Signaling Specific Skills and the Labor Market of College Graduates

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Abstract

We study how signaling skills specific to the major affects labor market outcomes of college graduates. We rely on census-like data and a regression discontinuity design to study the impacts of a well-known award given to top performers on a mandatory nationwide exam, which constitutes a graduation requirement for college seniors in Colombia. Students who can rely on the signal when searching for a job have a wage premium of 7 to 12 percent compared to otherwise identical students. This positive return persists even five years after graduation. The signal mostly benefits workers who graduate from low-reputation colleges, and allows workers to find jobs in more productive firms and in sectors that better use their skills. We rule out that the positive wage returns are explained by human capital. The signal favors mostly less advantaged groups, implying that less information frictions about students' skills could potentially reduce earnings gaps. Our results imply that information policies like those that formally certify specific skills can improve the efficiency in talent allocation of the economy and level the playing field for workers who come from disadvantaged backgrounds.

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1 Introduction

Employers make job and wage offers based on asymmetric information as they do not usually observe the full set of skills and abilities of the candidates they consider for any given job position (Spence, 1973, 1974). When searching for workers higher in the skills distribution, however, firms have an increasing number of tools at their disposal to make hiring decisions. Academic degrees or diplomas, the reputation of the institutions granting those degrees, and diplomas' characteristics, have all been shown to reduce information frictions by providing job seekers with a signal about their skills, and firms with a valuable screening device to compare candidates.[1] In this paper we show that even in a high-skilled labor market, a salient signal on specific skills (i.e., skills learned at a college-major program) has a positive and persistent information value: workers who are able to use the signal earn higher wages and find better job matches (in high paying firms that better use those skills). The signal also levels the playing field by benefiting more those workers that come from disadvantaged backgrounds.

We study the labor market effects of a national distinction award given to top-scorers in field-specific evaluations. College students in Colombia are assessed by a college-exit exam that evaluates skills *specific* to the field of study as well as a *core* component that evaluates general cognitive skills such as reading and English proficiency. Test takers with exceptional performance in the field-specific component of the test receive a salient and well-publicized national distinction award.[2] The college-exit exam is taken by graduates of every college. Thus, the signal given by the national distinction award identifies high-skilled students irrespective of the college they graduate.

We exploit the discontinuity in the assignment of the national distinction award to implement a regression discontinuity design that examines the casual effect of obtaining the award on recipients' initial earnings and firms' hiring decisions. Our design compares otherwise identical students (i.e., with similar average characteristics and skills) with and without the award, to estimate the labor-market returns of the signal itself. We use census-like, longitudinal labor market data from Colombia, linking these to college records and the universe of test scores from both high school and college exit exams. We focus on the universe of college students who took the college-exit exam between 2006 and 2009, and

[1]For articles addressing the return to academic degrees see: Hungerford and Solon (1987), Kane and Rouse (1995), Jaeger and Page (1996), Tyler et al. (2000), Clark and Martorell (2014), and Jepsen et al. (2016). For articles about the returns to college reputation see: MacLeod et al. (2017), Barrera and Bayona (2019), and Bordon and Braga (2020). For articles estimating the returns for diploma's characteristics (e.g. Latin Honors) see: Khoo and Ost (2018) and Freier et al. (2015).

[2]Graduates include the award in their CVs, and colleges strongly publicize their awardees in order to increase their reputation.

identify those who received the national distinction award by using the publicly available lists of the universe of awardees. Our data allow us to use a rich set of controls – including measures of pre- and post-college general skills– to examine the extent to which the signal or the skills account for the labor-market impacts.

We show that the award increases recipients' initial earnings by 7 to 12 percent – equivalent to an additional year of education in Colombia. This treatment effect persists for at least five years after college graduation, in line with career-development models that highlight the role of job-ladders in the career of high-skilled workers (Gibbons and Waldman, 1999a,b). Our estimates are robust to alternative estimation strategies and different outcome measures. We provide evidence that our results are not driven either by manipulation of the running variable nor by selective attrition. In addition, we present evidence consistent with the fact that the estimated effects are not due to differences in general skills around the cutoff. This allows us to interpret the earning returns of the national distinction award as those that accrue solely from the signaling effect of the award (i.e., not from differences in human capital).

