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Increased Learning or GPA Inflation? Evidence from GPA-Based University Admission in Chile

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A student's ranking in the grade point average (GPA) distribution has emerged as an admission variable that increases admission rates of both segregated minorities and high-performance individuals. In 2012, Chile's centralized university admission system introduced a GPA ranking variable relative to the previous cohorts' average GPA. Such a system introduces academic incentives to exert effort, but also to inflate GPA. In this paper, we analyze the effects of that reform on the GPA distribution and achievement measures. Our results, based on difference-in-differences and simulated instruments methods, suggest that: (i) GPA increased across the entire distribution, independently of the incentive structure; and (ii) GPA increases were unrelated to improvements in achievement. We interpret the results as evidence that the introduction of the new variable caused GPA inflation rather than increased learning.

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Increased Learning or GPA Inflation? Evidence from GPA-Based University Admission in Chile

Eduardo Fajnzylber[*], Bernardo Lara[†], Tomás León V.

April 23, 2018

Abstract

A student's ranking in the grade point average (GPA) distribution has emerged as an admission variable that increases admission rates of both segregated minorities and high-performance individuals. In 2012, Chile's centralized university admission system introduced a GPA ranking variable relative to the previous cohorts' average GPA. Such a system introduces academic incentives to exert effort, but also to inflate GPA. In this paper, we analyze the effects of that reform on the GPA distribution and achievement measures. Our results, based on difference-in-differences and simulated instruments methods, suggest that: (i) GPA increased across the entire distribution, independently of the incentive structure; and (ii) GPA increases were unrelated to improvements in achievement. We interpret the results as evidence that the introduction of the new variable caused GPA inflation rather than increased learning.

Keywords: College admissions; Rankings; Incentives; Moral hazard.

JEL: H32, I21, I24, I28, J24.

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1 Introduction

In the United States, a major focus of higher education policy has been to increase the enrollment rates of racial minorities, particularly at flagship institutions. To achieve this goal, higher education institutions introduced explicit affirmative action policies. However, in some cases (e.g., *Hopwood v. Texas*, 1996; *Johnson v. University of Georgia*, 2001), courts have declared such policies unconstitutional. In response, policymakers have changed admission criteria to include observable variables that are correlated with academic skills, but independent of race or family income.

For example, after the ruling of *Hopwood v. Texas*, Texas introduced for all its public universities guaranteed admission to students with GPAs within the top 10% of each high school.[1] Given that Texas high schools have high racial segregation, within-school ranking would be a performance indicator uncorrelated with race or family income (Cortes, 2010). However, the introduction of such policies can have effects beyond admissions: on the one hand, ranking-based admission increases the marginal reward of studying and thus might increase learning; on the other hand, it can incentivize strategic behavior to manipulate the ranking variable (Cullen et al., 2013).

In this paper, we study the effects of a similar nationwide admission policy on high school students' academic performance in Chile. Although Chile is largely racially homogeneous (Alesina et al., 2003), socioeconomic status (SES) is an especially strong determinant of achievement in a country with high SES segregation across schools (Mizala and Torche, 2012). Meanwhile, university admission is based on the *Prueba de Selección Universitaria* (PSU) admission exam, which replicates the SES segregation pattern and results in highly unequal access to flagship institutions. For example, 37.7% of the 2011 entering class at *Universidad de Chile*, the flagship public univer-

[1] In *Fisher v. University of Texas at Austin* (2016), the court upheld affirmative action for admission of students below the top 10%.

sity, came from unsubsidized private schools,[2] where students from top decile income families represent the largest share by far of enrollment (Mizala and Torche, 2012). Even higher numbers are observed at *Pontificia Universidad Católica de Chile*, the flagship private university, where 65.9% of the 2011 entering class came from private unsubsidized schools.

It is this unequal access to flagship institutions, in addition to the financial pressure that tuition fees put on families, that precipitated the 2011 Chilean students' movement for education reform.[3] One of the policy responses to the student movement was the introduction of within-school GPA ranking in the admission criteria of the main public and private universities. In particular, the new admission criteria increased the importance of high school GPA and introduced a score bonus to reward students with GPAs exceeding the average GPA of their high school's last three graduating cohorts.

The potential effects of such a policy can be summarized in three hypotheses. First, the new criteria may increase incentives for students to study harder, which should result in higher achievement. Second, the new criteria may increase schools' incentives to engage in strategic behavior, such as artificially inflating grades to increase their students' university admission rates. Third, the new criteria may induce strategic behavior by students in their choice of high school. In this paper, we provide empirical evidence about the first two hypotheses. Using a difference-in-differences identification strategy, we observe that a cohort exposed for three years to the new admission criteria increases its 12th grade GPA by about 0.164 points, or 30.7% of a Chilean GPA standard deviation. Later, we use simulated instruments to test if the marginal incentives, in the form of a marginal score bonus for a subset of students in the GPA distribution, produce different effects. Our findings do not show evidence

[2]Source: *Consejo Nacional de Educación - Indices* database, available at https://www.cned.cl/indices/ficha-institucional-individual-anos-2007-2016.

[3]See With Kiss-Ins and Dances, Young Chileans Push for Reform (New York Times, 2011).

of differences in GPA increases within a cohort. Instead, they show that the GPA increase took place across the entire cohort.

To test whether the GPA increase may be due to increased learning, we investigate whether GPA increases predict changes in standardized test scores or university admission exam taking rates or performance. None of these achievement indicators show any significant correlation with the GPA increase, suggesting that the GPA increase is due to grade inflation rather than increased learning. In consequence, these results suggest that schools have adjusted grading strategically in response to the new university admission criteria.

The paper is organized as follows. Section 2 describes the Chilean university admission system. Section 3 reviews the literature related to ranking-based admission. Section 4 provides a simple conceptual framework to understand students' decisions under the new admission criteria. Section 5 describes the data and methodologies used in the paper. Sections 6 and 7 provide the estimated effects of the new admission criteria on GPA and achievement, respectively. Section 8 concludes.

2 University admission in Chile

2.1 Background

To apply to universities in Chile, students submit an ordered list of their selected program-university combinations to a centralized and transparent system, which fills the available spaces with the applicants with the highest application scores.[4] The main variable in the application score is the *Prueba de Selección Universitaria* (PSU) university admission exam score, which is similar to the SAT exam of the United States. PSU scores range from 150 to 850 points, with an average of 500 points and a

[4] For further details about the application system, see Hastings et al. (2013).

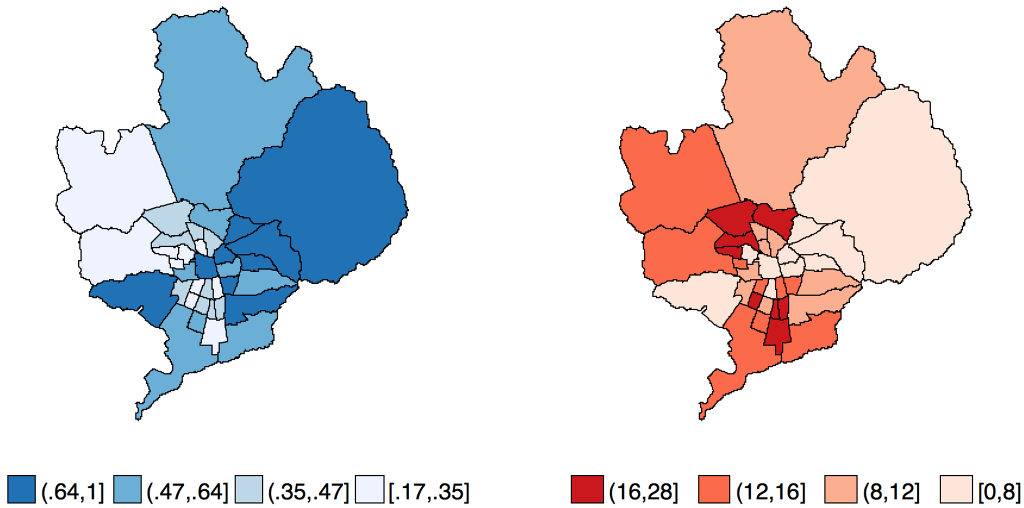
standard deviation of 110 points. Every student applying for university admission is required to take the two PSU core tests (Math; and Language and Communications) and at least one of two PSU subject tests (Science; and History, Geography, and Social Sciences). Before 2012, universities assigned every applicant an application score based solely on PSU scores and high school GPA, usually weighted at an 80:20 ratio, respectively.

