286	3.05	3.31	1302	288	3.05	2.89	1105
Accounting	305	3.23	3.25	134	307	3.27	2.59	144
Business	288	3.03	3.36	236	286	2.99	2.8	323
Computer	304	3.08	3.19	125	301	3.12	2.87	95
Education	280	3.19	3.2	161	273	3.14	3.34	108
Physical Education	253	3.03	2.81	67	250	2.94	3.02	58
Electronics	290	2.83	4.14	140	292	2.88	2.88	58
Engineering Technologies	267	2.68	4.0	39	271	2.71	3.59	29
Materials Management	273	2.78	4.5	40	277	2.86	3.57	30
Biology	307	3.10	3.01	93	304	3.14	2.42	127
Office Systems	268	3.02	2.8	206	266	2.88	3.07	74
Other Programs	299	3.21	3.51	61	296	3.18	3.22	59
				1302				1105

Notes: *n* = sample size, $\overline{t}^* =$ average graduation lag (semesters).

Table 4: GGPA by academic programs and graduation lags

Program	$-1 \le t^* \le 0$	$t^* = 1$	$t^* = 2$	$3 \le t^* \le 5$	$6 \le t^* \le 8$	$t^* \ge 9$
Accounting	3.50 (41)	3.32 (55)	3.23 (58)	3.14 (77)	3.20 (38)	2.90 (9)
Business	3.28 (92)	3.06 (83)	3.00 (108)	2.95 (164)	2.84 (100)	2.67 (12)
Computer Science	3.49 (13)	3.41 (33)	3.16 (75)	2.93 (71)	2.81 (22)	2.82 (6)
Education	3.45 (8)	3.31 (32)	3.26 (75)	3.12 (125)	2.92 (23)	2.70 (6)
Physical Education	3.38 (4)	3.30 (8)	3.10 (48)	2.89 (56)	2.71 (9)	N/A
Electronics	3.41 (13)	3.11 (14)	2.88 (61)	2.72 (54)	2.76 (49)	2.57 (7)
Engineering Technologies	3.43 (1)	2.56 (1)	2.73 (26)	2.62 (28)	2.71 (8)	2.66 (4)
Materials Management	3.09 (3)	3.50 (3)	2.93 (20)	2.69 (25)	2.73 (15)	2.57 (4)
Biology	3.37 (39)	3.37 (14)	3.22 (68)	2.97 (77)	2.83 (20)	2.90 (2)
Office Systems	3.41 (8)	3.19 (46)	3.08 (99)	2.82 (102)	2.75 (22)	2.68 (3)
Other Programs	3.57 (15)	3.29 (14)	3.47 (19)	3.13 (46)	2.88 (23)	2.63 (3)
Total	237	303	657	825	329	56
Females	72%	66%	62%	66%	52%	48%
Males	28%	34%	38%	34%	48%	52%

Note: Sample sizes are in parentheses.