We examine the mechanisms behind the estimated positive effect of the award. To guide the discussion, we introduce a stylized conceptual framework that highlights the role of human capital and of colleges and majors of study with heterogeneous reputations. We find that three mechanisms seem to be at work behind our main result.

First, we find evidence consistent with the fact that the national distinction award is a labor market signal. We build a college reputation index which captures how selective programs are when accepting applicants. We show that the award yields larger wage returns for those workers who enter the labor market without a string credible signal. That is, those who graduated from less reputable schools. The magnitude of the returns to the signal is such that it allows these workers to obtain a wage similar to the one they would have obtained had they graduated from a college with a higher reputation.

Second, the signal improves the allocation of talent in the economy. We build an index that assesses how good the match is between the field of study to industry of employment. We show that the information provided by the award regarding specific skills allows firms across industries to identify candidates with the qualifications needed to fill positions. This effect is driven by students from lower-reputation colleges, indicating that the signal allows them to match specialized firms and increase their earnings. Signals on the student's field-specific skills increase the likelihood of working on the same field, especially for those who are not able to signal through college reputation.

Third, we find that the signal allows high-paying, plausibly high-productivity, firms to hire higher-skilled workers. We build measures of firm rent-sharing (i.e, a potential proxy for productivity) by computing time-invariant rankings of firms (within their narrowly defined industry) according to: (i) the average wages paid to their employees; and (ii) the wage decomposition methodology in Abowd et al. (1999). We show that the signal given by the national distinction award leads to an increase of 0.18 of a standard deviation in the ranking. Students who won the national distinction award are significantly more likely to work in better paying firms.

The wage effects of the national distinction award are persistent, and we provide evidence that the persistence could be explained by the presence of job ladders. Award recipients who initially match with better paying firms could enter a learning and promotion trajectory that allows them to continuously increase in the firm ranking. We show that awardees are more likely to move to higher paying firms after graduation compared to equally endowed students without the signal. These moves among higher paying firms provide strong evidence for the existence of job ladders that induce the persistence of the wage effect, at least for five years after graduation –the time lapse we are able to observe.

Our estimated labor market returns to the signal are not driven by differences in human capital. The combination of the regression discontinuity estimates combined with our ability to control for workers' general skills allow us to compare workers with and without the award who are otherwise observationally identical (*before* the national distinction was awarded). In particular, our research design lets us compare the earnings of those workers who can provide a signal to the labor market with workers that have the same level of skills (as well as other similar observable characteristics) who cannot provide such a signal. In addition, we show that the distinction award did not lead to a differential human capital accumulation *after* the national distinction award was assigned: Awardees have a similar probability of attending graduate school after finishing college. For these reasons we interpret our results as the earning returns of job market signaling exclusively.

The distinction award is more beneficial for students of a less privileged background. We show that the positive wage return is driven primarily by high-skilled students who could not attend prestigious colleges; presumably because of income constraints (Chetty et al., 2020; Solis, 2017). We estimate heterogeneous effects of the signal and find that the distinction award mainly benefits individuals whose parents have no college degree, workers whose parents have blue collar jobs, workers with low access to job search networks, and women. We then compute counterfactual earning gaps with and without the award. We compare earnings around the cutoff of workers who won the award and that belong to the "disadvantaged" group (e.g., women) with earnings of those that did not win the award and belong to the "advantaged" group (e.g., men). We find that the signal reduces the earning gaps from about 20 percent in the case of women/men to almost entirely in the case of people with low/high access to job search networks. These results suggests that information policies like those that formally certify specific skills have the potential of reducing wage inequality.

