The Signaling Effect of Specific Skills on the Career of Young Professionals*

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Abstract

In this paper we evaluate the economic returns to signaling specific skills by means of a distinction that is given to top-scorers in field specific-exams awarded at the national level in Colombia. We employ a regression discontinuity design, and administrative earnings records, to document the effect of the distinction on earnings of young professionals. We find that the distinction increases initial earnings in about seven to twelve percent, which is equivalent to an additional year of education in Colombia. Our estimates are robust to alternative estimation strategies and alternative ways of measuring the outcome. In addition, we find strong evidence that the results are not due to differences in skills around to cutoff, nor driven by manipulation or by selective attrition. We explore potential mechanisms and find compelling evidence about two mechanisms. First, firms in highly specialized industries value signals of field-specific skills. Second, the signal given by the distinction substitutes the signal given by the college reputation, and benefits mainly income-constrained students who attend lower-ranked schools but are equally skilled before college sorting. These results suggest that the distinction is able to correct potential negative college sorting caused by income constraints.

Keywords: academic distinctions, signaling, skills, wages, graduation rates, Colombia.
JEL codes: J01, J31, J44

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1 Introduction

Education has been shown, theoretically and empirically, to increase earnings by either raising workers' productivity (traditionally called returns to education) or by helping them signal such productivity (traditionally called signaling). The returns to education have been highlighted continuously since the seminal work of Mincer (1958). Signaling effects, however, have proven to be more difficult to estimate, although some recent analysis have overcome the limitations and provide evidence of positive signaling effects. This small body of literature has mainly focused on estimating the returns to signals of general skills that are not necessarily specific to employers. Moreover, these signals usually correspond to awards given within schools (e.g. Latin honor awards or returns to certain education programs), providing employers with blurry information about the students' productivity because of the lack of comparability with students outside that school.

In this paper we evaluate the economic returns to signaling by means of a distinction that is given to top-scorers in a field-specific exam and awarded at the national level, rather than at the school level. Students in Colombia are evaluated in a high-stakes college-exit exam called the *Saber Pro*, which is mandatory for graduation and evaluates *core* and *field-specific* skills for every student. Test takers with exceptional performance in the *field-specific* component of the test receive an academic distinction, are publicly recognized in national news, and obtain a certificate during a highly publicized ceremony by the minister of education or, in some years, by the Colombian president.

Obviously, recipients of the distinction are expected to be more productive than non-recipients and therefore have higher future earnings. We employ a regression discontinuity design that gets rid of these differences and allows us to properly estimate the returns to getting the distinction across equally skilled students. Using measures of *general* skills as additional controls, we are able to test and rule out any confounding effects with potential differences in skills, reassuring that our strategy estimates the returns to signaling.

We use administrative longitudinal labor market data from Colombia, which we link to test score measures from *Saber Pro*, and administrative college records. We identify the distinction recipients by using the publicly available lists of awardees. Our data set includes all the test takers of *Saber Pro*, which we are able to observe in the labor market.

We find that the *Saber Pro* distinction increases initial earnings in about seven to ten percent, which is equivalent to an additional year of education in Colombia. The effects are persistent up to five years post college graduation, which is the further we are able to estimate with our data. Our estimates are robust to alternative estimation strategies and alternative ways of measuring the outcome. In addition, we find strong evidence that the estimated effects are not due to differences in skills around to cutoff, and that the results are not driven by manipulation nor by selective attrition.

To the best of our knowledge, this is the first paper that estimates the effect of a nation-wide signal among college graduates that provides employers with information about specific skills. Two recent papers study a similar topic by investigating the earnings effects of graduating with honors. First, Khoo and Ost (2018) use information of four-year college graduates from Ohio public universities, and employ a regression discontinuity design to estimate the impact of being awarded a Latin honors degree (e.g. cum laude). Second, Freier et al. (2015) use a differences-in-differences with entropy to estimate the effect of graduating with an honors degree in the bar exam for lawyers in Germany. Their results suggest that graduating with honors has a not persistent earnings premium; 3 percent in the case of Khoo and Ost (2018) and 14 percent in the case of Freier et al. (2015).

Even though these two papers estimate a signaling effect, the type of signal sent by a honors degree is very different from a nation-wide signal on specific skills. In fact, honors obtainment is based on a within school ranking that provides firms with a blurry signal of the quality of the students. Such signal confounds the pure signal effect with the effect of graduating from a specific school. The Saber Pro distinction, on the contrary, is awarded independently of the students' university, and based on a universal ranking that provides a much more accurate signal of the students' field-specific skills. Therefore, students who graduate from lower ranked programs would be able to signal their productivity even with respect to students from higher ranked universities, which is not the case when the signal is given by a honors degree award. Furthermore, in our case we use a setting that allows us to control for students *general* abilities and to test if students above and below the threshold are identical in terms of this set of skills.

This paper also relates to the literature that estimates the returns to signaling. Since Spence (1973, 1974) theory of signaling and screening in the labor market, multiple empirical studies have tried to estimate the effects of education signals. For instance, an early empirical literature on the topic found evidence of the so-called "sheepskin effect", which refers to the economic return of a college credential among equally educated individuals (Hungerford and Solon, 1987; Kane and Rouse, 1995; Jaeger and Page, 1996). These papers, however, relied on regression analysis that might have strong unobserved confounders. Other studies analyze signaling effects at the high school level, and either find positive effects for some groups or not sizable effects on initial earnings (Tyler et al., 2000; Jepsen et al., 2016; Clark and Martorell, 2014). Some papers have also documented the effect of disclosing certificates on workers' skills on assortative matching and earnings (Bassi and Nansamba, forthcoming), while others have investigated the effect of awards on direct measures of worker's productivity (Neckermann et al., 2014; Chan et al., 2014). A paper by Barrera and Bayona (2019) estimates the effect of being admitted at a highly prestigious university in Colombia on human capital and labor market outcomes, finding no effect in the former but positive effects on the latter, suggesting that college reputation is a strong signal for the labor market. Finally, a close paper by MacLeod et al. (2017) estimates the returns to college reputation using the signal created by *Saber Pro* for identification. Even though these two papers use the Colombian setting, the aim of our paper is very different.

2 Background

The higher education system in Colombia includes public and private institutions (colleges from now on) that offer programs on different fields of study. Two types of programs are offered, vocational or technical programs with a length of two or three years, and professional programs designed to be completed in four or five years.[1] Students apply to specific programs in different colleges. A key component of the application is the high school standardized exit exam (*Saber 11*) which all students take at the end of grade 11. Programs and colleges are heterogeneous in their selectivity, the quality of the education they provide, and their tuition fees.

Since 2004, college students take mandatory standardized tests before graduation.[2] These college exit exams (*Saber Pro*) are designed to assess the level of skills on different subjects and are used to measure the quality of schools and programs. Most students take the exams one year before their graduation term. The exam is high-stakes. It matters for colleges because test scores are used to create nation-wide rankings of colleges, and, furthermore, are public information that can determine the college's ability to attract good students in the future. Some schools provide internal incentives and tools to prepare and motivate students to perform well. The exam also matters for students because there are several benefits for those who perform well (e.g., scholarships and study loans).

The college exit exam has been subjected to some changes throughout the years. However, the exam has always included two components. First, a core component that evaluates *general abilities* across fields by testing reading comprehension and English proficiency. The reading section examines the capacity to read analytically, understand college-level written material, identify different perspectives, and asses judgments. This section consists of 15 multiple choice questions based on two reading passages, one adapted from an academic journal and the other one from a news media document. The English section focuses on testing the ability to effectively communicate in written English. The English test includes 45 questions divided into 7 parts, where different types of information are shown and evaluated.

Second, college students are evaluated in a *specific* component which measures knowl-

[1]Colleges are autonomous to define the length of their programs. We focus on professional programs, which are equivalent to a Bachelor's degree in the US.

[2]These exams were introduced by the Decree 1781 of 2003, enacted by the Colombian Ministry of Education. The Decree established the *Saber Pro* exam (formerly known as National Exam of the Quality of Higher Education or ECAES by its acronym in Spanish) as a tool to measure the skills of college graduates, and a source of information for policy decisions. The exam was created to be compulsory for all students enrolled in their last year of college education and enrolled in a program in which there existed a specific exam. It also made tertiary education institutions responsible for all their senior students' registration to take the exam, under penalty of facing legal consequences (Articles 1 and 5). In 2007, the decree was ruled unconstitutional by Colombia's Constitutional Court (Sentence C-782), which mandated the Congress to regulate the exam. The exam, however, kept its compulsory condition until December 2008 (ICFES, 2010). In 2009, the Congress approved Law 1324, in which the college exit exam adopted its present name and was established as a graduation requirement for all college students. After 2010, the law was enforced and the exam has been mandatory ever since for every single student who wishes to graduate irrespective of its program.

edge on the students' field of study. There is a total of 55 specific exams, one per field of study.[3] Students are evaluated in different subjects, deemed to be essential in each field, and ranging between four and twelve depending on the specific test. Questions are designed by experts in each area and follow well-defined standards so that test scores are comparable across years. For instance, students enrolled in economics are evaluated in microeconomics, macroeconomics, econometrics, and economic history, whereas physics students are tested in electromagnetism, electrodynamics, thermodynamics, quantum physics, and classic statistics. Up to 2009, the exam was applied in two sessions, one of four and half hours in the morning, and the second one of four hours in the afternoon.[4]

Before 2010, there was no formal system assigning college programs to specific exams. However, almost all registered students took the exam designed for their own fields.[5] The mandatory condition of the exam was also not well enforced by the Ministry of Education during this period, particularly for programs in fields without a closely related specific exam. Nevertheless, the majority of senior students in fields for which a specific exam was available took the exam (MacLeod et al., 2017). From 2010 onwards, the exam became compulsory for all college students to graduate, even for those enrolled at programs lacking a field-specific exam, who are only required to take the core component.

The top-scorers in the *field-specific* component are awarded an academic distinction, ever since the creation of the college exit exam in 2004.[6] This is a national award, thus, the signal given by it is different from the signal given by graduating with honors from each college. An important feature of the award is that students are ranked within their fields of specialization (independently of the college where they study). This allows students from lower ranked universities to signal their *field-specific* abilities relative to other students. Recipients of the award receive public recognition throughout national news media and a ceremony held by the Ministry of Education to hand in the certificates. Given their regularity every year, the announcement of the best test-takers is well known by the Colombian population, and thus it's very likely that also employers are aware of the national academic award.[7]

[3]Out of these 55 field exams, 48 were designed to be taken by students in bachelor's programs, 6 by vocational programs, and a remaining one by students from Escuelas Normales (i.e. 2-year programs intended to form elementary school teachers).

[4]In 2010, the test authorities added new exams to the core component and eliminated the specific exams of fields with few students. Other introduced changes are related to the number of questions and the amount of time allowed to students to answer both components of the exam.

[5]See Appendix Figure A.1 that gives strong evidence about the remarkable correlation between the fields of study and the specific exam that the students take.

[6]The Decree 1781 of 2003 also established that the top ten scores from each field were to receive a distinction certificate (i.e. the national academic award), and highlighted that these students would have priorities among applicants for public scholarships and study loans intended to promote further education (Articles 7 and 8).

[7]Colombia has a long tradition of granting national awards based on standardized tests. The Ministry of Education, throughout Decree 89 of 1976, instituted classification and follow-up tests for elementary and high school students, as well as scholarships and recognition for the best test-takers. Since 1994, the Ministry of Education has also awarded to top-scorers in the exit high school exam the "Andres Bello" distinction, in honor of a famous philosopher and educator who participated in the process of independence in the early XIXth century.

3 Data

Our universe of analysis consists of 313,363 students who were enrolled in four- and five-year programs and took the exit exam between 2006 and 2009. We merge four data sets using individual-level identifiers. First, administrative records of the college exit exam, both the core and the specific components.[8] Second, among these students we identified the 2,693 award recipients from publicly available records that are published online.[9] Third, we use administrative records of the universe of students who ever registered to higher education institution in Colombia. These data include information about the field of study and the institution where the student enrolled, and their high school exit exam score. Fourth, we also use administrative social security records from 2007 to 2015. These records include monthly earnings in the formal sector (measured in the latest observed month between the second and third quarters of every year). We lack labor market information for those individuals out of the labor force, unemployed, or working in the informal sector of the economy.[10]

Table 1 displays descriptive statistics for our sample. About 57 percent of college graduates are women. On average, they are 26 years old and belong to the lower-middle class household.[11] The majority of graduates are first-generation college students: only a third have a mother who graduated from a 2- or a 4-year college. Most students attend a private college.