However, one problem of PSU-based admission is the high correlation between PSU scores and family income. To illustrate this, Figure 1(a) shows the geographical distribution of 2010 PSU results, defined as the probability of scoring above 450 points,[5] across municipalities in the city of Santiago. As we can see, there is much geographical segregation in PSU performance. In most eastern municipalities, more than 64% of students score above 450 points. Meanwhile, less than 35% of students in many western and central-southern municipalities score above 450 points. As shown in Figure 1(b), municipal segregation patterns in PSU performance align with municipal poverty rates. The higher scoring eastern municipalities have lower poverty rates (at most 8%), while the lower scoring western and central-southern municipalities have higher poverty rates (at least 16%). In sum, geographic segregation in PSU performance mirrors geographic segregation in income, showing that PSU scores are strongly correlated with family income.

In response to Chilean students' demand to break the link between family income and university admission, the *Consejo de Rectores de las Universidades Chilenas* (CRUCH) announced in 2012 a variant of GPA ranking for introduction to the admission criteria beginning in 2013. As in Texas, such a change should increase the admission rates of disadvantaged groups, without explicitly using SES as an admission criterion (Cortes, 2010). In addition, there is evidence that high school GPA

[5] A minimum score of 450 is required to apply to CRUCH institutions (the most traditional universities) and to qualify for government student aid. For more details, see Solis (2017).

Figure 1: PSU performance and poverty rates across municipalities in Santiago, Chile, 2010.



(a) Probabilities of PSU score≥450

(b) Poverty rates

Source: *Ministerio de Educación* and *Ministerio de Desarrollo Social*, Chile.

ranking is a good predictor of university performance (Contreras et al., 2009, 2017). As a result, the introduction of high school GPA ranking to the admission criteria was regarded as a good policy by both government and students representatives.

2.2 The Chilean GPA ranking score

As mentioned above, the main state and private universities, which comprise CRUCH, introduced a high school GPA ranking score to the 2013 admission criteria. While universities' admission criteria have always included GPA in application scores, with weights ranging between 20% and 40% across programs, the new 2013 admission criteria set a 10% weight to a new GPA ranking score (Demre, 2012). Given the competitive structure of the Chilean university admission system, such a percentage is enough to make the GPA ranking score important in university admission.

There are important differences to note between the US and Chilean definitions of GPA ranking. First, as policymakers did not want to induce competition between classmates (Gil et al., 2013), the Chilean GPA ranking score is a function of the average GPA of a high school's three previous graduating cohorts (historical average) rather than the current graduating cohort.[6] Second, the function translating Chilean GPA to application scores is not a step function, as in the case of Texas. Instead, GPA in Chile translates to a ranking score $r(x)$ that is the sum of:

1. A linear function $z(x)$ that converts GPA to a score ranging from 150 points for a 4.0 GPA (the minimum passing grade) to a maximum of 850 points for a 7.0 GPA (a perfect score);[7] and

2. A score bonus $b(x)$, which is defined as:

   (a) $b(x) = 0$, if the student's GPA is below the historical average ($\bar{x}_{previous}$);

   (b) $b(x) > 0$, if the student's GPA is above the historical average and below the average GPA of the three previous valedictorians ($\mathbf{Max}(x_{\text{previous}})$); or

   (c) $b(x) = 850 - z(x)$, if the student's GPA is above the average GPA of the three previous valedictorians ($\mathbf{Max}(x_{\text{previous}})$), which results in a perfect ranking score ($r(x) = 850$).

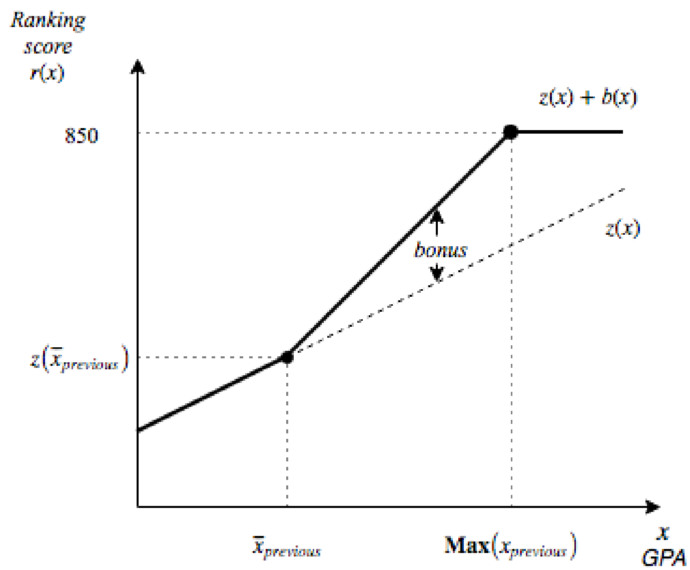
To illustrate the ranking score scheme, Figure 2 shows the relationship between GPA and the ranking score. The score bonus is the distance between the solid $z(x)+b(x)$ ranking score line and the dashed $z(x)$ line. Consequently, the closer the historical average and the maximum GPA are, the greater the marginal score bonus is. As we can see, such a scheme encourages schools to engage in strategic behavior in the form of GPA inflation, but also provides an extra incentive to students with GPAs

[6]Later, this was changed to the three previous cohorts' graduates from all high schools where the student was enrolled (González and Johnson, 2018).

[7]For a conversion table showing how GPA is converted to an application score, see *Tabla Transformación NEM.*

above the historical average to exert effort, which allows us to analyze the effects of variations in the marginal incentives.

Figure 2: Ranking score scheme.



3 Literature review

The literature examining ranking-based admission programs focuses mainly on Texas' Top 10% GPA university admission policy. Despite its popularity, Cortes (2010) shows that the top 10% admission policy was unable to replicate the benefits of affirmative action policies to underrepresented minorities, particularly among minority individuals below the top 10% that would have been admitted under affirmative action policies. Meanwhile, Cullen et al. (2013) provide evidence of strategic choice of high schools to enter the top 10% GPA group. Similarly, Cortes and Friedson (2014) provide evidence of real estate price increases near low-performing schools being driven by demand for increased probability of university admission.

There is less literature about the effects of GPA ranking-based admission on achievement. If GPA captures student effort better than admission exam scores, then

GPA-based criteria will provide greater incentive to exert effort than exam-based criteria. Cortes and Zhang (2011) provide evidence that Texas' top 10% admission policy had incentive effects on students' school performance; that is, increases in effort among students in low-performing schools exceeded increases in effort among students who would have been admitted regardless of the policy. The authors also found that students from low-performing schools took less challenging upper-level courses.[8]

Related literature examines the effects of financial incentives on achievement. Kremer et al. (2009) find that financial incentives to score in the top 15% on academic exams had positive effects on achievement as well as positive externalities to non-incentivized students. Meanwhile, Bettinger (2012) finds significant positive effects from financial incentives on math test scores, but not on other subjects. In New York, Chicago, and Dallas, Fryer Jr (2011) finds little effect on state test scores from financial incentives to read books and improve test scores and classroom grades, despite multiple experimental interventions. Finally, Hirshleifer (2015) finds that financial incentives to increase inputs generate greater achievement gains than incentives to increase outputs, which suggests that students' myopic behavior makes GPA-based admission more incentivizing to effort than test score-based admission.

With regard to Chile, Contreras et al. (2017) evaluate a 2007 CRUCH policy that gave special admission to students with GPAs in the top 5% of each high school who scored within 5% of the application score cutoff. Using a regression discontinuity design, they find that these special admission students performed well academically, in terms of retention, due to non-cognitive skills. In consequence, they suggest that the GPA ranking-based criterion would achieve equity goals without efficiency costs.