Our paper is closely related to a recent and growing literature that analyzes the labor-market effects of introducing signals about workers' skills in the job matching process. This literature provides experimental evidence showing a positive effect of signaling general cognitive skills (such as numeracy, linguistic abilities, or abstract reasoning) and non-cognitive abilities (such as grit, creativity, or trustworthiness) on current and future labor-market outcomes of unskilled workers in low-information settings (Abebe et al., 2021; Bassi and Nansamba, 2022; Carranza et al., 2022; Pallais, 2014). We contribute to this literature in three ways. First, we show that signals are valued in the labor market even in the context of high-skilled workers for whom a signal already exist (i.e., college reputation). Even though one might expect that the information asymmetry between job applicants and employers would be smaller in the cases of college graduates, we nonetheless find sizable earnings impacts of the signal for those in these groups. Second, the signal analyzed in our paper constitutes a national policy that is well recognized by employers and can potentially affect all firms and industries (and for that reason, have larger general equilibrium effects in the economy). Our results suggest that the experimental effects carry over to more general settings. Third, the national distinction award signals a set of skills that are specific to the field of study, which is less transferable across industries than cognitive and non-cognitive skills. Finally, we are able to follow workers for five years after the signal was introduced to show that their effects do not fade out.

Ever since Spence (1973, 1974) established a theory of signaling and screening in the labor market, multiple empirical studies have tried to estimate the effects of education signals and separate them from the human capital content which is usually attached to them. One set of studies have analyzed the effects of obtaining a diploma by measuring the size of the so-called "sheepskin effect", which refers to the economic return of completing a degree, among otherwise similarly educated individuals who graduated from high school (Tyler et al., 2000; Jepsen et al., 2016; Clark and Martorell, 2014) or college (Hungerford and Solon, 1987; Kane and Rouse, 1995; Jaeger and Page, 1996). Several related studies have shown not only that diplomas are labor market signals but that their *characteristics* matter as well for labor market performance. First, the reputation of the institution granting the diploma plays an informational role when students enter the labor market and is therefore positively correlated with college graduates' earnings (MacLeod et al., 2017; Barrera and Bayona, 2019; Bordon and Braga, 2020).[3] Second, the students' within-

[3] Arteaga (2018) shows that a reform that decreased the content of human capital in a prestigious

university ranking also has a positive wage return (e.g., Khoo and Ost (2018); Freier et al. (2015) analyze the effect of Latin honors).[4] Our paper contributes to this broad literature by providing evidence on the returns of a pure signal in a labor market where the signals sent by diplomas, college reputation and Latin Honors are already operating. The signal studied in this paper allows employers to fully and properly compare workers across schools (reducing the role of the college reputation in the formation of the signal). Different from Latin honors and other college-specific attributes, the national distinction award is a signal which is independent of the student's college: it is based on a universal ranking of the students' field-specific skills among a nationwide cohort of graduates who take the test in a given year. Therefore, the exam gives students who graduate from lower-ranked programs a way to signal their productivity among their peers in other schools.

The rest of the paper is organized as follows. In section 2 we present the institutional background, showing that the college exit exam is a high-stakes test, and demonstrating that the distinction award is a valuable signal, given how widely known it is in Colombia. Section 3 describes the data sources and reports summary statistics for our estimation sample. In section 4 we describe the empirical strategy. In Section 5 we validate our identifying assumptions and present the main results. Section 6 presents a theoretical framework and empirical evidence on different mechanisms that can explain the positive and large effects that we find. Section 8 discusses the implications for inequality. Section 9 concludes.

2 Setting and institutional background

The higher education system in Colombia includes public and private institutions (referred to as colleges in this paper) that offer programs on different fields of study. Two types of programs are offered: technical programs, with a length of two or three years, and professional programs, designed to be completed in four to five years.[5] Admissions are decentralized. Applicants seek admission to specific majors in different colleges with programs usually having different requirements across and within colleges. A key component of students' applications is the performance in a high school exit exam, which all students must take. Programs and colleges are heterogeneous in terms of their selectivity, the quality of the education they provide, their tuition fees and, as a result, their perceived

university led to a reduction in earnings after graduation, ruling out a pure signaling effect.

[4] A number of studies have also documented positive effects of awards on workers' productivity (Neckermann et al., 2014; Chan et al., 2014). That is, outside an education setting.