Figure 1: High-school and UPR-Bayamón GGPA by gender

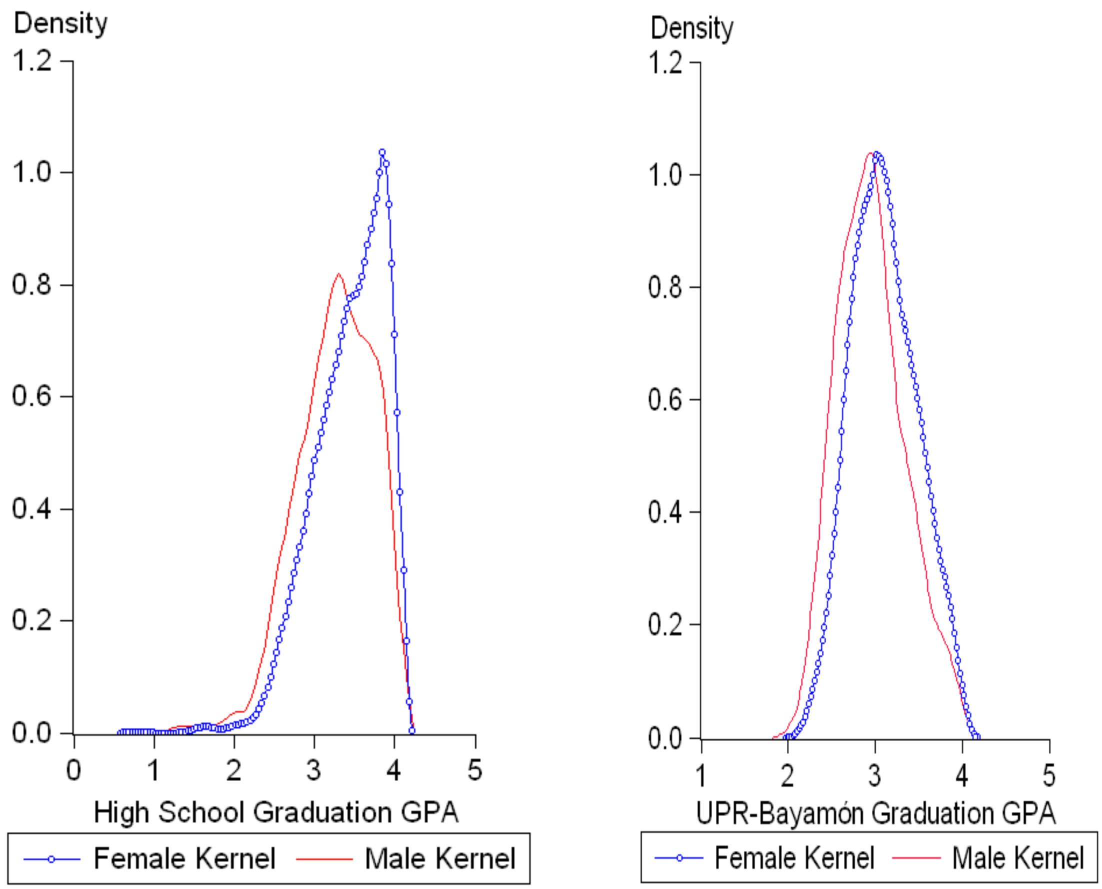


Table 5: Determinants of GGPA

Variables	Model 1	Model 2	Model 3
Constant	3.49**		
	(0.0421)		
Biology	-0.1452**	-0.1251**	-0.4854**
	(0.0338)	(0.0363)	(0.1203)
Electronics	-0.2909**	-0.2749**	-1.0194**
	(0.0382)	(0.0422)	(0.1381)
Computer Science	-0.1107**	-0.1035**	-0.4137**
	(0.0361)	(0.0383)	(0.1274)
Accounting	-0.0310	-0.0261	-0.1395
	(0.0352)	(0.0376)	(0.1227)
Business	-0.1873**	-0.1787**	-0.6384**
	(0.0320)	(0.0344)	(0.1110)
Materials Management	-0.2475**	-0.2488**	-0.7630**
	(0.0434)	(0.0454)	(0.1639)
Engineering Technologies	-0.4395**	-0.4100**	-1.3713**
	(0.0529)	(0.0548)	(0.1877)
Education	0.0559†	0.0620†	0.0596
	(0.0334)	(0.0355)	(0.122)
Physical Education	0.0025	0.0203	-0.0813
	(0.0388)	(0.0425)	(0.14)
Office Systems	-0.1365**	-0.1343**	-0.4211**
	(0.0354)	(0.0383)	(0.1234)
Baccalaureate	-0.1424**	-0.1333**	-0.4082**
	(0.0234)	(0.0243)	(0.0845)
Female	0.0664**	0.0753**	0.1733**
	(0.0158)	(0.0174)	(0.0566)
Private High School (PHS)	-0.0214†		-0.0427
	(0.0127)		(0.0471)
GAI	0.1847**	0.1776**	0.6119**
	(0.0151)	(0.0165)	(0.0604)
$t^* = 1$	-0.1230**	-0.1285**	-0.3906**
	(0.0277)	(0.0289)	(0.1028)
$t^* = 2$	-0.2112**	-0.2178**	-0.6518**
	(0.0246)	(0.0255)	(0.0947)
$t^* = 3$	-0.3113**	-0.3165**	-0.9850**
	(0.0282)	(0.0294)	(0.1105)
$t^* = 4$	-0.3614**	-0.3600**	-1.1856**
	(0.0265)	(0.0279)	(0.1042)
$t^* = 5$	-0.3949**	-0.3845**	-1.242**
	(0.0334)	(0.0345)	(0.1296)
$t^* = 6$	-0.4165**	-0.4128**	-1.3969**
	(0.0318)	(0.0338)	(0.1215)