In analyzing the effects of the introduction of the ranking score, González and Johnson (2018) present descriptive evidence of high school GPA increases relative

[8] Song (2017) provides evidence of increases in students' school performance due to a policy in China guaranteeing high school admission to the top 10% GPA students in each middle school.

to the GPA at the last middle school grade level. They also find little evidence of strategic school choice, observing that each year only 0.7% of students switched schools to increase their application scores. Thus, the authors conclude that strategic behavior by students or their parents has not been prevalent thus far.

In sum, the literature provides some support to the idea that incentives might result in higher achievement and strategic school choice. However, little has been written about strategic behavior by schools.

4 Conceptual framework

In order to formalize the effects of the new admission criteria, this section introduces a simple model of a student deciding for what GPA x to study. First, We assume that the student has a skill θ, such that an effective study effort of $1/\theta$ delivers one GPA point. In addition, we assume that: (1) the probability of admission $P(x)$ is only a function of the GPA x; (2) the expected utility given admission is v_H; and (3) the expected utility given non-admission is v_L. Thus, the student's expected utility is:

$$u(x,\theta) \equiv P(x) \cdot v_H + (1 - P(x)) \cdot v_L - \phi\left(\frac{x}{\theta}\right) \tag{1}$$

where $\phi(\cdot)$ is the disutility of effective study effort. For the problem to have a simple solution, we need $\phi(\cdot)$ to be convex and $P(x)$ to be increasing (higher GPA improves admission probabilities) and concave. Also, we assume that $v_H > v_L$, so that enrollment is always preferred given admission.

As we know, the optimal decision of the student is characterized by the first order condition. Therefore, the student should equalize the increase in the expected utility due to a marginal increase in GPA, with the marginal disutility of study effort:

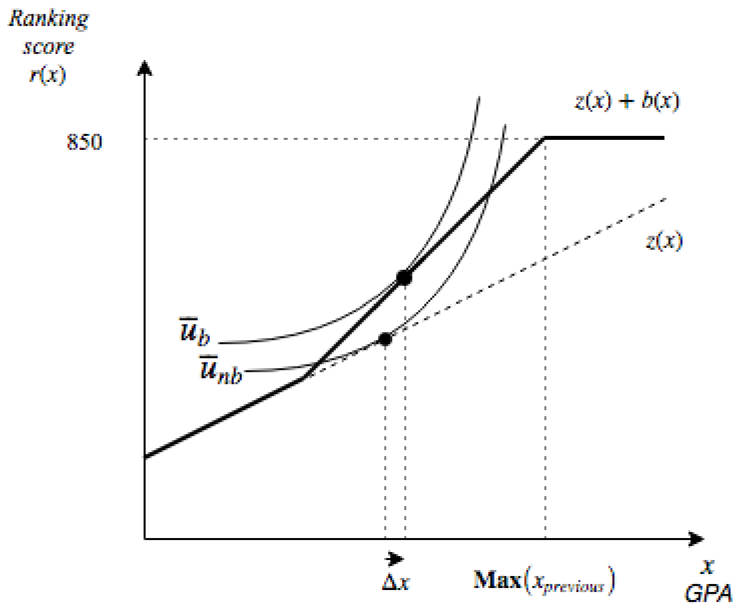
$$P'(x) \cdot (v_H - v_L) = \frac{1}{\theta} \cdot \phi'\left(\frac{x}{\theta}\right) \tag{2}$$

This simple result summarizes the idea that students should change their behavior with the marginal incentives, which in this case is $P'(x) \cdot (v_H - v_L)$. As the introduction of the ranking score increases $P'(x)$, we expect that the new admission criteria induce more student effort and, therefore, higher achievement.

To analyze the consequences of the unusual Chilean policy assigning application score bonuses to students with GPAs above the historical average, Figure 3 presents the optimal choice for a student whose GPA exceeds the historical average, with and without the score bonus. Similar to a graph of income before and after tax, Figure 3 shows that individuals have a preference for the ranking score (vertical axis), but to increase it they must exert effort represented by the GPA (horizontal axis). Meanwhile, a government schedule annually assigns ranking scores to GPAs within each high school. Without the score bonus, the schedule would be $z(x)$, but with the score bonus, the schedule is $z(x)+b(x)$. The student should choose the point where the indifference curve, which increases utility upward to the left, is tangent to the government schedule. That point is in the indifference curve $\bar{u}_{nb}$ for a schedule without the score bonus, and in the indifference curve $\bar{u}_b$ for the real schedule with the score bonus. If the substitution effect dominates the income effect (which is equal to increases in admission probabilities diminishing effort), we can expect that the presence of the score bonus increases GPA by Δx.

If we assume that $P'(x) = \alpha$ is in the neighborhood of a point x_0 and that the values of α vary in the data, then we can estimate the relationship between α and x. In other words, we can estimate the elasticity of GPA with respect to marginal academic incentives.

Figure 3: Student decision under different GPA-ranking score schedules.



5 Data and methodology

The first goal of the empirical analysis is to estimate the effect that the introduction of the ranking score had on high school GPAs. However, since it is possible that GPAs change due to inflation rather than increased student effort or learning, a second goal is to look at the relationship between GPA increases and changes in other achievement measures. To achieve that goal, we relate at an aggregate (municipality) level the effects of the policy with the changes, between the years 2010 and 2014, on the 10th grade universal standardized test (SIMCE) and PSU admission exam results. For that purpose, this section will describe the data, provide graphical evidence of the effects, and discuss the methodological approach.

5.1 School Data

To measure students' school performance, we use publicly available administrative data on students that graduated high school in Chile between 2011 and 2014, including all year-end individual GPAs after 7th grade for the period 2007 to 2014, linked to basic individual-level demographic information. In the analysis, we use the 8th grade (last middle school grade) GPA to construct a pre-ranking measure of individual performance. Then, we use the change in GPA in each grade between 8th and 12th as a dependent variable. Finally, the school identifier can be used to add school-level information, such as the ranking parameters, the type of school (public, private subsidized, or private non-subsidized), geographic location (urban or rural) and a general measure of socioeconomic status (SES).

Table 1 shows basic statistics on the main variables used in the empirical analysis. We have around 730,000 students at each grade level, associated with 2.9 million annual observations.[9] The average GPA (on a scale of 1 to 7) is slightly above 5.5, with a standard deviation around 0.535. Public and private subsidized schools are similarly represented in the database (43% and 51% of the total, respectively). Of the students, 34.5% are tagged as low SES, almost half are male, and 3.6% come from rural schools.

Given our interest in measuring the changes in the GPA used to apply for university admission, a number of filters were applied to the original dataset. In addition to requiring a balanced panel, we dropped any individuals with contradictory data and any years in which a student did not pass (the GPAs of which are excluded from university application GPAs in Chile).[10]

To diminish potential bias from individuals that strategically choose high schools, we only use data from individuals that had already entered high school at the time of the policy announcement. In addition, González and Johnson (2018) estimate that the use of the ranking score for university admission induced a during-high school

[9]The working database represents a balanced panel, with students observed in all 4 years of high school.

[10]More details about the data cleaning are presented in Appendix Table A.1. The graphical analysis with the full sample is in Appendix Figure A.3.

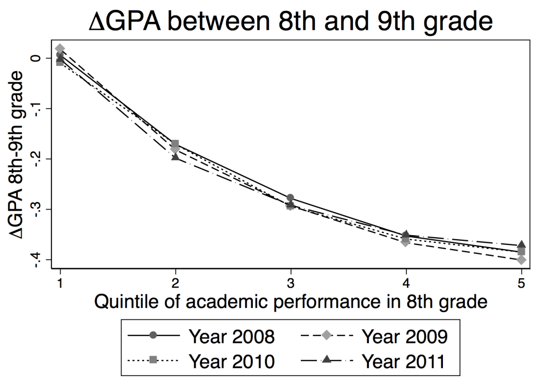
Table 1: Summary statistics.