[8] We exclude from the sample a small subset of students, registered to take specific exams for which we do not observe the overall score used to assign the national award (architecture, physical education, and education majors) or we lack such data in certain years: psychology (Nov. 2007), occupational therapy (Nov. 2009), geology (Nov. 2009), English language education (June 2007, June 2008 and Nov. 2009).

[9] See: `http://www2.icfesinteractivo.gov.co/result_ecaes/sniee_ins_mej.htm`.

[10] In Colombia, 75 percent of workers with college education are employed in the formal sector.

[11] Households in Colombia are classified in 6 socio-economic strata with the purpose of targeting social programs and different public subsidies. Stratum 1 is very low, stratum 3 is medium-low, stratum 6 is high.

Table 1: Summary Statistics of Saber Pro Test-Takers, 2006-2009

	Mean	Std. Dev.	Min.	Median	Max.
	(1)	(2)	(3)	(4)	(5)
Individual Characteristics :					
1(Saber Pro Distinction)	0.01	0.09	0.00	0.00	1.00
1(Female)	0.57	0.49	0.00	1.00	1.00
Age at Exam Date	25.80	4.82	19.00	24.00	45.00
Socioeconomic Stratum	3.04	1.11	1.00	3.00	6.00
1(Mother's Educ. : HS)	0.17	0.37	0.00	0.00	1.00
1(Mother's Educ. : College)	0.36	0.48	0.00	0.00	1.00
College Characteristics :					
Private College	0.63	0.48	0.00	1.00	1.00
1(Top 5)	0.11	0.32	0.00	0.00	1.00
1(Top 6-20)	0.13	0.34	0.00	0.00	1.00
Field of Study :					
1(Agricultural Sciences)	0.04	0.19	0.00	0.00	1.00
1(Health)	0.14	0.35	0.00	0.00	1.00
1(Social Sciences)	0.25	0.43	0.00	0.00	1.00
1(Business and Economics)	0.29	0.45	0.00	0.00	1.00
1(Engineering)	0.25	0.44	0.00	0.00	1.00
1(Math and Natural Sc.)	0.03	0.17	0.00	0.00	1.00

Notes. $N = 313,363$. Summary statistics pooling all students taking the Saber Pro exam between 2006 and 2009. Socioeconomic stratum takes values between 1 and 6, with 1 being the lowest stratum and 6 the highest one. Sample size could be smaller for some variables due to missing data. The university ranking is based on information gathered from QS-Ranking.

4 Empirical Strategy

We use a sharp regression discontinuity design to estimate the causal effect of winning the national academic award on labor market outcomes. Let $D_{ijt} = 1(\text{Score}_{ijt} \geq c_{jt})$ be an indicator variable that assigns a value of one if student i, enrolled in field of study j and taking the exam at year t, obtains a score in the field-specific component above a threshold c_{jt} and, thus, is awarded the distinction.[12] Additionally, we define the (running) variable Z_{ijt} as:

$$Z_{ijt} = (\text{Score}_{ijt} - c_{jt})/\sigma_{jt},$$

where σ_{jt} represents the standard deviation of the specific exit college exam score computed for students in field of study j taking the exam in year t.

Using these measures, we estimate the following equation:

$$Y_{ijs} = \alpha + \beta Z_{ijt} + \delta D_{ijt} + \tau(Z_{ijt} \times D_{ijt}) + X_i'\gamma + \varepsilon_{ijs}, \tag{1}$$

where Y_{ijs} represents a student i's outcome in year $s > t$. Our main outcome of interest is the log of average monthly wages earned after graduation and before students are 26 years old (i.e. wages observed at an early stage of the career of college graduates). Results are robust to alternative measures of earnings.[13] Our parameter of interest, δ, is estimated as:

$$\delta(c_{jt}) = \lim_{c \downarrow c_{jt}} E[Y_{ijs}|D_{ijt} = 1, \text{Score}_{ijt} = c, X_i] - \lim_{c \uparrow c_{jt}} E[Y_{ijs}|D_{ijt} = 0, \text{Score}_{ijt} = c, X_i].$$

Equation (1) represents the reduced form approach of a sharp regression discontinuity design.[14] We present estimates for different bandwidths and use local polynomial regressions of different orders (Imbens and Lemieux, 2008). We consider bandwidths computed by minimizing mean square errors (MSE) as well as coverage error expansion bandwidths (CE) as suggested by Calonico et al. (2020).

To further ensure comparability between award recipients and non-recipients, our benchmark specification consider as well a vector of control variables, X_i (Calonico et al., 2019). Such vector includes age, gender, socioeconomic status, mother's education, test scores from the high school exit exam, and test scores from the core component of the college exit exam. In addition, the vector includes a set of six study areas $\times$ year fixed effects which capture differences across the different test editions and controls for variation across programs since the cutoffs are field-specific. Standard errors are clustered by area of study and test year.

[12] We do not have information to directly observe c_{jt}, but we can easily compute it by finding the minimum score among the recipients of the award for every program and test edition.

[13] For instance, we consider earnings observed one year after college graduation as the outcome and the result remain unchanged, although we lose statistical power.

[14] Appendix Figure C.1b, plots the probability of being awarded the distinction as a function of the running variable. All students above the threshold are recipients of the award and no student below the threshold receives the award.

5 Results

We start by checking our identifying assumptions, namely that there was no manipulation of the running variable Z_{ijt} and that individuals around the threshold are similar except for the fact that some received the distinction award. We then show that we are equally likely to observe wages of all students around the eligibility threshold. We finish the section by estimating the effect on winning the distinction award on initial earnings after graduation and investigate how persistent the effect is several years after students entered the labor market.

5.1 Validity of the Research Design

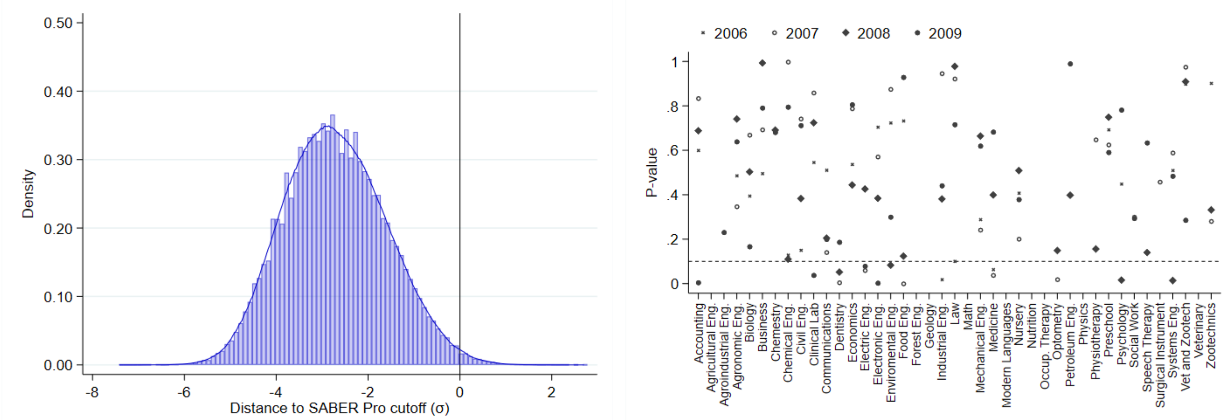
A first threat to the validity of our empirical strategy comes from the potential manipulation of the threshold used to assign the national distinction award. The threshold is not known ex-ante by test takers or schools so it is unlikely that either of them could act strategically to receive (or not receive) the award. Detecting a lack of smoothness in the density of the running variable (i.e., bunching) around the cutoff would be evidence of manipulation. We consider the non-parametric test developed by Cattaneo et al. (2020), who propose a novel testing procedure to check for discontinuities based on the density estimator of Cheng et al. (1997). The null hypothesis of this test is no manipulation around the threshold.

Figure 1 provides evidence of no manipulation. Figure 1a presents the estimated density of the running variable pooling all test-takers between 2006 and 2009.[15] Smoothness is observed around the cutoff from this graphical representation of the density. Figure 1b provides the p-values of the formal manipulation test that we run for all field-specific exams across years. We can't reject the null hypothesis for most of the exams. Furthermore, there is no field in which no manipulation is rejected consistently across years. Based on these results we can rule out manipulation as a threat to the validity of the RD estimates. Notice as well that the possibility of manipulation in our context is very low given that the score used to determine which students receive the national academic award is the overall score computed from different subjects of the *specific* component of the *Saber Pro*. Such cutoff is, in addition, not publicly known and may change from one year to another for all field exams, reducing even more the likelihood of manipulation.

[15]Figure C.1a displays all thresholds used by the exam authority to award the national distinction award across fields and years, and then used to compute our running variable.

Figure 1: Density Smoothness around the Cutoff

(a) Running Variable Density (b) Manipulation Test



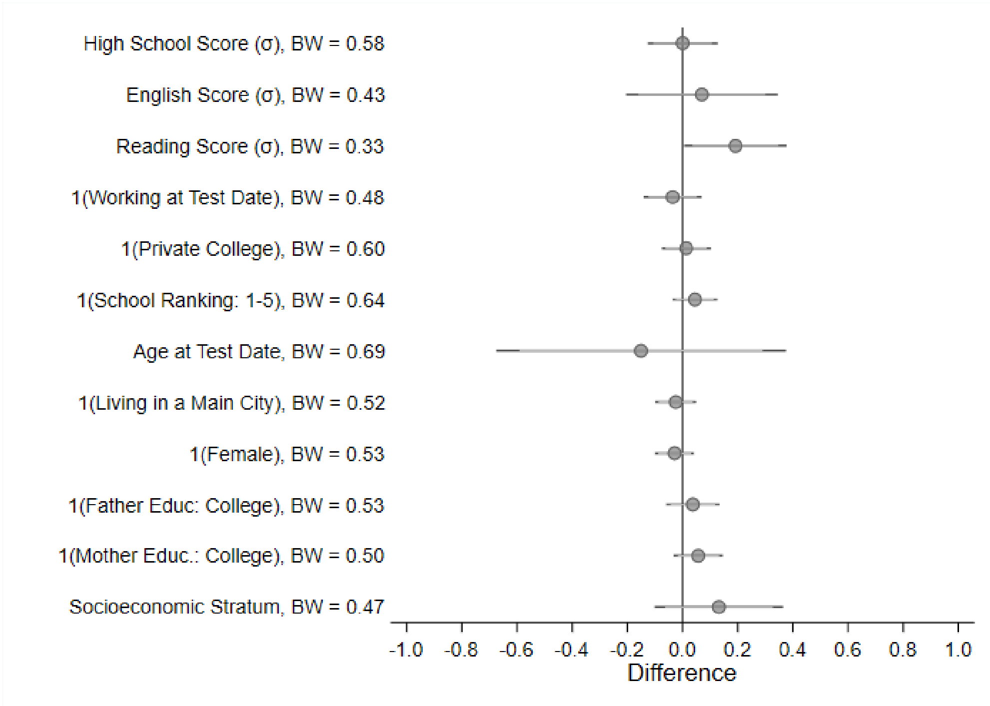
Notes. Figure 1a plots the estimated density of the running variable. Figure 1b presents the results of the manipulation test proposed by Cattaneo et al. (2020). The null hypothesis for this test is no manipulation in the density of the running variable around the cutoff, normalized to be zero. Plotted dots represent the p-value of the run test. A horizontal line is drawn to represent a significant level of 10%.

Our identification relies on the assumption that students around the threshold are identical. In other words, the RD estimates could be biased if the marginal recipients of the national academic award are systematically different from the students closer to the cutoff who were not awarded the distinction. We consider this to be a reasonable assumption, so we estimate Equation (1) – setting $\gamma = 0$ – on a set of variables that predict entry into the labor market using the MSE-optimal bandwidth selected for our main outcome of interest. We plot the results in Figure 2, where we observe that the distinction recipients and non-recipients have similar characteristics.