Table 5: Continued

$t^* = 7$	-0.5258**	-0.5407**	-1.8481**
	(0.0393)	(0.0413)	(0.1572)
$t^* = 8$	-0.4899**	-0.4815**	-1.5151**
	(0.0442)	(0.0452)	(0.1812)
$t^* = 9$	-0.5500**	-0.5346**	-1.7727**
	(0.0468)	(0.0501)	(0.187)
T_2	-0.0098	0.0008	0.0434
	(0.0227)	(0.0242)	(0.0829)
T_3	0.0482*	0.0512*	0.1644*
	(0.0214)	(0.0224)	(0.078)
T_4	0.0511*	0.0586**	0.2212**
	(0.0212)	(0.0230)	(0.079)
T_5	0.0502*	0.0531*	0.1557*
	(0.0211)	(0.0228)	(0.0772)
T_6	0.0328	0.0435†	0.1604*
	(0.0223)	(0.0243)	(0.0830)
$\text{GAI} \cdot T_2$	-0.1302**	-0.1177**	-0.4415**
	(0.0208)	(0.0224)	(0.0784)
$\text{GAI} \cdot T_3$	-0.0195	-0.0072	-0.0797
	(0.0212)	(0.0222)	(0.0808)
$\text{GAI} \cdot T_4$	-0.0434*	-0.0320	-0.2048*
	(0.0219)	(0.0235)	(0.0867)
$\text{GAI} \cdot T_5$	-0.0204	-0.0072	-0.0506
	(0.0197)	(0.0210)	(0.0746)
$\text{GAI} \cdot T_6$	-0.0407†	-0.0195	-0.1832*
	(0.0210)	(0.0224)	(0.0804)
Limit points			
μ_1			-3.2466**
			(0.1874)
μ_2			-1.4882**
			(0.1759)
μ_3			-0.5024**
			(0.1728)
μ_4			0.7479**
			(0.1718)
$\bar{R}^2$	0.41	0.43	
Pseudo *R*-square			0.16
"log likelihood"			-2,791
Sample sizes	2,407	2,407	2,407

Notes: **†, *, **** = Statistically significant at the 0.10, 0.05 and 0.01 level, respectively. Standard errors are in parentheses. Models 1 and 2 utilize White heteroskedasticity-consistent standard errors and covariances. Model 3 utilizes QML (Huber/White) standard errors and covariances. GAI variable is standardized. Model 2 also control for the unobservable effects of 223 high school of origin.

Table 6: Determinants of GGPA: Quantile regression

	Model 1	Model 2	Model 3	Model 4	Model 5
Variable	(τ = 0.15)	(τ = 0.25)	(Median)	(τ = 0.75)	(τ = 0.85)
Constant	3.05*	3.15**	3.34**	3.60**	3.74**
	(0.065)	(0.052)	(0.055)	(0.062)	(0.07)
Female	0.059*	0.077**	0.067**	0.059**	0.052*
	(0.023)	(0.023)	(0.019)	(0.023)	(0.024)
PHS	0.006	-0.009	-0.012	-0.045**	-0.036*
	(0.019)	(0.017)	(0.017)	(0.017)	(0.017)
GAI	0.14*	0.147**	0.168**	0.203**	0.20**
	(0.036)	(0.024)	(0.017)	(0.023)	(0.021)
$\text{GAI} \cdot T_2$	-0.118*	-0.118**	-0.119**	-0.138**	-0.134**
	(0.042)	(0.031)	(0.026)	(0.028)	(0.028)
$\text{GAI} \cdot T_3$	-0.021	-0.015	-0.025	-0.008	0.029
	(0.039)	(0.03)	(0.025)	(0.029)	(0.024)
$\text{GAI} \cdot T_4$	-0.029	-0.022	-0.025	-0.056†	-0.037
	(0.041)	(0.037)	(0.028)	(0.03)	(0.031)
$\text{GAI} \cdot T_5$	0.004	0.001	-0.019	-0.038	-0.018
	(0.044)	(0.034)	(0.025)	(0.028)	(0.026)
$\text{GAI} \cdot T_6$	-0.015	-0.02	-0.024	-0.049†	-0.066**
	(0.05)	(0.034)	(0.025)	(0.03)	(0.027)
Pseudo R-squared	0.22	0.22	0.25	0.28	0.29
Sample sizes	2407	2407	2407	2407	2407