Variable	Mean	Std. Dev.	N
Ranking score in place	0.382	0.486	2,906,544
9th grade GPA	5.492	0.534	726,636
10th grade GPA	5.537	0.535	726,636
11th grade GPA	5.557	0.535	726,636
12th grade GPA	5.654	0.548	726,636
Dummy year 2008	0.063	0.243	2,906,544
Dummy year 2009	0.126	0.332	2,906,544
Dummy year 2010	0.188	0.391	2,906,544
Dummy year 2011	0.241	0.427	2,906,544
Dummy year 2012	0.19	0.392	2,906,544
Dummy year 2013	0.128	0.334	2,906,544
Dummy year 2014	0.064	0.245	2,906,544
Public school	0.434	0.496	2,906,544
Private school, subsidized	0.512	0.5	2,906,544
Private school, non-subsidized	0.054	0.227	2,906,544
Low SES student	0.345	0.475	2,906,544
Male student	0.478	0.5	2,906,544
Rural school	0.036	0.187	2,906,544

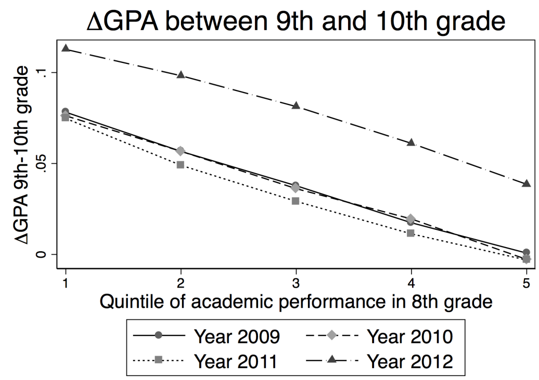
migration of only 0.7%. Given the low prevalence of during-high school ranking-induced migration and the difficulty in identifying ranking-induced migration versus migration for other reasons, we do not drop individuals that have migrated schools after entering high school.

The theoretical model suggests that the introduction of the ranking score could affect the performance of all students, but especially of those who have a pre-ranking GPA between the average and maximum GPA of the three previous graduating cohorts. To graphically evaluate its effect over the GPA distribution, we categorize students by their 8th grade GPA quintile within the same school and cohort. Figure 4 shows the average change in yearly GPA (with respect to the previous grade level) as a function of the year and 8th grade GPA quintile. We include 4 years of analysis per grade level, which corresponds to students that should graduate between 2011 and 2014. Because the ranking score was announced in 2012, only observations after that year could be affected by the policy; those include the GPAs of 10th grade students in 2012, 11th grade students in 2012-2013, and 12th grade students in 2012-2014.

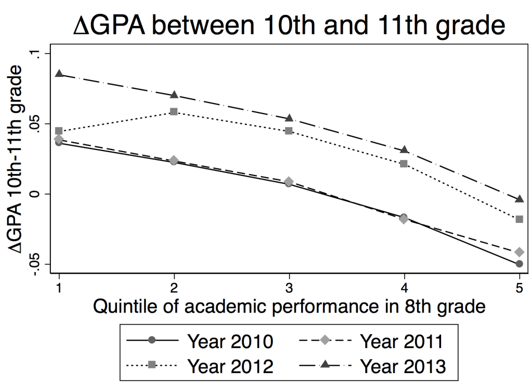
Figure 4: Change in yearly GPA by 8th grade GPA quintile, years 2008-2014.



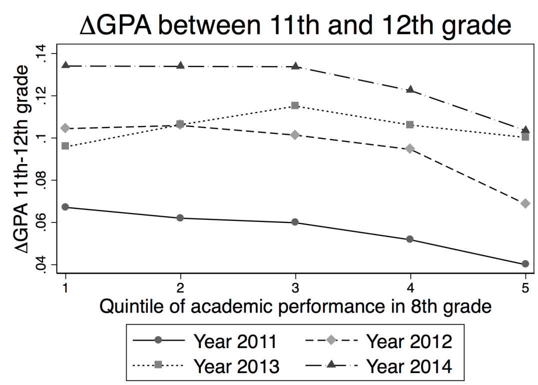
(a) Between 8th and 9th grade



(b) Between 9th and 10th grade



(c) Between 10th and 11th grade



(d) Between 11th and 12th grade

A number of patterns appear from this graphical analysis. First, Figure 4(a) shows that, in general, GPA decreases when entering high school, especially among students in the upper part of the GPA distribution. More importantly, the change in yearly GPA between 8th and 9th grade appears essentially the same for the 4 cohorts under analysis in 2011 before the ranking score was announced. A second pattern is that after 9th grade, GPA increases over time for almost all quintiles in all years. However, the most salient observation from Figure 4 is that the GPA increases are higher after the announcement of the ranking score in 2012. In other words, the graphical analysis suggests that the introduction of the ranking score had positive effects on GPA. In fact, the observed effect seems to be similar over the entire GPA distribution. Even if the quintiles are an imperfect measure of the student's position relative to the mean and maximum GPA at the end of high school, we would have expected greater effects in the upper half of the distribution. We will further pursue this finding in the empirical analysis.

5.2 Empirical methodology

Typically, we could use a simple difference-in-differences estimation model with cohort and grade level fixed effects, such as:

$$\Delta GPA_{ilt} = \alpha_0 + \delta \cdot P_{lt} + \pi_l + \nu_t + \varepsilon_{il} \tag{3}$$

where i represents the individual, l represents the grade level, t represents the cohort, and P_{lt} is a "ranking score in place" dummy variable.

However, formalizing the graphical analysis in Figure 4 requires the inclusion of dummies $Q_i^1 - Q_i^5$ for each quintile of 8th grade academic performance.

$$\Delta GPA_{ilt} = \alpha_0 + \sum_{q=1}^{5} (\delta_q \cdot P_{lt} \cdot Q_i^q) + \sum_{q=1}^{5} (\pi_{ql} \cdot Q_i^q) + \nu_t + \varepsilon_{il} \tag{4}$$

This model includes a joint quintile/grade level fixed effect π_{ql}, which captures the average change in GPA before the ranking score, at grade l, for quintile q of 8th grade academic performance. Meanwhile, the interaction term $P_{lt} \cdot Q_i^q$ indicates whether the ranking score is in place for quintile q, and accordingly, coefficient δ_q estimates the effect of the ranking score introduction for each quintile q.

As suggested in Section 4, greater marginal incentives may result in greater GPA increases. To test that hypothesis, we estimate models that include the marginal incentive faced by each student, which we measure as the marginal score bonus that a student would receive if she increased her GPA slightly. The model includes a single post-reform dummy (P_{lt}), a set of quintile dummies (Q_i^q), and the extra marginal incentive that the student faces (B_{il}). We also control for individual level covariates with dummies (X_{il}), such as for low SES, gender, and the enrolled school type (public, private subsidized, or private non-subsidized):

$$\Delta GPA_{ilt} = \alpha_0 + \delta \cdot P_{lt} + \beta \cdot B_{il} + \sum_{q=1}^{5} (\pi_{ql} \cdot Q_i^q) + \nu_t + \Theta' X_{il} + \varepsilon_{il}. \tag{5}$$

Given that the introduction of the ranking score affects all students, the coefficient δ estimates the average effect of the policy among students that do not face a marginal score bonus. Meanwhile, the coefficient β estimates whether changes in the marginal score bonus (the slope of $b(x)$ in Figure 3) induce changes in GPA. If marginal incentives are indeed effective, as shown in Figure 3, then β will be positive.

Nevertheless, our OLS estimates of Equation 5 are potentially biased, since students might endogenously choose their marginal incentives by changing their GPAs[11] or by switching high schools. Therefore, we also estimate two-stage least squares (2SLS) models using as an instrument a simulated marginal score bonus based on the ranking score formula, the 8th grade GPA (which is not part of the ranking score), and the average and maximum GPAs of the student's 9th grade high school (chosen before ranking scores were announced). The advantage of such a simulated instrument is that it is based on variables that should not be affected by the posterior introduction of the ranking score. With those variables at hand, we calculate the simulated marginal score bonus in the following steps:

1. **Simulate the high school GPA**: Using the 8th grade GPAs and assuming

[11] This is similar to the problem of endogeneity of marginal income tax rates after labor supply adjustments.

that GPAs evolve like they did for the 2011 cohort (before rankings were announced), we simulate the GPAs of the $2012-2014$ cohorts in the 9th, 10th, 11th, and 12th grade levels.