Note that an important source of bias, for which we are able to provide a formal test given the richness of our data, comes from the fact that awardees are more skilled than the rest of the test-takers. Using the overall scores from the high school exit exam, to proxy initial abilities, and the reading and English test scores from the *core* component of *Saber Pro*, we find that there is no differential level in skills between recipients and non-recipients around the cutoff. Another source of potential bias could arise if students at top-ranked universities are more prepared to take the *specific* component of *Saber Pro*, or if the exam is designed to fit better the material covered by these students. In this case, the best test-takers would be systematically drawn from top schools, creating a discontinuity in the probability of being enrolled at top-ranked colleges. No evidence of such discontinuity around the cutoff is found. Figure 2 shows that awardees and non-awardees close to the cutoff are also identical in other pretreatment covariates such as gender, age at the exam date, family background, the proportion of students enrolled at private colleges, and the proportion of students who report that are working at the test date.[16]

[16]Graphical representation of continuity around the cutoff for pretreatment covariates are displayed in Appendix Figures C.2 and C.3.

Figure 2: Covariate Balance around the National Academic Award Cutoff

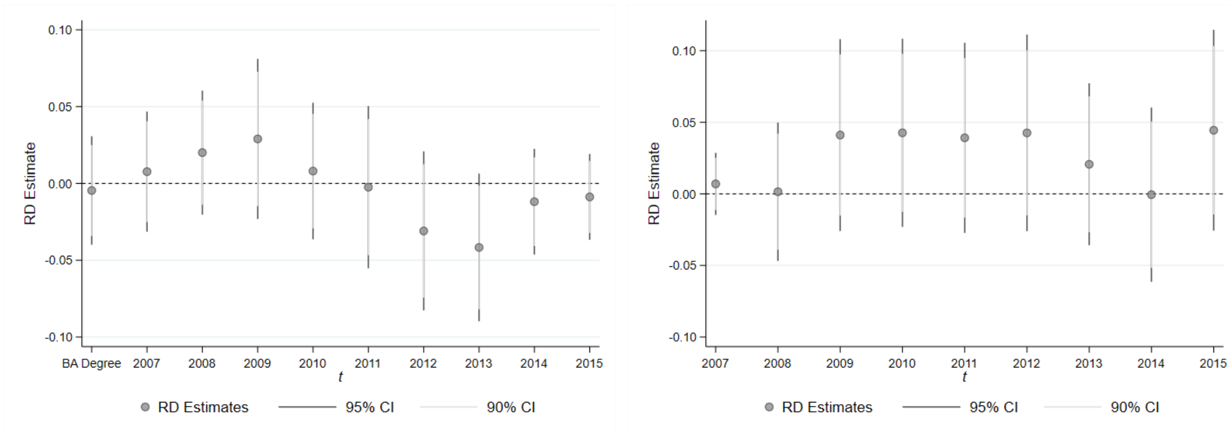


Notes. Plotted dots represent RD estimated coefficients for each pretreatment covariate using local linear regressions, an Epanechnikov kernel and MSE-optimal bandwidths, displayed next to each each variable's name. 95% and 99% confidence intervals are provided.

A final threat to the validity of our results is related to the possibility that national awardees are more likely to be found in the administrative records used to draw education and labor market information after college completion. This threat is related to the potential effect that the distinction could have on the probability of graduating from college and of being employed as a formal worker. Figure 3 presents evidence regarding this concern. Figure 3a shows that the marginal recipients of the award are not more likely to graduate from college, while 3b reveals that such students are neither more likely to work in the formal sector.

Figure 3: Continuity in the Probability of Graduating and Work in the Formal Sector

(a) Probability of Graduating From College (b) Probability of Being a Formal Worker



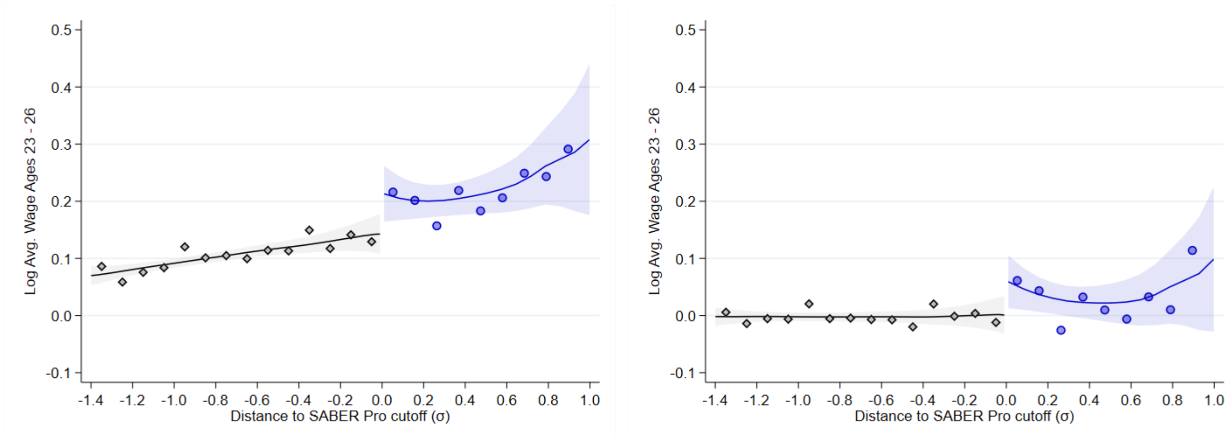
Notes. Evidence on selective attrition or significant differences in the likelihood of finding award recipients in the social security records and college graduation records between 2007 and 2015. All regressions include Area-of-study×Year fixed effects. Standard errors clustered at the area of study and test year level. 90% and 95% confidence intervals are plotted

5.2 Effect on Initial Earnings

Figure 4 plots the causal effect of the national academic award on earnings after graduation. The effect is measured by the discontinuity observed between recipients and non-recipients around the normalized cutoff of zero. Recipients are located to the right of the cutoff, whereas the rest are located to the left. We observe a positive and statistically significant premium on wages from being awarded the distinction. Figure 4a displays the discontinuity on earnings without controlling for any additional control. Observe that this simple RD estimate may suffer from sample composition effects as a result of pooling students taking their field-specific exam in different years. Figure 4b addresses such concern by estimating the discontinuity on the log of earnings conditional on initial and general skills, different pretreatment covariates, and areas of study $\times$ test year fixed effects, as specified in Equation (1). The results don't change significantly after.

Figure 4: Effect of National Distinction Award on Early-Career Earnings

(a) Log Average Earnings (b) Residualized Average Earnings



Notes. The outcome variable is the log of average monthly wage earned after graduation and before students are 26 years old. Plotted dots represent local averages of the log earnings within bins of the running variable. The running variable is the score in the college exit exam (specific skills component) minus the cutoff value used to assign the distinctions to the best test-takers. Data is displayed using the optimal MSE-bandwidth: 0.297. The solid lines represent linear local regressions around the cutoff. Confidence intervals at the 90% level are displayed for each local regression. Panel (a) represents the regression discontinuity on log earnings without including any controls. Panel (b) represents the discontinuity on log earnings around the threshold after controlling for age, gender, socioeconomic status, mother's education, test scores from the high school exit exam, test scores from the core component of the college exit exam and Area×Year-of-exam fixed effects as discussed in section 4.

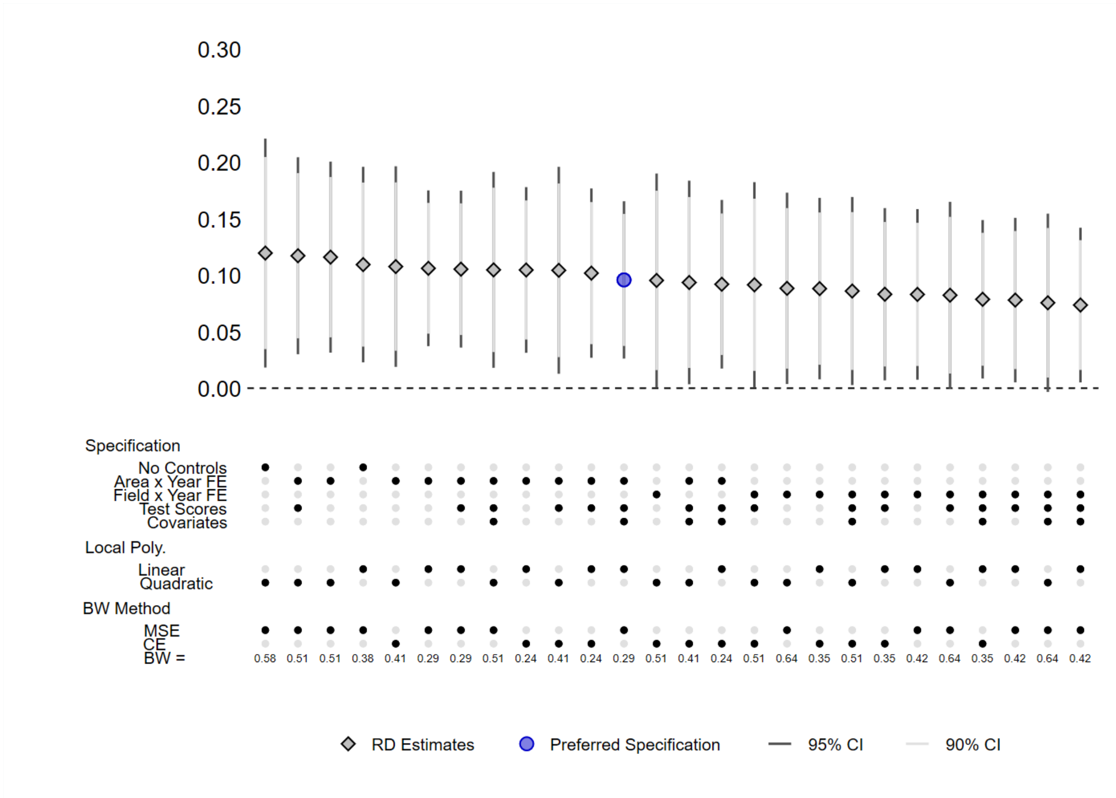
We also provide formal estimates of Equation (1) in Figure 5, where we display the results using alternative bandwidths and local polynomial regressions of different order. The bottom of the figure describes the specification that we vary in three dimensions. First, we present estimations with no controls, with field-year fixed effects, controlling by test score measures, and with the full set of individual-level controls (labeled "covariates"). Second, we present estimates using local linear regression or local quadratic regression. Third, we present estimates obtained using Mean Square Error (MSE) bandwidths or using Coverage Error (CE) bandwidths.[17]

We observe very robust point estimates between, roughly, seven to twelve percent. These magnitudes remain robust to alternative polynomial regressions and bandwidths.[18] In general, we find that the signaling effect of the *Saber Pro* distinction is of around seven percent, which is comparable to an additional year of education in Colombia as suggested by Tenjo et al. (2017).

[17]Note that CE bandwidths are smaller than commonly used MSE bandwidths. As mentioned by Calonico et al. (2020), in comparison with MSE bandwidths, the inference using the CE bandwidths will remain valid when the goal is to construct robust bias-corrected confidence intervals.

[18]We show in Appendix Figure D.1 that the estimated effect is remarkably robust in magnitude to a large set bandwidths, and even below the optimally computed MSE- and CE-bandwidths. We additionally explore the effects using the first observed earnings as outcome in Appendix Figure D.2. We find that the effects remain robust although a little more imprecise due to a loss in the number of observations.