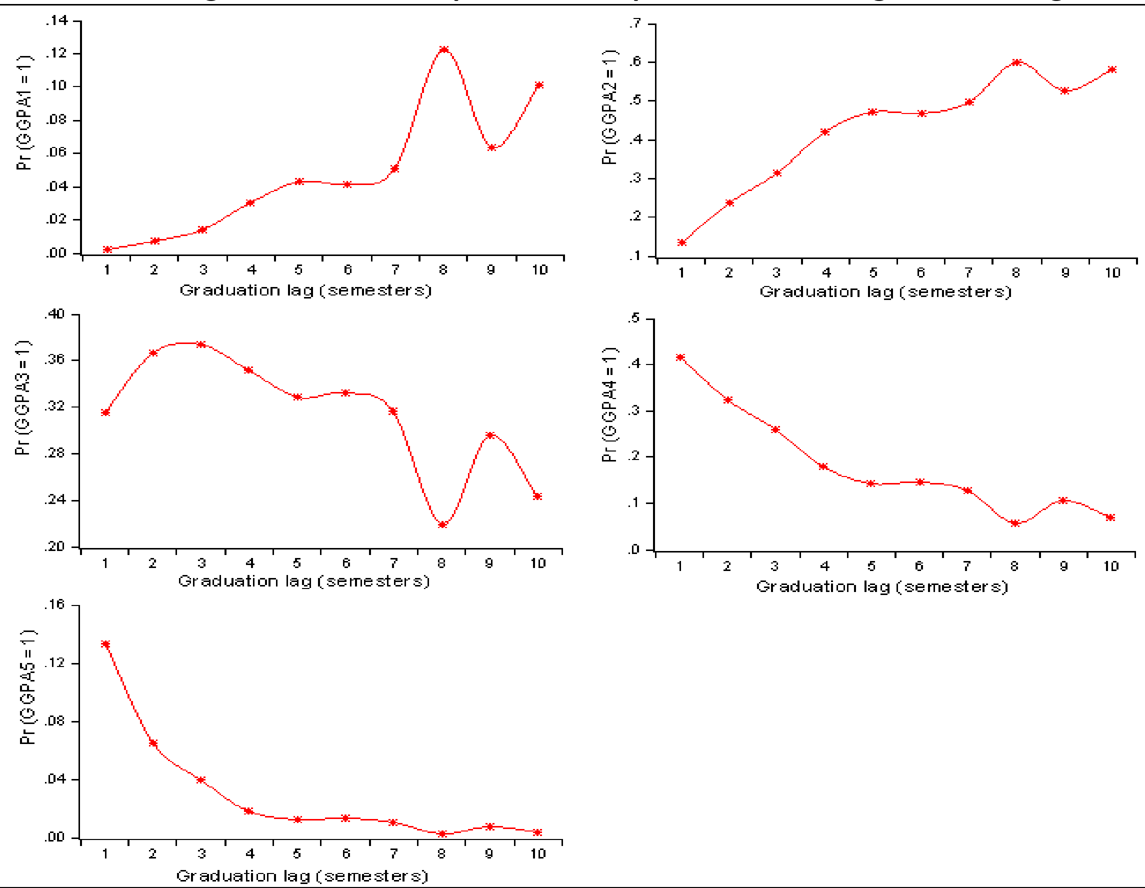
Notes: **†, *, **** = Statistically significant at the 0.10, 0.05 and 0.01 level, respectively. Standard errors are in parentheses. GAI variable is standardized. Models also control for academic programs, graduation lags, bachelor's degree, and temporal trend.

Table 7: GGPA's response to changes in graduate's quality (GAI)

Standard deviations from the mean	Expected GGPA					
	GGPA1	GGPA2	GGPA3	GGPA4	GGPA5	Total
$\Delta\sigma_{(GAI)} = -3$	0.141181	0.664838	0.182852	0.011127	0.000015	1
$\Delta\sigma_{(GAI)} = -2$	0.076180	0.498038	0.329639	0.095212	0.000931	1
$\Delta\sigma_{(GAI)} = -1$	0.040414	0.318458	0.345682	0.269025	0.026421	1
$\Delta\sigma_{(GAI)} = 0$	**0.021249**	**0.185356**	**0.263347**	**0.379241**	**0.150808**	**1**
$\Delta\sigma_{(GAI)} = 1$	0.011120	0.102395	0.167912	0.345096	0.373478	1
$\Delta\sigma_{(GAI)} = 2$	0.005805	0.054999	0.097268	0.243090	0.598838	1
$\Delta\sigma_{(GAI)} = 3$	0.003026	0.029106	0.053553	0.148611	0.765704	1

Notes: $GGPA1 \leq 2.49$, $2.50 \leq GGPA2 \leq 2.99$, $3.00 \leq GGPA3 \leq 3.32$, $3.33 \leq GGPA4 \leq 3.74$, $GGPA5 \geq 3.75$. Simulations come from model 3, Table 2, and were performed under the assumption that $T_t = 1$ and $t^* \leq 0$, while all other variables were evaluated at their mean values.

Figure 2: Relationship between expected GGPA and graduation lag



Simulations come from Model 3, Table 4, and are based on the first cohort $(T_T = 1)$, while all other variables are evaluated at their mean values.