2. **Simulate the ranking score**: We use the simulated GPAs and the ranking score formula based on the parameters of the student's 9th grade high school to calculate simulated ranking scores.

3. **Simulate the marginal score bonus**: Finally, we calculate the simulated marginal score bonus as the difference between the simulated marginal incentives with and without the score bonus.

In sum, we build a simulated instrument that represents the extra incentives a student in the bonus area faces before she makes adjustments.[12] Therefore, the identification comes from the student's initial GPA and the particular ranking parameters (her school's average and maximum historical GPA) that she faces. Finally, we must note that the main assumption of our 2SLS estimator is that the simulated instrument is orthogonal to the error term, given the 8th grade GPA.[13] Therefore, we include the quintile dummies Q_i^q to control for the student's normal level of effort or ability.

5.3 Standardized tests

Figure 4 shows that the introduction of the ranking score affected GPA, and its effects appear homogeneous across the GPA distribution. Such a result is consistent with a general increase in student effort after the introduction of the ranking score. However, the result is also consistent with schools inflating GPAs in order to improve their students' prospects, which may also benefit schools in the competitive Chilean

[12] This is similar to the income tax rate that an individual faces before adjusting labor income to a tax rate change.

[13] In other words, we assume that the changes in marginal incentives are exogenous, given previous academic performance.

school market. To disentangle these alternative hypotheses, we analyze the correlation between the GPA increases and the changes in other achievement statistics, since increased student effort should increase achievement, while GPA inflation should not.

As we are not able, with public data, to match individual-level GPA to individual-level achievement measures, we use municipality-level achievement measures and estimate the effects of the ranking score on GPA for each municipality. Specifically, we use achievement results from two standardized tests in the years 2010 (pre-ranking) and 2014 (post-ranking): the 10th grade SIMCE national standardized test (scores) and the PSU university admission exam (take-up rates and scores).[14]

In practice, we use Equation (3) to estimate the average GPA increase in each municipality. Since we want a certain precision in our estimates, we do not include quintile dummies and restrict our analysis to municipalities with at least 250 GPA observations in the sample.[15] As a final step, we use the municipality-level estimates to show both graphical and OLS evidence of the correlation between the ranking score effects on GPA and the variations in SIMCE/PSU achievement measures.

6 Results

In this section, we present estimation results for the two types of analyses described in the previous section: a difference-in-differences estimation of the effect of the ranking score introduction on GPA; and the OLS and 2SLS estimations of the effect of the marginal score bonus incentive on GPA.

[14] The PSU admission exam is taken after graduation and administered on a national level.
[15] Other binding criteria provide similar results.

6.1 Difference-in-differences results

Table 2 presents the OLS results of the difference-in-differences model. In columns (1) and (2), the first row coefficients show the estimated average effect of the ranking score on GPA. Our results suggest that the policy increased GPA, from one year to the next, by approximately 0.054 points.[16] Assuming a GPA standard deviation of 0.535 (Table 1), the estimated effect is equivalent to a yearly increase of 10.1% of a GPA standard deviation. Table 2 also shows that the yearly change in GPA is, on average, smaller for low SES students, male students, and students enrolled in private schools (especially in non-subsidized institutions).

Also in Table 2, columns (3) and (4) show the estimation results with five interaction dummies of the ranking score policy with the within-school quintile of 8th grade GPA, which allows us to examine the heterogeneity in effects. In both specifications, the introduction of the ranking score seems to have increased GPA for students throughout the entire distribution, although with slightly greater effects in the intermediate quintiles. In particular, the last row shows that the hypothesis of homogeneous effects is rejected at a 1% significance level.

Table 3 shows the estimation results of the following re-parameterized version of the difference-in-differences model, which captures the total effect between the 10th and 12th grade levels in a single coefficient β_1:

$$\Delta GPA_{ilt} = \alpha_0 + \beta_1 \cdot P_{lt} \cdot \mathbb{1}_l^{12} + \beta_2 \cdot P_{lt} \cdot (\mathbb{1}_l^{10} - \mathbb{1}_l^{12}) + \beta_3 \cdot P_{lt} \cdot (\mathbb{1}_l^{11} - \mathbb{1}_l^{12}) + \sum_{q=1}^{5} (\pi_{ql} \cdot Q_i^q) + \nu_t + \varepsilon_{il} \quad (6)$$

where the dummy variable $\mathbb{1}_l^g$ indicates whether the grade level l of the observation is equal to g. Most importantly, the coefficient β_1 corresponds to the sum of effects in the 10th, 11th, and 12th grade levels, whereas coefficients β_2 and β_3 estimate the one year effects in the 10th and 11th grade levels, respectively.

[16] Results of similar size, available in Appendix Table A.2, were found with simple grade level dummies, instead of quintile-level interaction dummies.

Table 2: Effect of ranking score introduction on yearly change in GPA, cohorts 2011-2014.

VARIABLES	(1) ΔGPA per grade	(2) ΔGPA per grade	(3) ΔGPA per grade	(4) ΔGPA per grade
Ranking score in place	0.0538***	0.0537***		
	(0.00426)	(0.00426)		
Ranking effect on quintile 1			0.0511***	0.0514***
			(0.00410)	(0.00410)
Ranking effect on quintile 2			0.0562***	0.0565***
			(0.00407)	(0.00406)
Ranking effect on quintile 3			0.0565***	0.0564***
			(0.00428)	(0.00429)
Ranking effect on quintile 4			0.0560***	0.0557***
			(0.00461)	(0.00461)
Ranking effect on quintile 5			0.0495***	0.0488***
			(0.00542)	(0.00542)
Low SES student		-0.0286***		-0.0286***
		(0.00133)		(0.00133)
Male student		-0.0181***		-0.0181***
		(0.00154)		(0.00154)
Private school, subsidized		-0.00682**		-0.00682**
		(0.00315)		(0.00315)
Private school, non-subsidized		-0.0357***		-0.0357***
		(0.00797)		(0.00798)
Constant	-0.373***	-0.361***	-0.373***	-0.361***
	(0.00789)	(0.00852)	(0.00789)	(0.00852)
Observations	2,906,544	2,906,544	2,906,544	2,906,544
R-squared	0.161	0.163	0.161	0.163
Quintile-level dummies	Yes	Yes	Yes	Yes
Cohort dummies	Yes	Yes	Yes	Yes
p-value heterogeneous effects			0.000478	0.000453

Clustered standard errors at the school level in parentheses.
*** p<0.1, ** p<0.05, *** p<0.01.

Finally, Table 3 shows that the estimated 3-year effect is 0.164 GPA points, equivalent to 30% of a GPA standard deviation. This result is robust to the introduction of covariates, as shown in column (2). Since, in the long term, the ranking scores will include all 4 years of high school, we can extrapolate a 4-year effect of 0.219 GPA points, equivalent to 40% of a GPA standard deviation.

Table 3: Effect of ranking score introduction on yearly change in GPA, reparametrized model, cohorts 2011-2012.

VARIABLES	(1) ΔGPA per grade	(2) ΔGPA per grade
Ranking score in place through 3 grade levels	0.165***	0.164***
	(0.0129)	(0.0129)
Treatment 10th - treatment 12th	0.0477***	0.0476***
	(0.00516)	(0.00516)
Treatment 11th - treatment 12th	0.0479***	0.0478***
	(0.00467)	(0.00467)
Low SES student		-0.0286***
		(0.00133)
Male student		-0.0181***
		(0.00155)
Private school, subsidized		-0.00680**
		(0.00315)
Private school, non-subsidized		-0.0357***
		(0.00797)
Constant	-0.371***	-0.359***
	(0.00789)	(0.00852)
Observations	2,906,544	2,906,544
R-squared	0.161	0.164
Quintile-grade dummies	Yes	Yes
Cohort FE	Yes	Yes

Clustered standard errors at the school level in parentheses.
*** p<0.1, ** p<0.05, *** p<0.01.