Figure 5: Robustness of the Effect Winning the Award on Early-Career Earnings

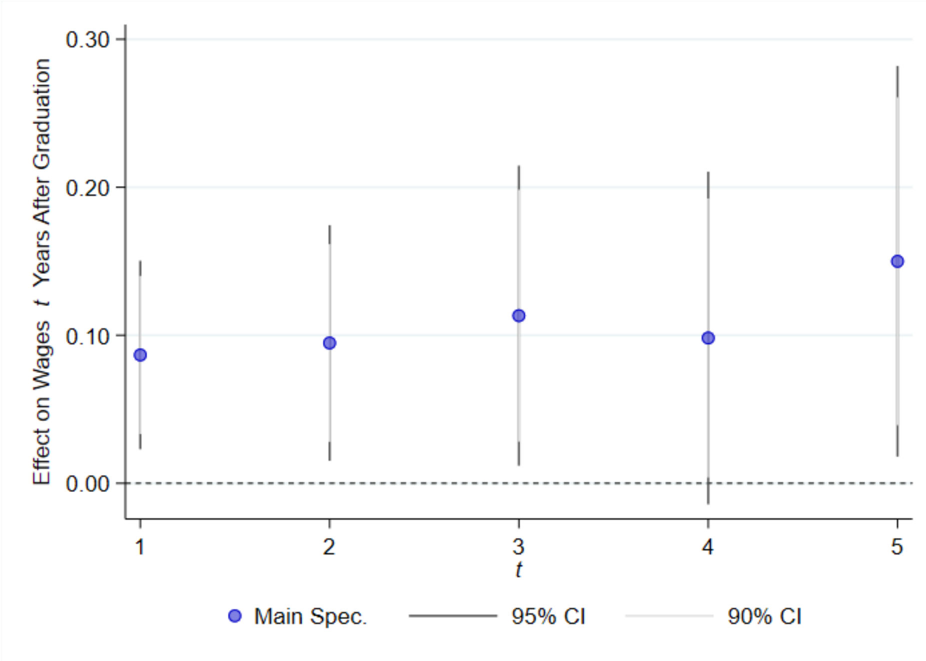


Notes. The outcome variable is the log of average monthly wage earned after graduation and before students are 26 years old. Plotted dots represent the RD estimated coefficients using linear and quadratic local regressions, an Epanechnikov kernel and bandwidths as displayed in the bottom of the figure. Specific-exams are grouped in 6 areas of study: Agricultural Sciences, Health, Social Sciences, Business and Economics, Engineering, and Math and Natural Sciences. Area×Year-of-Exam fixed effects are computed based on these 6 larger fields. Estimates conditioning on Field×Year fixed effects, are computed using the residuals of the outcome variable from an OLS regression in which we control for a set of dummies defined by Field×Year. Test scores include: the High-School-Exit exam scores (Saber 11), and the Reading and English Proficiency scores applied as part of the common component of the College-Exit exam (Saber Pro), which are omitted to determine the Saber Pro distinction recipients. Covariates include: dummies for gender and mother's education level, socioeconomic stratum and age at exam. Confidence intervals at the 90% and 95% levels are displayed for each coefficient, and computed using standard-errors clustered by Area×Year-of-exam.

5.3 Effect on Future Earnings

Our measure of initial earnings only captures the effect of the distinction at the moment of entry to the labor market. However, it is natural to investigate whether this effect persists or not. We use a balanced sample of individuals for whom we observe earnings consistently during the first three years after graduation to determine if the positive effect is temporary or permanent in a five years window. Figure 6 presents the results of such analysis and shows that the effect is persistent, around a a magnitude of about ten percent. We lose some precision in our estimate of the effect during the fourth year, but this coefficient is still comparable to the results observed for previous years.

Figure 6: Not Fade out Effect of the National Award on Earnings



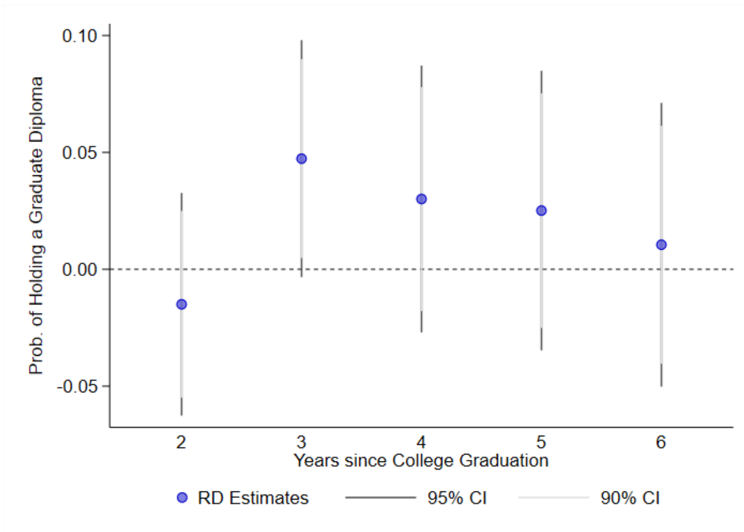
Notes. For each plotted coefficient, the outcome variable is the log of earnings t years after college graduation. Estimates use local linear regressions, an Epanechnikov kernel and MSE-optimal computed bandwidths. The analysis is restricted to a "balanced" panel of individuals for whom we observe earnings during the first three years after graduation, in order to maintain a consistent sample across specifications. Confidence intervals at the 90% and 95% levels are displayed for each coefficient, and computed using standard-errors clustered by Area$\times$Year-of-exam.

The economic returns to graduating with honors, found by Khoo and Ost (2018) and Freier et al. (2015), dissipate three years after graduation, suggesting that the returns to their studied signals are transitory. The signaling effects of the *Saber Pro* are not necessarily the same than the signal of obtaining honors. In fact, honors obtainment is based in a within program–school ranking that provides firms with a blurry signal of the quality of the students. The *Saber Pro* distinction, on the contrary, is awarded independently of the students' university, and based on a universal ranking that provides a much more accurate signal of the students' specific skills. Therefore, students who graduate from lower ranked programs are able to signal their performance even with respect to students from higher ranked universities, which is not the case when the signal is given by an honors degree award. In this case we observe that the returns to the *Saber Pro* signal are more persistent than the returns to graduating with honors.

5.4 Effect on Graduate Education Attainment

We finally study if getting an academic distinction has an effect on its recipient's graduation rates from graduate programs. Figure 7 presents regression discontinuity estimates of the effect on the probability of graduating from a graduate program for different years after college completion. We observe a positive effect only for the the third year after a college student's graduation date. The effect is of about four percent points, but it fades away for later years. The academic distinction seems to have an impact on graduate education attainment in the short run, but, after the fourth year, this effect fades until it completely disappears. This is evidence that the distinction accelerates graduation rates among people that in the long run would have pursued and completed a graduate program. We believe two main channels that may be leading this effect are a motivation shock and the effectiveness of the set of policies that the Colombian government, and some universities, have implemented to promote graduate education among distinction recipients.

Figure 7: Effect on the Probability of Completing a Graduate Program



Notes. Graphic representation of the effect of the Saber Pro distinction on the probability of graduating from a graduate program. Plotted dots represent regression discontinuity estimates using local linear regressions, an Epanechnikov kernel and different optimal MSE bandwidths computed for each year after college graduation. 90% confidence intervals are displayed for each estimate.

6 Mechanisms

To understand the mechanisms behind the national field-specific award and wages, we first present a conceptual framework that rationalizes the findings, builds some potential mechanisms, and poses some predictions. We then present empirical tests of the predictions to validate the mechanisms highlighted in the conceptual framework.

6.1 Conceptual Framework

6.1.1 Students Sorting and Signaling

Following MacLeod et al. (2017) , consider a continuum of students endowed with ability $\theta_i^0 \sim F$ and initial wealth $I_i^0 \sim G$. Ability is not observable, but it is signaled by a high-school exit exam,

$$T_i = \theta_i^0 + \epsilon_i,$$

that is a function of the innate ability, and some noise parameter, $\epsilon_i \sim N(0, \sigma_\epsilon^2)$. Consider also a second measure of ability corresponding to college reputation, defined as:

$$R_s = E[T_i | i \in s],$$

which is equal to the average admission scores to college s.

Colleges are selective, and only accept students who have test scores above a threshold and who have the means to pay for tuition. For simplicity, we assume that colleges have either high reputation, R_s^+, or low reputation, R_s^-, and denote the cost of tuition as $\bar{I}_s$. Thus, the probability of attending a high reputation college is given by,

$$\lambda(T_i, I_i^0) = P[R_i = R_s^+] = P[T_i > \bar{T} | I_i^0 > \bar{I}_s],$$

whereas the probability of attending a low-reputation college is:

$$1 - \lambda(T_i, I_i^0) = P[R_i = R_s^-] = P[T_i \leq \bar{T}] + P[T_i > \bar{T} | I_i^0 \leq \bar{I}_s].$$ [19]

After college graduation, students' skills include additional attributes that vary by the college of attendance and field of specialization. We assume that college inputs (i.e. professors, teaching, and peers) increase students' skills. However, these set of skills are given either by the school s and/or the field j. In other words, it is not the same to study economics or medicine in a given school. Formally, the post-college level of skills is given by:

$$\theta_{ijs}^1 = \theta_i^0 + \eta_i + v_s + v_j,$$

where η_i is a component that captures the students' learning environment (neighborhood, school,etc.), $\eta_i \sim N(x_i, \sigma_x^2)$, and v_s and v_j correspond to college- and field-specific attributes, which are not observable. However, following MacLeod et al. (2017), the college-specific component satisfies that:

$$E[v_s | R_s] = \left[\lambda R_s^+ + (1 - \lambda) R_s^-\right].$$

Students that go to school with high reputation send a signal equal to R_s^+ whereas students who go to low-reputation schools send a signal $R_s^- < R_s^+$. The field-specific component, v_j, is also not-observable but is signaled for those who obtain the distinction in the *specific*-component of the college-exit exam, such that:

$$A_{ij} = \delta_i(v_s + v_j + \nu_{ij}),$$

where δ_i takes the value of one if i receives the award and $E[v_s + v_j | \delta_i] = A_{ij}$. The distinction not only reveals information about the field-specific skills, but also information about the school-specific component (i.e. professor, peers, alumni networks, etc).

[19] We assume that everyone attends college.

6.1.2 Firms offers and wage setting

Employers cannot observe skills but they do observe the signals given by the labor market reputation of the college of graduation and the *field-specific* exam, which are public information usually shown in a CV. Using this information they can compute the expected skills of a graduate from school s in field j as:

$$
\begin{aligned}
E[\theta_i^1|\lambda_i = 0, \delta_i = 0] &= T_i + x_i + R_s^- \\
E[\theta_i^1|\lambda_i = 1, \delta_i = 0] &= T_i + x_i + R_s^+ \\
E[\theta_i^1|\delta_i = 1] &= T_i + x_i + A_{ij}
\end{aligned}
$$

The value of A_{ij} varies by field j denoting that the signal embodies information about field-specific skills of the individual.

Worker's i productivity in field j and year t is given by,

$$y_{ijt} = \theta_{ij}^1 + y_{ij,t-1} + \varepsilon_{ijt}.$$

Firms, at every period t, cannot directly observe productivity, but they have access to a time-changing vector of information, $\mathbb{I}_{it} = (\lambda_i, \delta_i, y_{i,0}, ..., y_{i,t-1})$ (Farber and Gibbons, 1996), that allows them to compute an expected performance measure of the way:

$$
\begin{aligned}
p_{ijt} &= E[\theta_i^1|\lambda_i, \delta_i] + y_{i,t-1} + u_{it} \\
&= \lambda_i R_s + \delta_i A_{ij} + T_i + x_i + y_{i,t-1} + u_{it},
\end{aligned}
$$

So, in order to maximize profits, conditional on the signals, the firms offer an equilibrium wage equivalent to the performance measure:

$$\hat{w}_{ijt} = \beta_r D_{R_s} + \beta_s D_{A_{ij}} + \beta_a T_i + x_i, \tag{2}$$

where D_{R_s} takes a value of one if the individual attended a high-reputation college, $D_{A_{ij}}$ takes the value of one if was a student who received the distinction, and $\hat{w}_{it}$ corresponds to the wages net of human capital growth.[20]

6.1.3 Predictions

Equation 2 implies that the distinction can increase wages by two potential mechanisms. First, the award provides information about the awardees' field-specific skills, which are valued by firms in the same field, especially those in highly specialized industries. Firms in these industries will offer higher wages to graduates who received the distinction in that specific field because they have a clear signal about the specific skills applied in such industry. From this, it follows that:

Prediction 1. *The return to the distinction is bigger in more specialized industries, if firms value field-specific skills and the distinction provides this information.*

[20] These correspond to wages minus human capital accumulation of time-varying characteristics, such as in MacLeod et al. (2017).

Second, the national field-specific exam substitutes the signal given by college reputation, and gives more accurate information about the recipients' skills. In other words, the return to the distinction captures the skill component of the college attributes and substitutes the information given by college reputation. If this is the case, then firms will value more the signal given by the distinction than the signal given by college reputation, and we will observe that awardees in high-reputation colleges do not benefit from the distinction but awardees from low-reputation colleges do benefit. In general, if the national field-specific distinction substitutes the signal given by college reputation, then:

Prediction 2. *The returns of the national distinction is bigger for awardees who graduate from low-reputation colleges than for awardees who graduate from high-reputation colleges;*

Prediction 3. *College reputation does not predict wages among awardees;*

Prediction 4. *And, awardees work in higher-paying firms because employers value more the information given by the distinction than by college reputation.*

One last prediction implies the existence of a pre-college student sorting in which highly skilled students attend low-reputation schools because of income constraints. In other words, the national field-specific distinction corrects potential negative sorting caused by income constraints in access to college. The distinction rewards those students who were sufficiently skilled to access high-reputed colleges, but did not have the means to cover the tuition. If this is the case, then we should observe that:

Prediction 5. *Awardees in low-college reputation schools are more income constrained but equal in terms of innate abilities.*

6.2 Empirical Tests of the Mechanisms

We provide empirical evidence for Prediction 1 by comparing the returns to the distinction across fields with different degree of specialization. We compute the level of specialization of a field j by summing the number of four-digit industries in which graduates from field j work after graduation.[21] We find that Business is the industry that provides the largest amount of industries (387), which means that is the least skill-specific of the fields. We also observe that Modern Languages is the most specific, and it supplies to 28 industries on average. We estimate Equation 1 by fields above and below the median of the level of specialization, and present the results in Table 2.

[21]To do this we collapse our estimation data set at the 41-field levels and count the number of four-digit industries per field and year. Then, we compute the average per year (from 2009 to 2015) of industries that are supplied by a given field.

Table 2: Effect on Initial Earnings by High and Low Specialized Fields

	Dependent Var. : Log Avg. Wage Ages 23 - 26			
	Highly Specific	Low Specific	Highly Specific	Low Specific
	(1)	(2)	(3)	(4)
RD Estimate	0.127***	-0.011	0.139***	-0.069
	[0.034]	[0.089]	[0.044]	[0.140]
Mean control	13.88	14.35	13.90	14.26
Observations	69,193	38,897	69,193	38,897
Bandwidth	0.278	0.226	0.486	0.358
Effect. obs. control	1156	186	2551	360
Effect. obs. treat	742	146	1014	181
Local Regression	Linear	Linear	Quadratic	Quadratic

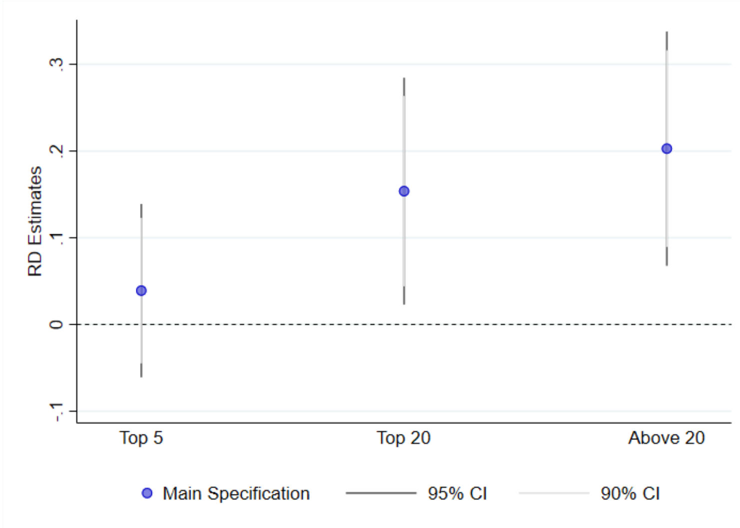
Notes. This table estimates Equation 1, but splitting the sample between fields with high and low level of specialization. Specialization per field is measured as the number of industries that are supplied by college graduates of that same field. We average the number between 2009 and 2015, and create a ranking. Highly Specific fields are those above the median. Low specific fields are those below the median. All specifications control by gender, socioeconomic status, mother's education, test scores from the high school exit exam, test scores from the core component of the college exit exam and Field$\times$Year-of-exam fixed effects. Errors are clustered at the Field$\times$Year-of-exam level.

The results show that the distinction has positive returns among those fields that are highly specific. Such result poses strong evidence about the distinction providing employers with information about specific skills that are very valued at the moment of hiring, which is the first mechanism detailed in section 6.1.

We also find strong evidence about the second mechanism. The information provided by the distinction substitutes the information provided by the reputation of the college, and is more valued by firms. To test this claim, we start by providing evidence for Prediction 2 by estimating Equation 1, and splitting the sample between differently ranked universities.[22] We provide the results of the estimation in Figure 8. We observe that students who graduate from top five universities do not benefit from the distinction when compared to other graduates from the same universities. However, awardees who graduate from universities with lower reputation do have a remarkable increase in earnings compared to those that graduate from the same universities.

[22] We use the QS World University Rankings to classify colleges between the Top 5, Top 6-20, and above.

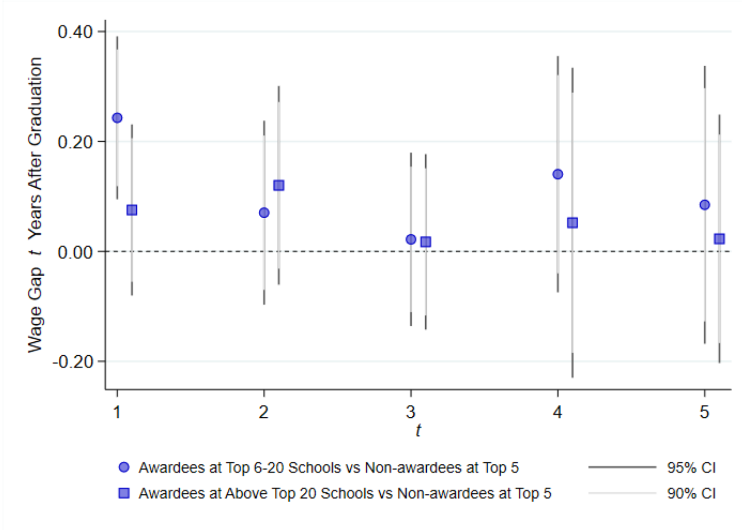
Figure 8: Effect of the Distinction on Initial Wages by University Ranking



Notes. Estimated coefficients using local linear regressions, an Epanechnikov kernel and bandwidths as displayed in the top of every column. All columns include fixed effects of field-of-study-year-of-exam. Test scores and covariates as described in Figure 4. Standard errors are clustered at the Area × Year level.

The distinction, in fact, increases the wages of students in less ranked universities, compared to their peers in the same universities, but is this increase enough to compensate for the earnings premium of graduating from a top 5? We test for this using the same specification, but using as control only those non-awardees that graduated from a top 5 university. We present the dynamic effects in Figure 9. We see that the increase in wages for awardees who graduated from worse-ranked universities is equivalent to the return obtained from graduating from a top 5. This is true except for awardees who graduated from top 6-20 who have a higher salary exclusively in their first year, although after the second year this gap disappears. These results suggest that the distinction provides information that replaces the information given by the college reputation.

Figure 9: Dynamic Effects of the Distinction using Non-awardees in Top 5 Universities as Controls



Notes. Estimated coefficients using local linear regressions, an Epanechnikov kernel and bandwidths as displayed in the top of every column. Test scores and covariates as described in Figure 4. Standard errors are clustered at the Area × Year level.

We reinforce such result by testing Prediction 3, to evaluate if college reputation does not predict wages among awardees. We run a regression between wages and college reputation around the cutoff point only for awardees.[23] We include test scores in this specification trying to fully control for innate individual abilities. The results are presented in Table 3. Columns (1) to (3) include awardees whereas columns (4) to (6) includes non-awardees. We observe that college reputation only predicts wages of non-recipients, whereas it has no relationship when considering individuals who received the distinction.

Table 3: College Reputation Does not Predict Earnings Among Awardees

	Dependent Var : Log Avg. Wage Ages 23 - 26					
	Awardees			Non-Awardees		
	(1)	(2)	(3)	(4)	(5)	(6)
College Reputation	0.005*	0.004	0.004	0.006***	0.006***	0.006***
	[0.003]	[0.002]	[0.002]	[0.001]	[0.001]	[0.001]
Observations	1,691	1,691	1,691	102,741	102,741	102,741
R-squared	0.056	0.115	0.134	0.099	0.128	0.150
Test Scores	Yes	Yes	Yes	Yes	Yes	Yes
AreaxYear FE		Yes	Yes		Yes	Yes
Covariates			Yes			Yes

Notes. .

If firms value the information given by the distinction, is then expected that awardees are

[23]We compute college reputation following MacLeod et al. (2017) as the average high school exit exam of the entering class of students to college-program s.

hired by higher paying firms. We also test for this, which constitutes Prediction 4. We again estimate Equation 1 but using as outcome a ranking of firms created by sorting the firms by the average wages they pay. We compute a time-invariant ranking of firms and then compute an individual measure as the average of the rankings of the worker across time.[24] The results are shown in Table 4, where we present multiple specifications varying the local polynomial. We observe that obtaining the distinction induces college graduates to be hired by higher paying firms, suggesting that firms do value the information given by the distinction.

Table 4: Effect of the Distinction using a Firm Wage Ranking as Outcome

	Dependent Var. : Avg. Firm Ranking Across Years					
	(1)	(2)	(3)	(4)	(5)	(6)
RD Estimate	0.030***	0.028***	0.029***	0.033**	0.031**	0.031**
	[0.010]	[0.010]	[0.010]	[0.014]	[0.013]	[0.013]
Mean control	0.583	0.542	0.509	0.575	0.536	0.517
Observations	249,028	249,028	249,028	249,028	249,028	249,028
Bandwidth	0.409	0.409	0.409	0.545	0.545	0.545
Effect. obs. control	3,761	3,761	3,761	5,748	5,748	5,748
Effect. obs. treat	1,579	1,579	1,579	1,873	1,873	1,873
Local Regression	Linear	Linear	Linear	Quadratic	Quadratic	Quadratic
Area×Year	Yes	Yes	Yes	Yes	Yes	Yes
Test Scores		Yes	Yes		Yes	Yes
Covariates			Yes			Yes

Notes. .

Finally, we test if the signal given by the distinction is related to income constraints. In other words, if the information in the national field-specific distinction substitutes the information given by college reputation, then we would expect that awardees have a similar level of pre-college skills but differences in pre-college income. To test this, we compare the test scores in the high-school exit exam and the socio-economic strata among awardees who went to top 5 colleges versus those who did not.[25] We present the results in Table 5. We do observe a clear difference in income before college, but a similar level of skills. Such result indicates that, given that the distinction provides more information than college reputation, then income constrained students are able to compensate the wage losses created by an unequal access to college.

[24] We construct a wage-ranking of firms by computing the average wages paid at the firm and year level. Then, we compute the percentile of the distribution per year, and average the percentiles across years. We then merge this time-invariant ranking year-by-year to the wage data, and construct a time-invariant measure per individual as the average of the ranking of the firms that person worked at.

[25] We residualize test scores to account for time differences in the exam's editions and to account for accumulated human capital at the beginning of college. We compute the residuals of a regression that uses the high school exit exam as outcome conditioning on test edition fixed effects and high-school fixed effects.

Table 5: Sorting to Top Schools by Wealth and not by Skills

	Dependent Variable :			
	1(High Income)		Saber 11 Score	
	(1)	(2)	(3)	(4)
1(Top 5 College)	0.060**	0.060**	0.250	-0.086
	[0.026]	[0.026]	[0.227]	[0.217]
Constant	0.299***	0.299***	6.029***	6.196***
	[0.019]	[0.019]	[0.266]	[0.107]
Observations	2,672	2,672	1,773	1,773
R-squared	0.004	0.004	0.001	0.064
AreaxYear FE		Yes		Yes

Notes. 1(High Income) corresponds to a dummy that takes the value of one if the individuals lived in a neighborhood in the two top socioeconomic strata (strata five or six). Saber 11 scores corresponds to the residuals of a regression that uses the raw scores as dependent variable and test edition and school fixed effects.