6.2 Simulated instrument results

In this subsection, we present the estimation results of the effect on GPA of the marginal score bonus incentive, which is the difference between the slopes of the two curves depicted in Figure 2: the slope of $z(x)+b(x)$ minus the slope of $z(x)$. Equivalent to column (2) of Table 2, the first column of Table 4 presents the simple OLS result, which now includes in the first row the marginal score bonus coefficient. Once again, we include in the estimation quintile-grade dummies and cohort fixed effects. Given that the marginal score bonus variable might be endogenous, the second column of Table 4 presents the first stage of the 2SLS estimation, where the dependent variable is the observed marginal bonus and the omitted instrument is the simulated marginal score bonus. Finally, the third column presents the second stage results.

Table 4: OLS and 2SLS effect of the ranking score bonus.

VARIABLES	(1) ΔGPA OLS	(2) Marginal bonus	(3) ΔGPA 2SLS
Marginal score bonus	-0.0389***		-0.00215
	(0.00101)		(0.00296)
Simulated marginal bonus		0.245***	
		(0.00539)	
Ranking score in place	0.0689***	0.276***	0.0546***
	(0.00426)	(0.00466)	(0.00430)
Low SES student	-0.0276***	0.0139***	-0.0285***
	(0.00132)	(0.00183)	(0.00132)
Male student	-0.0178***	0.00432***	-0.0181***
	(0.00154)	(0.00142)	(0.00154)
Private school, subsidized	-0.00707**	-0.00587**	-0.00683**
	(0.00316)	(0.00280)	(0.00315)
Private school, non-subsidized	-0.0363***	-0.0185***	-0.0357***
	(0.00799)	(0.00640)	(0.00797)
Constant	0.0332***	-0.00733***	0.0336***
	(0.00457)	(0.00178)	(0.00456)
Observations	2,906,544	2,906,544	2,906,544
R-squared	0.166	0.217	0.164
Quintile-grade dummies	Yes	Yes	Yes
Cohort FE	Yes	Yes	Yes

Clustered standard errors at the school level in parentheses.
*** p<0.1, ** p<0.05, *** p<0.01.

The OLS estimation suggests that the introduction of the ranking score had a positive effect on GPA, while the marginal score bonus had a negative effect. Specifically, the third row coefficient in column (1) indicates that the introduction of the ranking score is correlated with a yearly GPA increase of 0.0689 points for students outside the marginal score bonus area (low performance students). Meanwhile, the marginal score bonus coefficient suggests that these incentives had negative effects on GPA. Such a result is counterintuitive and may be due to biases in the OLS estimation.

In column (2) of Table 4, the first stage results show that the simulated instrument (second row) is strongly related to the endogenous variable and significant at 1%. In fact, the Cragg-Donald and Kleibergen-Paap weak identification test statistics reject the underidentification hypothesis. As expected, the coefficient of the simulated score bonus suggests that our instrument has a positive relationship with the real score bonus.

In opposition to the OLS results, the 2SLS results (in column 3) are more in line with the expected effect of the reform.[17] We estimate that the introduction of the ranking score increased GPA by 0.0546 points per year, which is significant at 1% and equivalent to 10.2% of a GPA standard deviation. Meanwhile, the marginal score bonus coefficient is close to zero and not significant at 10%, despite the large sample size. The coefficient suggests a GPA decrease of 0.002 points per unit of bonus, which is equivalent to 0.48% of a GPA standard deviation, and thus also insignificant in practice.[18] In conclusion, the main effect comes from the existence of the ranking score, rather than the marginal score bonus incentives for a subset of students.

7 Relationship with other achievement measures

In the previous section, we showed robust evidence of a generalized increase in GPAs due to the introduction of the ranking score, which can be explained by a generalized increase in student effort or grade inflation. To distinguish between those hypotheses, we study the correlation between the increases in GPAs and the changes in achievement measures at the municipality level.

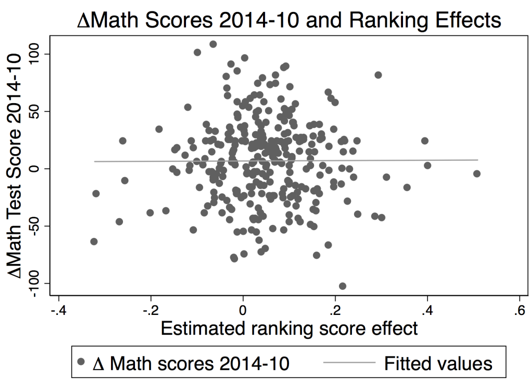
[17] As an alternative way to control for previous performance, Appendix Table A.3 shows similar results with linear controls.

[18] The average marginal score bonus is 1.184 in the range where it is positive, which suggests an effect of -0.002 for the average beneficiary of the bonus.

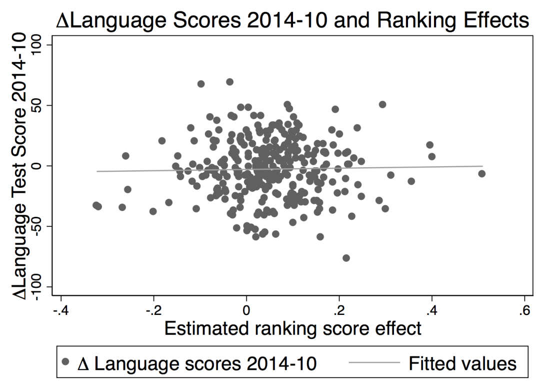
7.1 Effect on standardized test scores

First, we study the correlation between the estimated effects on GPA and the 10th grade national standardized test (SIMCE) scores. Figures 5(a) and 5(b) show scatter plots of the changes in SIMCE (Math and Language) scores and the estimated effect of the ranking score on GPA. The plots show no pattern in the data and simple linear fits show no correlation between variables.

Figure 5: Graphical evidence: ΔTest scores 2014-2010 and effect of ranking score introduction, municipality-level data.



(a) ΔMath test scores



(b) ΔLanguage test scores

The formal OLS analysis is presented in Table 5, where columns (1) and (2) show the estimation results for Language, while columns (3) and (4) show the results for Math. Notice also that specifications (2) and (4) include municipality-level controls for the student-teacher ratio (education quality measure) and 2010 poverty rate (SES measure). In all columns, the correlation between the estimated effect and the change in achievement is positive, but small and non-significant.[19] Therefore, the results indicate that the increases in GPA are not related to increases in achievement; in consequence, they fit better the GPA inflation hypothesis than the increased student effort hypothesis.

[19]Assuming that the average effect of ranking scores on GPA is 0.05 points, the effect on achievement would be 0.32 SIMCE points in Language and 0.16 SIMCE points in Math. The

Table 5: OLS evidence: ΔLanguage and ΔMath test scores 2014-2010 and effect of ranking score introduction, municipality-level data.

VARIABLES	(1) ΔLang 2014-10	(2) ΔLang 2014-10	(3) ΔMath 2014-10	(4) ΔMath 2014-10
Estimated effect in municipality	5.167	6.302	1.654	3.144
	(12.50)	(12.07)	(18.85)	(18.03)
Students per teacher, 2010		1.123***		2.180***
		(0.383)		(0.509)
Poverty rate, 2010		-0.456**		-0.793***
		(0.177)		(0.256)
Constant	-2.920*	-15.99**	6.816***	-20.05*
	(1.511)	(7.908)	(2.275)	(11.23)
Observations	311	311	312	312
R-squared	0.001	0.056	0.000	0.087