7 Conclusions

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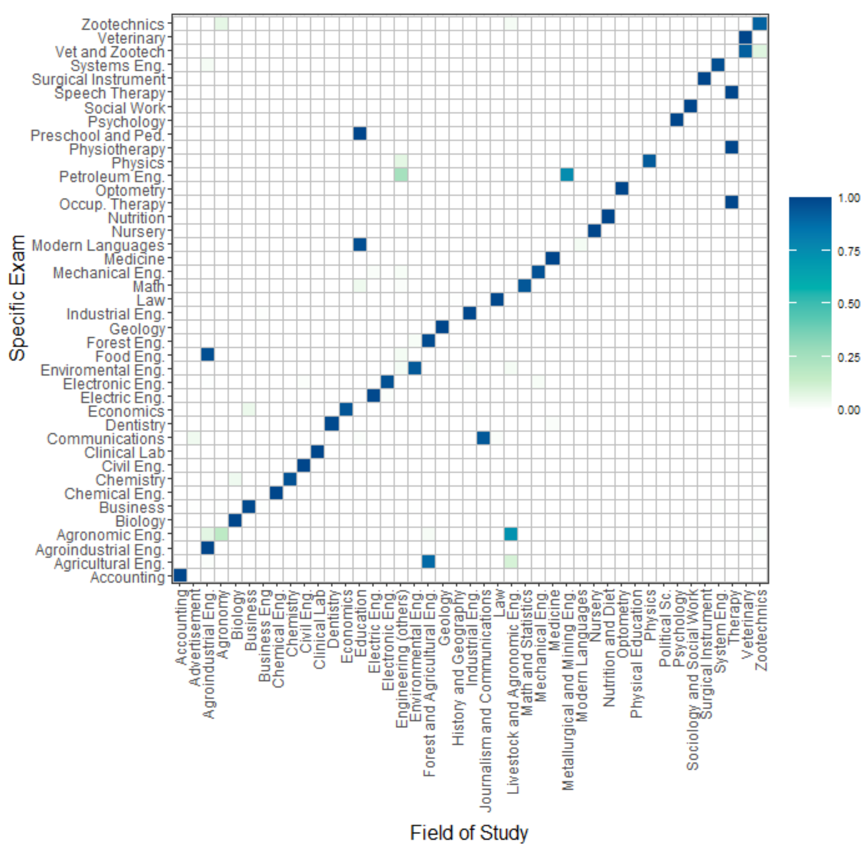
A Appendix: Saber Pro Exam and the National Award

In 2004, the Colombian government introduced the college exit exam, Saber Pro, as a tool to measure the quality of the higher education system (Decree 1781 of 2003). Until 2009, the exam focused on testing field-specific skills rather than general skills of senior college students. However, during these initial years of the Saber Pro exam, there was no formal system to assign students from different programs to a field-specific exam. Using information from the Colombian Ministry of Education, which classifies all college programs into 56 different fields of study, Figure A.1 shows that each specific exam was mainly taken by the students from the field of study for which it was designed.[26]

Figure A.1: Relationship between Students' Fields of Study and their Specific Exams

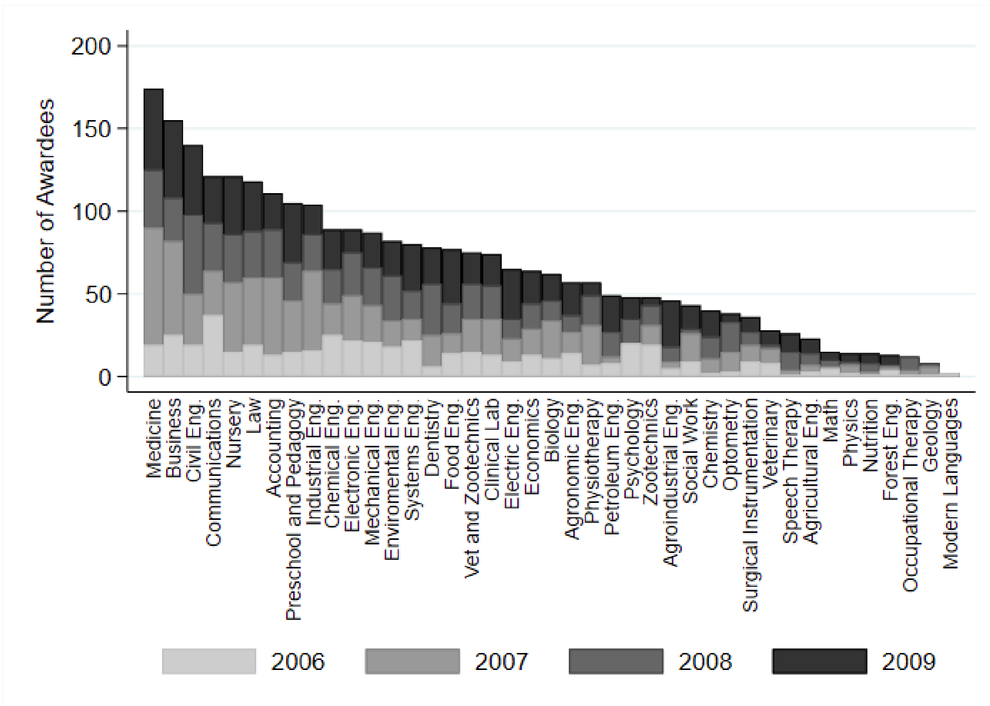


Notes. College students from 43 fields of study (as classified by the Colombian Ministry of Education) took the exam between 2006 and 2009. The graph plots the share of students from different fields who were registered to take each of the available specific exams. Rows add up to one.

[26]The fields of study defined by the Ministry of Education aggregate programs or majors with names that may vary across and within colleges. Thus, if for instance there are two programs with names "Economics" and "Economics and Finance", these might belong to the same field (MacLeod et al., 2017).

Along with the introduction of the exam, it was also introduced a policy to recognize top scorers from each field, the Saber Pro national academic award. Recipients of this award benefit from priorities when applying to scholarships and education loans offered by the government, as well as from public recognition and media coverage at an event yearly held by the Colombian Ministry of Education. Award certificates are assign to the best ten overall scores from each field. Notice that based on this rule, the national award might go to more than ten students, for instance, if more than one student got the same score among the top ten ones. Figure A.2 shows that the number of awardees might vary across field-specific exams and years. It also shows that more popular fields might assign more than ten national awards.

Figure A.2: Distinction Recipients by Field of Study and Exam Year



Notes. Distinction recipients or awardees across years and stacked by field-specific test. The Saber Pro exam apply 45 field-specific tests to four- and five-year college students, however, information is only available for the 41 fields displayed in this figure.

B Appendix: Data Construction

In this appendix we describe the process that we followed to assemble our sample. We first downloaded the public information of students who received the national academic award from the web page of the Colombian Institute For the Assessment of Education (ICFES, by its acronym in Spanish). Using the students' names, and their college program's and school's names, we identified the awardees in the universe of test-takers from 2006 to 2009. We managed to perfectly match the list of awardees. To obtain labor market information of students, we use individual identifiers to merge the test-takers data to administrative records of higher education graduates, linked by the Ministry of Education to Social Security information.

[Include Table Describing Merge Between Datasets]

Table B.1 presents the number of students from four- and five-year college programs taking the Saber Pro exam between 2006 and 2009, as well as the number of earnings that we observed each year from 2007 to 2015. Earnings observed yearly after college graduation are also displayed. The last two rows of this table show the number of colleges and college programs whose students are evaluated during these years.

Table B.1: Estimation Sample Description

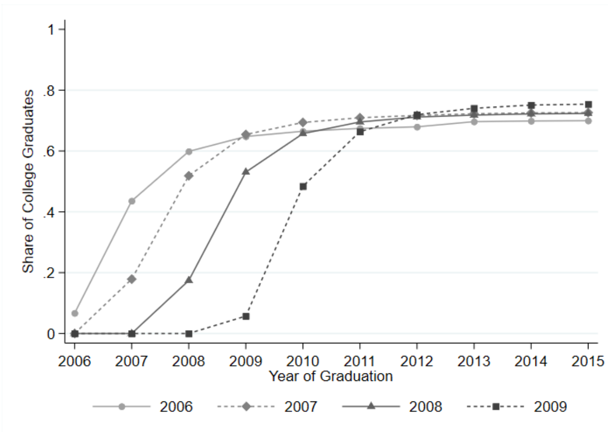
	All Test-Takers				Distinction Awardees			
	2006	2007	2008	2009	2006	2007	2008	2009
Number of Students	60,736	68,748	65,478	119,128	493	757	675	765
By Area of Study :								
Agricultural Sc.	2,673	2,276	2,219	4,689	64	62	61	90
Health	6,434	11,852	11,255	14,169	75	208	183	164
Social Sciences	18,884	13,220	18,268	28,690	104	116	98	121
Business & Econ.	11,586	22,642	17,264	39,239	51	120	70	89
Engineering	19,594	16,778	14,899	28,330	153	189	209	235
Math & Sciences	1,565	1,980	1,573	4,011	46	62	54	66
By Observed Earnings :								
2007	8,292				66			
2008	20,362	14,355			209	257		
2009	25,734	26,488	15,935		263	387	241	
2010	28,105	30,840	24,475	25,964	265	411	326	198
2011	31,309	35,247	30,744	46,512	287	429	384	361
2012	33,055	37,557	34,440	59,626	306	456	399	436
2013	35,521	40,186	37,417	66,905	314	474	424	459
2014	36,637	41,602	39,269	70,473	324	479	427	491
2015	37,141	42,215	40,378	71,943	317	483	443	504
By Earnings Post-Graduation :								
$t = 1$	22,956	27,437	26,200	53,776	255	391	368	422
$t = 2$	24,650	29,562	28,816	57,196	250	414	382	447
$t = 3$	25,503	31,150	29,792	56,307	278	428	382	435
$t = 4$	26,327	31,891	29,981	48,466	276	432	395	422
$t = 5$	26,974	31,584	27,145	20,594	297	436	378	214
Number of Colleges	172	182	189	202	78	85	80	85
Number of Programs	1,438	1,462	1,488	1,703	221	276	252	282

Notes. Count of college students taking the Saber Pro exam between 2006 and 2009. Earnings post-graduation refer to the number of years after a students graduation date (e.g. $t = 1$ means 1 year after college graduation). The number of schools and college programs evaluated during these years is displayed in the bottom of the table.

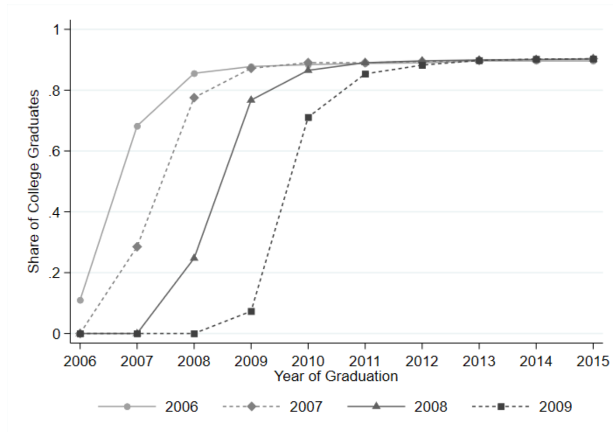
Note that the labor market data we use in our analysis cover only college graduates. Figure B.1 shows the graduation rates of students who took the Saber Pro exam during the four years we analyze. Graduation rates are around 80 percent, and most students graduate in the second or third year after they took the exam. Graduation rates among distinction awardees is 9 percent points higher, although the graduation timing of awardees follows the same pattern of the rest of the students.

Figure B.1: Graduation Rates among Saber Pro Test Takers

(a) All Test Takers



(b) Distinction Awardees



Notes. Panel (a) displays the graduation rates between 2006 and 2015 of all college students taking the Saber Pro exam between 2006 and 2009. Panel (b) displays the graduation rates for distinction recipients.

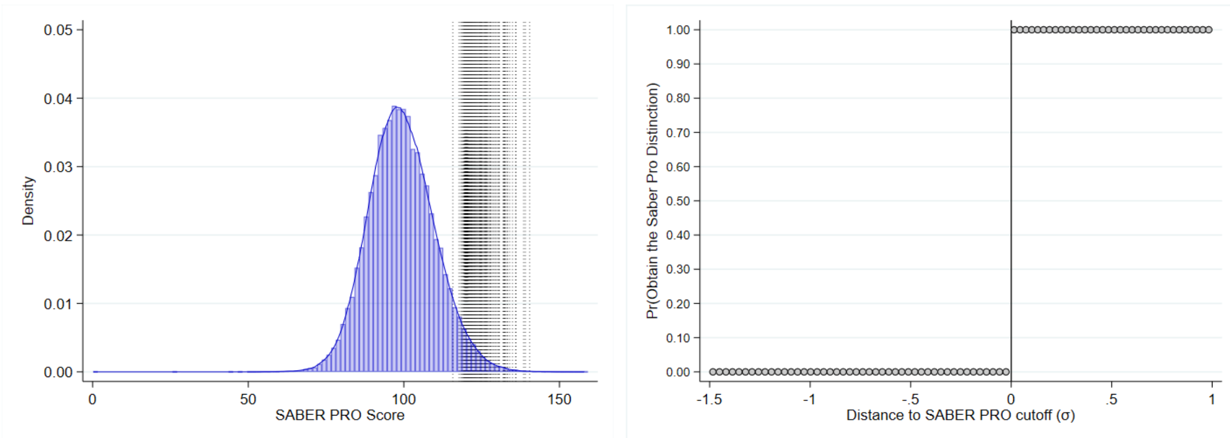
C Appendix: Additional Evidence on the RD Validity

In this appendix, we present complementary evidence regarding the identifying assumptions of our regression discontinuity strategy. Figure C.1a displays the estimated density of the overall score from the field-specific component of the Saber Pro exam. We pool the test-takers from all fields who took the exam between 2006 and 2009, and draw vertical lines representing the cutoffs used to assign the national academic award for all fields and years. This figure complements the evidence presented in Figure 1 on the smoothness of the running variable density around the threshold used to assign the award. Figure C.1b, on the other hand, shows how the probability of winning the award jumps discontinuously to the right of the cutoff, re-centered to be zero as described in Section 4.

Figure C.1: Field-Specific Exam Scores and RD First Stage

(a) Field-Specific Scores Density

(b) Probability of Winning the National Award

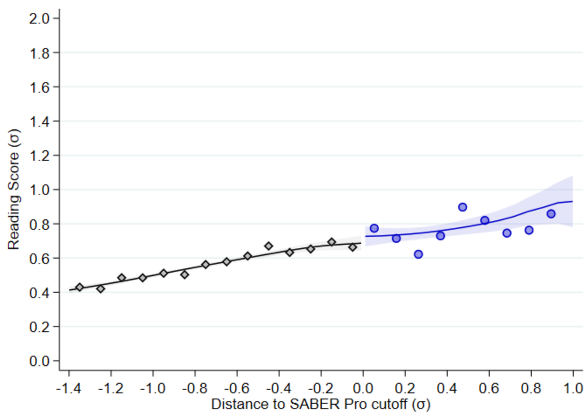


Notes. Panel (a) displays the estimated density of the scores from the field-specific component of the Saber Pro exam. Individuals from different fields taking the exam between 2006 and 2009 are pooled to estimate the scores density. The cutoffs used to assign the national award to all fields across years are plotted as vertical dotted lines. Plotted dots in Panel (b) represents the average mean within a bin around the cutoff defined to grant the Saber Pro distinction.

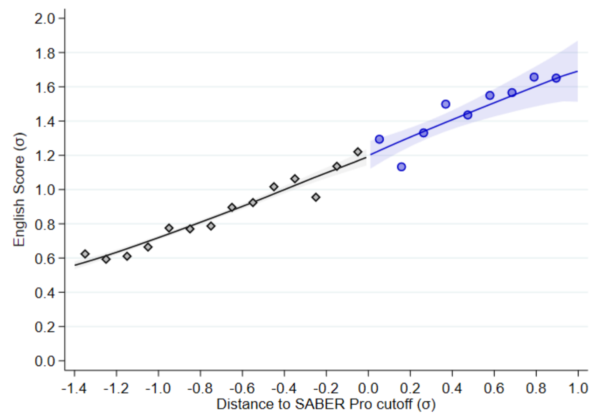
Figures C.2 and C.3 complements the evidence presented in Figure 2 regarding the comparability between award recipients and non-recipients around the cutoff. The empirical literature using sharp RD designs describes this assumption as continuity in pre-treatment covariates. Graphical inspection of these figures allows us to conclude that there are no significant differences (i.e. discontinuities) between the marginal awardees and non-awardees.

Figure C.2: Continuity in Pretreatment Covariates

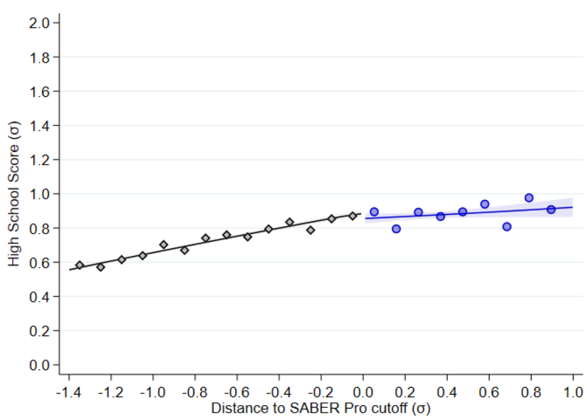
(a) Reading Score (sd)



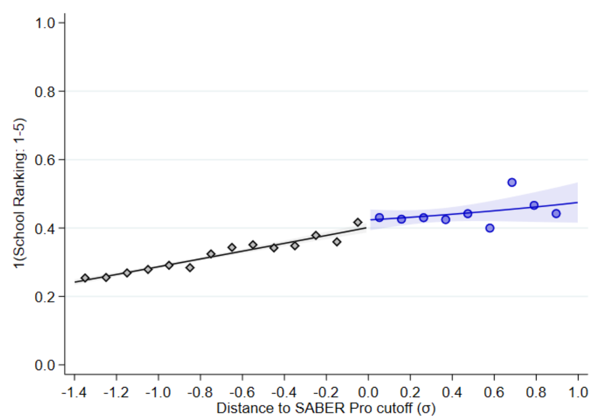
(b) English Score (sd)



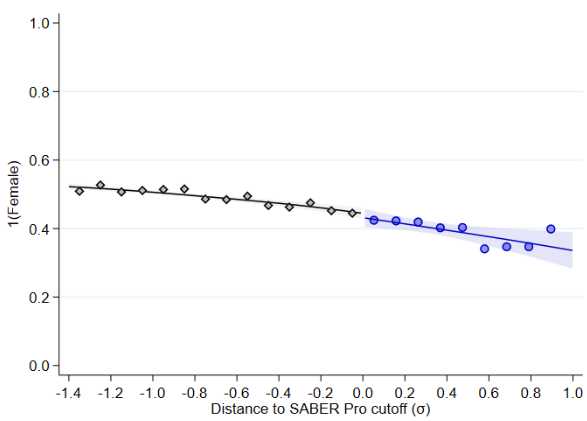
(c) High School Exit Exam (sd)



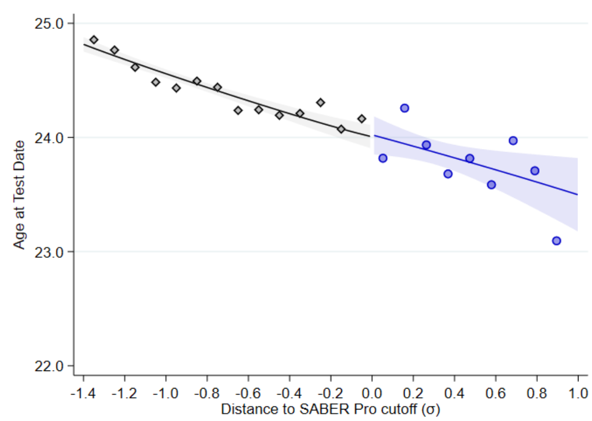
(d) Enrolled at a Top 5 University



(e) Female



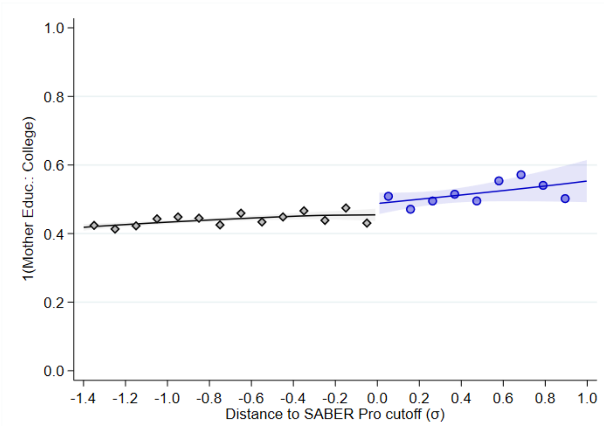
(f) Age at Test Date



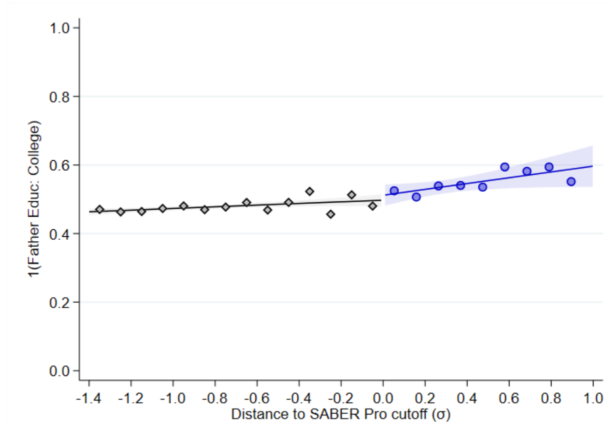
Notes. Evidence on covariate continuity or smoothness around the cutoff used to award the Saber Pro distinction to the best test-takers. The running variable is the score in the Saber Pro specific exam minus the threshold defined for each major to award the distinction to the best test-takers. All subfigures display data using a fixed bandwidth of 0.617, corresponding to the MSE-optimal bandwidth presented in Figure XXX. Plotted dots represent local averages of log earnings within bins of the running variable. Local linear regressions with 90% confidence intervals are also presented for each subfigure.

Figure C.3: Continuity in Pretreatment Covariates

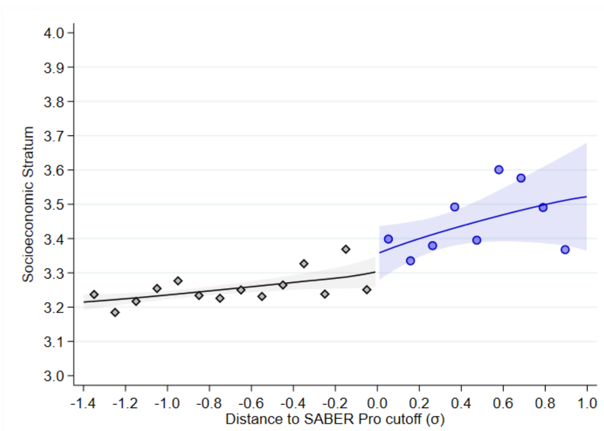
(a) Mother's Education: 4-year College



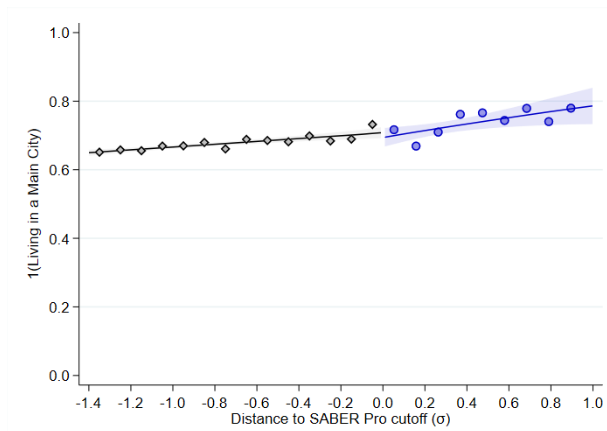
(b) Father's Education: 4-year College



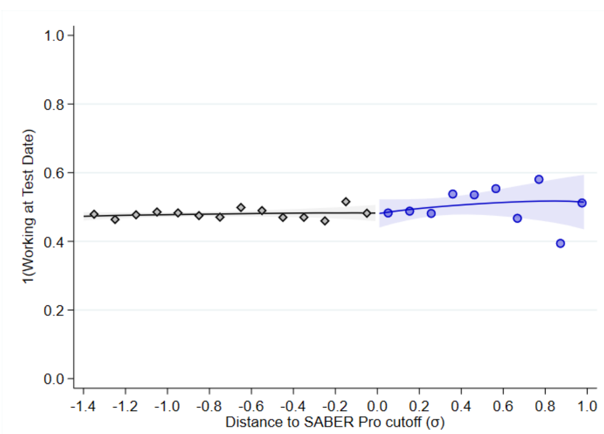
(c) Socioeconomic Stratum



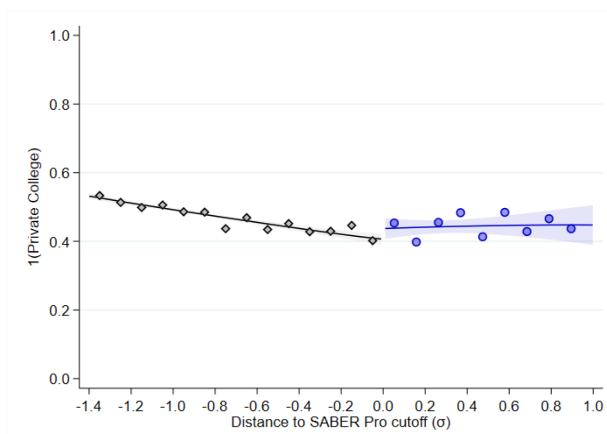
(d) Living at a Principal City



(e) Working at Test Date



(f) Enrolled at a Private University



Notes. Evidence on covariate continuity or smoothness around the cutoff used to award the Saber Pro distinction to the best test-takers. Plotted dots represent local averages of log wages within bins of the running variable. Local linear regressions with 90% confidence intervals are also presented for each subfigure.