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

7.2 Effect on admission exam results

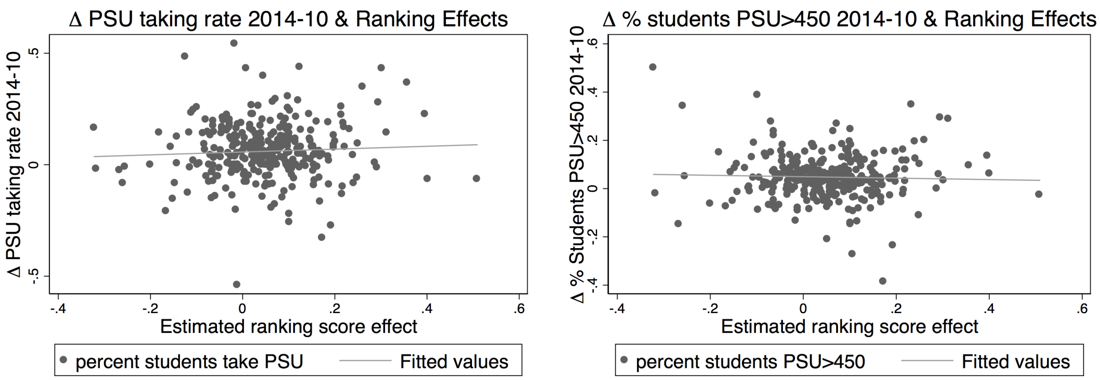
Next, we study the correlation between the estimated effects on GPA and the Chilean university admission exam (PSU) results. The PSU score is the average of the Math and Language component scores on a 150-850 point scale. Given that the PSU is a voluntary exam, we look at two measures of achievement change: the variation in PSU exam taking rate and the variation in the percentage of students scoring above 450 points.[20]

A graphical analysis is presented in Figure 6. Figure 6(a) shows little correlation between the estimated ranking score effect on GPA and the PSU exam taking rate, while Figure 6(b) shows similar results for the percentage of students scoring above 450 points on the PSU. Therefore, the graphical evidence suggests that GPAs increased due to GPA inflation rather than an increase in student effort.

SIMCE test is designed to have a standard deviation around 50 points.

[20] As explained in subsection 2.1, a minimum PSU score of 450 points is required to qualify for student financial aid.

Figure 6: Graphical evidence: ΔPSU admission exam taking rate and performance (2014-10), and effect of ranking score introduction, municipality-level data.



(a) ΔAdmission exam taking rate

(b) ΔPercentage scoring above 450

Finally, Table 6 shows the regression results for the PSU taking rate (columns 1-2) and the percentage of students that scored above 450 points (columns 3-4). Once again, the analysis suggests that the effect of the ranking score on GPA is not correlated with observable increases in alternative achievement measures, since all the relevant coefficients are small and not statistically significant.[21] Hence, we find no evidence of an improvement in the PSU admission exam results, which again suggests that the GPA increase was due to GPA inflation, rather than an increase in student effort.

8 Conclusions

In 2012, Chile announced that it would introduce to its university admission criteria a GPA ranking score variable whose characteristics include a score bonus to students with GPAs exceeding those of the same school's previous cohorts. As the new ranking score variable increases the importance of the student's grade point average (GPA), students are incentivized to exert more effort. However, the variable also incentivizes

[21] Assuming an average effect of 0.05 GPA points, the average effects are 0.29% in the PSU taking rate and -0.16% in the percentage of students scoring above 450 points.

Table 6: OLS evidence: ΔPSU admission exam taking rate and performance (2014-2010) and effect of ranking score introduction, municipality-level data.

VARIABLES	(1) Δ% stud. PSU	(2) Δ% stud. PSU	(3) Δ% stud. PSU>450	(4) Δ% stud. PSU>450
Estimated effect in municipality	0.0642	0.0578	-0.0297	-0.0325
	(0.0750)	(0.0743)	(0.0732)	(0.0733)
Students per teacher, 2010		-0.000339		0.000450
		(0.00192)		(0.00149)
Poverty rate, 2010		0.00196*		0.000676
		(0.00104)		(0.000698)
Constant	0.0570***	0.0298	0.0493***	0.0295
	(0.00765)	(0.0444)	(0.00655)	(0.0352)
Observations	320	320	320	320
R-squared	0.003	0.020	0.001	0.005

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

schools to inflate GPAs to improve their students' prospects for higher education. This paper contributes to the literature by identifying the effects on GPA of the introduction of a GPA ranking score variable in university admission criteria, as well as by disentangling the sources of those effects.

Specifically, we study the evolution of GPA before and after the introduction of the ranking score and analyze whether the changes in GPA correlate with changes in standardized achievement measures at the municipality level. Our main findings are three: (i) the introduction of the ranking score produced a yearly increase in GPA equivalent to 10.1% of a GPA standard deviation; (ii) the increase in GPA takes place throughout the entire GPA distribution, independently of the different incentives faced by individuals; and (iii) the GPA increase, when aggregated at the municipality level, is not correlated with improvements in other achievement measures. We believe all of these findings indicate that some schools opted to artificially inflate student GPAs, with no visible increases in student effort or learning.

While our results do not imply that the policy was unsuccessful in granting good students in poor schools a better chance to attend university, they do call attention to the potential for manipulation on the part of the high school when non-standardized measures of performance, such as GPA, are used in university admission criteria.

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Appendix

Figure A.1: 8th grade GPA by quintile (last grade level without university admission consequences), cohorts 2011, 2012, 2013, and 2014.

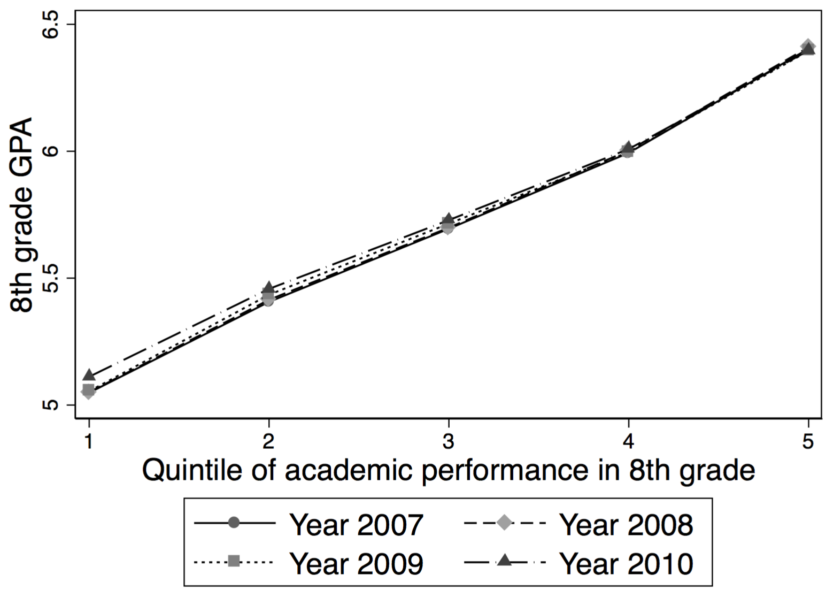
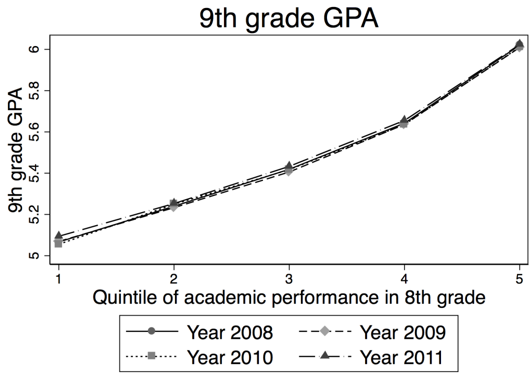
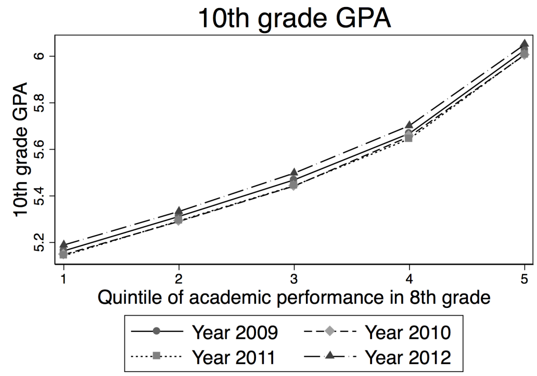


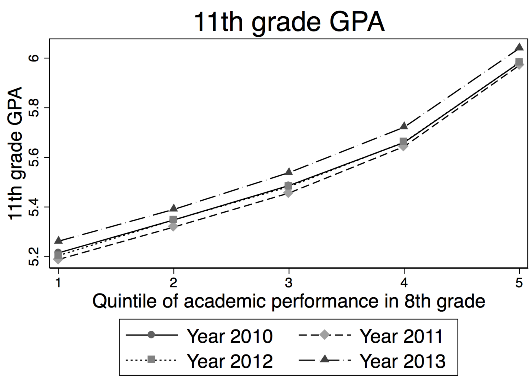
Figure A.2: Yearly GPA by quintile, cohorts 2011, 2012, 2013, and 2014.