D Appendix: Main Results, Additional Robustness Checks

In this appendix, we present further robustness checks for our main results. Table D.1 displays the estimated effect of the national academic award on our measure of initial earnings (i.e. the log of average monthly wages earned after graduation and before students are 26 years old). The jump observed in Figure 4a is estimated in Column (1), where no additional controls are used. Column (2) conditions on study-area × exam-year fixed effects, which is the baseline specification described in Section 4. Columns (3) and (4) further include test scores (i.e. the reading and English proficiency scores from the core component of the Saber Pro exam, and the high school exit exam scores) and individual characteristics as controls. Column (4) estimates the effect represented by the jump observed in Figure 4b, and labeled as our preferred specification in Figure 5. For dimensionality reasons, in columns (5) and (7) we residualized initial earnings using Field-specific exam × exam-year fixed effects, and estimate the effect using such outcome. The national award increases an early-career earnings between 8 and 10 percent.

Table D.1: Effect of *Saber Pro* Distinction on Initial Earnings

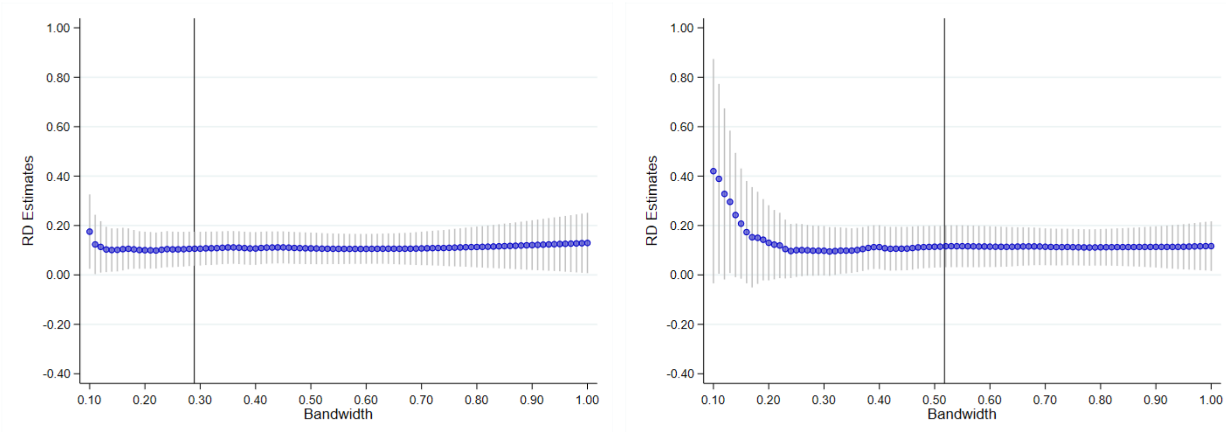
	Dependent Variable : Log Avg. Wage Ages 23 - 26						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
RD Estimate	0.112*	0.106***	0.105***	0.096***	0.091**	0.086**	0.081**
	[0.060]	[0.035]	[0.035]	[0.036]	[0.046]	[0.043]	[0.040]
Mean control	14.17	14.13	13.91	15	14.19	14.09	15.43
Observations	108,802	108,802	108,802	108,802	108,802	108,802	108,802
Bandwidth	0.291	0.291	0.291	0.291	0.291	0.291	0.291
Effect. obs. control	1475	1475	1475	1475	1475	1475	1475
Effect. obs. treat	913	913	913	913	913	913	913
Area×Year FE		Yes	Yes	Yes			
Field×Year FE					Yes	Yes	Yes
Test Scores			Yes	Yes		Yes	Yes
Covariates				Yes			Yes

Notes. Estimated coefficients using linear local regressions, an Epanechnikov kernel and a common bandwidth. The bandwidth was optimally computed to minimize the MSE using the specification displayed in column (2). We use the overall score in the High School Exit exam (Saber 11) and the Reading and English Proficiency exam from the *core* component of *Saber Pro* to control for initial abilities and general abilities as shown in in Columns (3) and (6). Covariates include : gender, age at test date, socioeconomic stratum, mother's education. Specific-exams are grouped in 6 areas of study: Agricultural Sciences, Health, Social Sciences, Business and Economics, Engineering, and Math and Natural Sciences. Area×Year-of-Exam fixed effects are computed based on these 6 larger fields. Estimates conditioning on Field×Year fixed effects, are computed using the residuals of the outcome variable from a OLS regression in which we control for a set of dummies defined by Field×Year. Standard errors are clustered at the Area × Year level and in squared brackets. * $p<0.05$, ** $p<0.01$, *** $p<0.001$.

Following Imbens and Lemieux (2008), we also estimate the effect on initial earnings using local polynomial regressions of different orders and considering multiple bandwidths. Using our preferred specification, Figure D.1 shows that our estimates are robust to a wide range of bandwidths, and to a quadratic local polynomial regression. As in any empirical work using a sharp regression discontinuity design, bandwidths closer to zero will reduce the bias but will also reduce the precision of the estimates, which can be seen in this figure.

Figure D.1: Estimates as Function of the Bandwidth

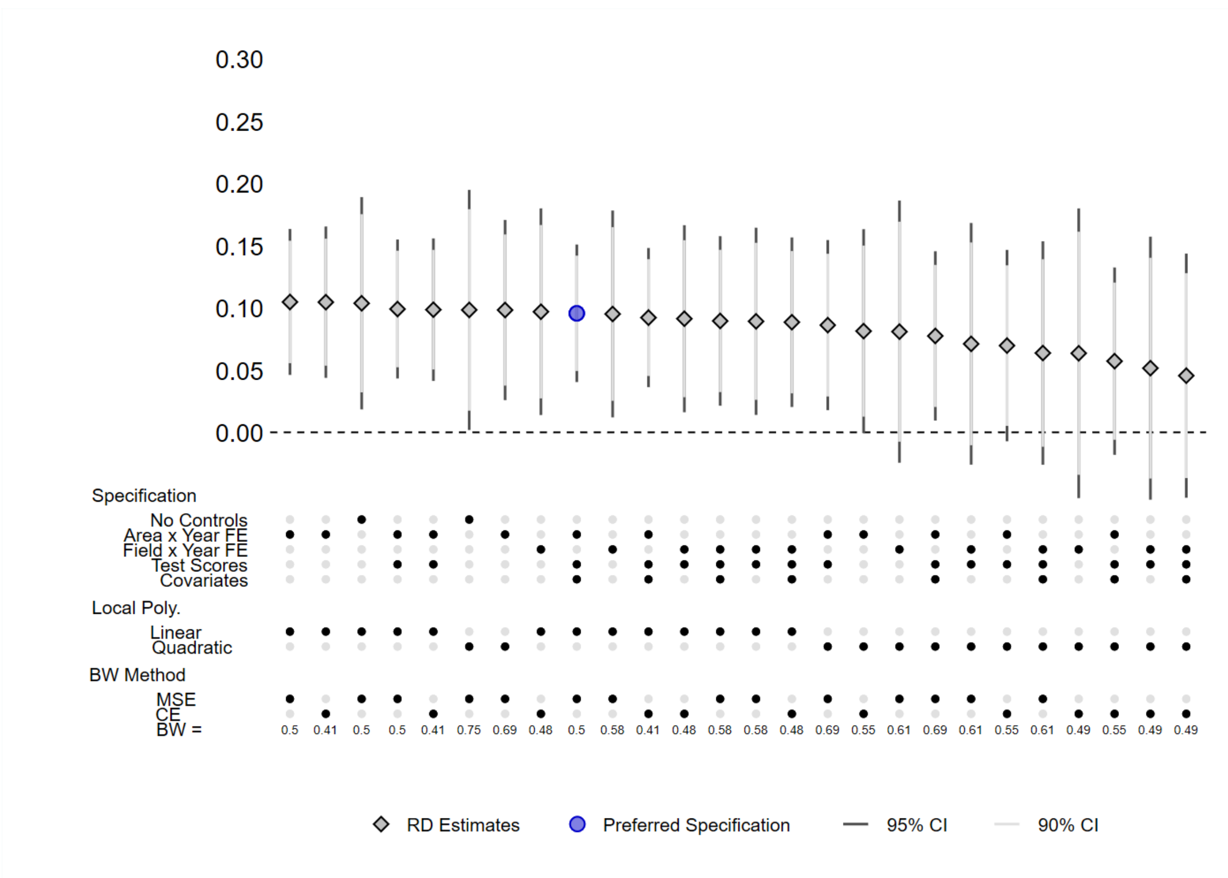
(a) Linear Polynomial (b) Quadratic Polynomial



Notes. Panels (a) and (b) presents the RD estimates as a function the chosen bandwidth. Plotted dots represent the estimates around the cutoff using our preferred specification. Estimates in Panel (a) use a linear local regression model, while estimates in Panel (b) use a quadratic local regression model. The vertical solid black line in both panels represent the computed MSE-optimal bandwidths for reference. Confidence intervals at the 95% level are displayed for each plotted dot, and computed using standard-errors clustered by Area×Year-of-exam.

Finally, our estimates are robust to an alternative measure of initial earnings, namely wages observed one year post college graduation. Figure D.2 displays point estimates using different specifications and methods to optimally choose bandwidths. These results are very similar to those presented in Figure 5 and Table D.1, although we lose some precision after we residualize the outcome from a regression including Field-specific exam × exam-year fixed effects. The estimated premium on wages observed after graduating from college ranges between 5 and 10 percent, using this alternative measure of early-career earnings.

Figure D.2: Robustness of the Effect of the National Award using an Alternative Measure of Early-Career Earnings



Notes. The outcome variable is the log of average monthly wage earned after graduation and before students are 26 years old. Plotted dots represent the RD estimated coefficients using linear and quadratic local regressions, an Epanechnikov kernel and bandwidths as displayed in the bottom of the figure. Specific-exams are grouped in 6 areas of study: Agricultural Sciences, Health, Social Sciences, Business and Economics, Engineering, and Math and Natural Sciences. Area×Year-of-Exam fixed effects are computed based on these 6 larger fields. Estimates conditioning on Field×Year fixed effects, are computed using the residuals of the outcome variable from an OLS regression in which we control for a set of dummies defined by Field×Year. Test scores include: the High-School-Exit exam scores (Saber 11), and the Reading and English Proficiency scores applied as part of the common component of the College-Exit exam (Saber Pro), which are omitted to determine the Saber Pro distinction recipients. Covariates include: dummies for gender and mother's education level, socioeconomic stratum and age at exam. Confidence intervals at the 90% and 95% levels are displayed for each coefficient, and computed using standard-errors clustered by Area×Year-of-exam.