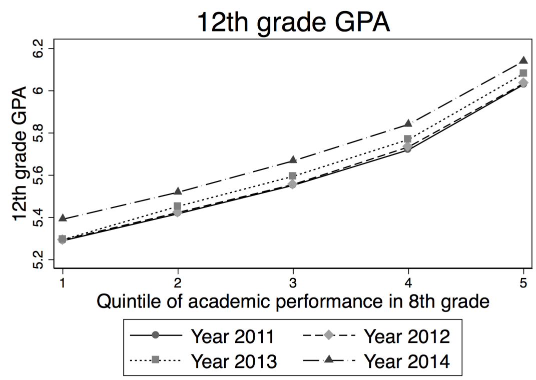
(a) 9th grade



(b) 10th grade



(c) 11th grade



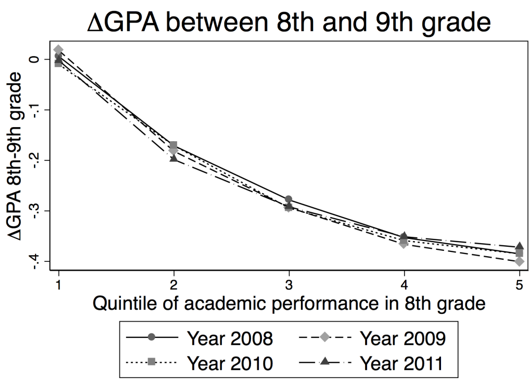
(d) 12th grade

Table A.1: Filters applied to the data.

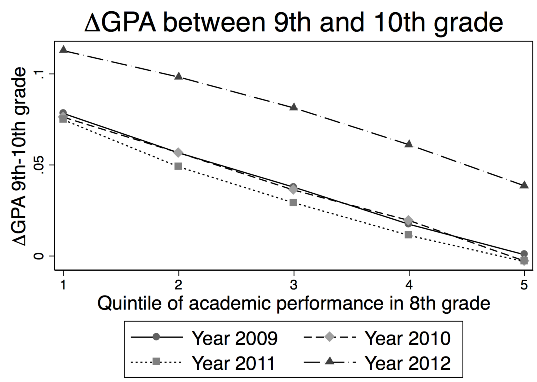
Sample	Individuals	Annual observations
Original sample: Students finishing high school between 2011 and 2014, one observation per level	1.064.269	3.638.991
Sample after restricting to balanced panel (5 observations per individual)	755.770	3.023.080
Sample after dropping any years in which a student did not pass* and individuals with contradictory level data	726.637	2.906.544

*GPAs from repeated levels are excluded from university application GPAs in Chile.

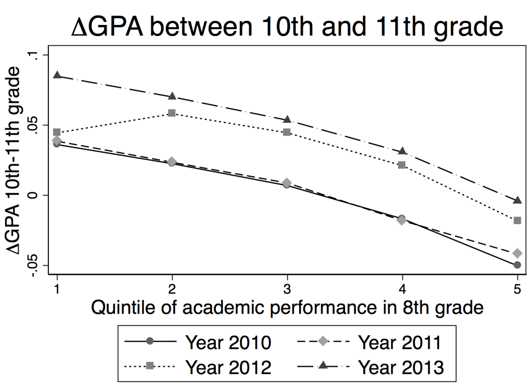
Figure A.3: Yearly change in GPA by quintile, years 2008-2014, full sample.



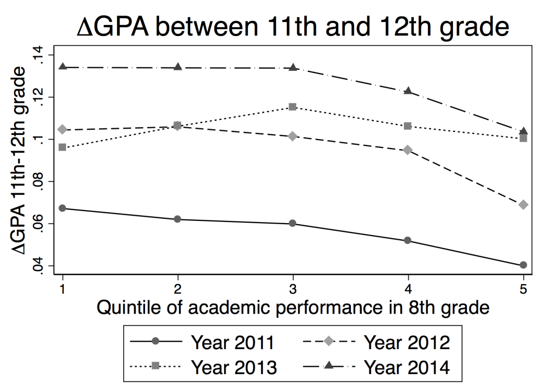
(a) Between 8th and 9th grade



(b) Between 9th and 10th grade



(c) Between 10th and 11th grade



(d) Between 11th and 12th grade

Table A.2: Effect of ranking score introduction on yearly change in GPA, estimation with simple grade level dummies, cohorts 2011-2014.

VARIABLES	(1) ΔGPA per grade	(2) ΔGPA per grade
Ranking score in place	0.0466***	0.0467***
	(0.00252)	(0.00427)
10th grade	0.280***	0.280***
	(0.00540)	(0.00551)
11th grade	0.243***	0.243***
	(0.00634)	(0.00663)
12th grade	0.307***	0.307***
	(0.00609)	(0.00682)
Cohort 2012		0.00447***
		(0.00126)
Cohort 2013		0.00663***
		(0.00215)
Cohort 2014		0.0115***
		(0.00320)
Low SES student		-0.0245***
		(0.00145)
Male student		-0.00627***
		(0.00170)
Private school, subsidized		-0.00860**
		(0.00369)
Private school, non-subsidized		-0.0407***
		(0.00900)
Constant	-0.246***	-0.234***
	(0.00545)	(0.00666)
Observations	2,906,544	2,906,544
R-squared	0.125	0.126

Clustered standard errors at the school level in parentheses.
*** p<0.1, ** p<0.05, *** p<0.01.

Table A.3: OLS and 2SLS effect of ranking score bonus including linear controls for 8th grade GPA.

VARIABLES	(1) ΔGPA OLS	(2) Marginal bonus	(3) ΔGPA 2SLS
Marginal bonus	-0.0389***		3.87e-05
	(0.00100)		(0.00287)
Simulated marginal bonus		0.248***	
		(0.00543)	
Ranking score in place	0.0691***	0.276***	0.0539***
	(0.00410)	(0.00462)	(0.00413)
Low SES student	-0.0291***	0.0153***	-0.0302***
	(0.00122)	(0.00170)	(0.00123)
Male student	-0.0189***	0.00372***	-0.0191***
	(0.00154)	(0.00143)	(0.00155)
Private school, subsidized	-0.00684**	-0.00606**	-0.00660**
	(0.00312)	(0.00279)	(0.00312)
Private school, non-subsidized	-0.0369***	-0.0185***	-0.0363***
	(0.00790)	(0.00638)	(0.00789)
10th grade	0.278***	-0.00737***	0.278***
	(0.00485)	(0.000719)	(0.00486)
11th grade	0.239***	-0.000734	0.239***
	(0.00613)	(0.00102)	(0.00614)
12th grade	0.303***	0.0222***	0.302***
	(0.00595)	(0.00184)	(0.00597)
(GPA 8^{th} - Mean GPA 8^{th}) $\cdot$ L9	-0.292***	0.00156***	-0.292***
	(0.00499)	(0.000283)	(0.00499)
(GPA 8^{th} - Mean GPA 8^{th}) $\cdot$ L10	-0.0582***	0.0359***	-0.0606***
	(0.00153)	(0.00211)	(0.00156)
(GPA 8^{th} - Mean GPA 8^{th}) $\cdot$ L11	-0.0638***	0.0892***	-0.0695***
	(0.00270)	(0.00407)	(0.00277)
(GPA 8^{th} - Mean GPA 8^{th}) $\cdot$ L12	-0.0159***	0.172***	-0.0249***
	(0.00219)	(0.00587)	(0.00230)
Constant	-0.221***	-0.00264	-0.221***
	(0.00546)	(0.00181)	(0.00545)
Observations	2,906,544	2,906,544	2,906,544
R-squared	0.166	0.215	0.164
Cohort FE	Yes	Yes	Yes

Clustered standard errors at the school level in parentheses.
*** p<0.1, ** p<0.05, *** p<0.01.