[5] Colleges define the length of their programs autonomously. We focus on professional programs, which are equivalent to a bachelor's degree in the United States.

reputation (MacLeod et al., 2017; Camacho et al., 2017).[6]

In 2003, the government introduced a mandatory exam as a graduation requirement for all college seniors. This college-exit exam, known as *Saber Pro*, aims to assess the skill levels of new graduates and the quality of the instruction provided by all colleges and programs in the country.[7] Students are allowed to take the exam after completing three-quarters of their program's coursework, but most students take it within one year before their graduation term. The exam is high-stakes for both students and colleges.[8] Exam results matter for colleges because test scores are used to create nationwide rankings, which constitute public information and can determine a college's ability to attract good students. Some schools provide internal incentives and tools to prepare and motivate students to perform well. Tests scores also matter for students because there are several benefits for high achieving test-takers, such as scholarships, remission of graduation fees, and study loan forgiveness.

The college-exit exam is comprised of two components. First, a *core component* assesses general abilities across fields by testing reading comprehension and English proficiency. This reading section examines the capacity to read analytically, understand college-level written material, identify different perspectives, and make judgments. Students answer 15 multiple-choice questions based on two reading passages, one adapted from an academic journal and the other from the news media. The English section, on the other hand, focuses on testing the ability to effectively communicate in written English. It includes 45 questions divided into 7 parts which require knowledge of different vocabularies.

Second, the college-exit exam includes a *specific component* which measures students' expertise in their own program's field of study. Depending on the field, students take between four and twelve sub-tests on subjects deemed to be fundamental for their fu-

[6] Among the top 5 most selective colleges, 3 are private; while among the top 20, 12 are private.

[7] Decree 1781 of 2003, enacted by the Colombian Ministry of Education, introduced the National Exam of the Quality of Higher Education (ECAES by its acronym in Spanish) as a tool to assess the quality of colleges and, additionally, as a source of information to make education policy decisions. The decree made colleges responsible for the compulsory compliance of their senior students to take the exam and considered administrative actions in case they fail to register students (Articles 1 and 5). However, given that exams for different fields of study were introduced gradually over the years, compliance was restricted to areas with available tests. In 2009, Congress approved Law 1324, and the exam became a graduation requirement for all college students. The law also changed the name of the exam to *Saber Pro*, as it is known nowadays, and the government started enforcing its compulsory mandate for students in all fields since 2010.

[8] The exam's authority – the Colombian Institute for the Evaluation of Education (ICFES in Spanish) – makes preparation material available online. In addition, colleges prepare their students for free. Students are allowed to take the exam more than once, but this is only frequent among students enrolled in more than one program, which represent a negligible portion of the population.

ture career as professionals in each area.[9] For instance, students enrolled in economics are evaluated, through four sub-tests, in microeconomics, macroeconomics, econometrics, and economic history; while physics students are tested in electromagnetism, electrodynamics, thermodynamics, quantum physics, and classic-, quantum-, and statistical-mechanics. Questions are designed by experts in each field and follow well-defined standards so that test scores are comparable across years.[10] The college-exit exam was rolled-out gradually across different fields from 2003 (27 field exams) to 2006 (55 field exams). Our analysis focuses primarily on the period 2006-2009 when 55 field-specific exams were consistently administered each year across all colleges in the country.[11]

The college-exit exam is almost universal. Most senior students in areas for which a specific exam was available took the exam before 2010 (MacLeod et al., 2017). Furthermore, most students took the exam specifically designed for their major's field of study.[12]

Every year, students who obtain a score in the top-ten scores of the *field-specific* component are given a national distinction award.[13,14] The annual public announcement of the top scorers is broadly publicized. Recipients receive public recognition throughout national news media and in a ceremony held by the Ministry of Education to hand out certificates. Universities also maintain a public list of awardees on their websites as a way to advertise the quality of their programs and, in turn, to attract the best students and boost their demand.[15]

The national distinction award is a signal for the labor market about students' specific

[9] In our period of analysis students had to take a preset number of sub-tests in all subjects defined by the exam's authority. Afterwards, the policy was changed so that colleges are now allowed to choose three sub-tests in which their students are assessed.

[10] See (ICFES, 2010) pp. 5 footnote 4.

[11] Out of these 55 field exams our analysis relies on the 48 exams that were designed for students in bachelor's programs. The other 7 were administered in vocational schools.

[12] In principle, students were allowed to register to take any field-specific exam. Using the Ministry of Education's classification of all college programs into fields of study, we determined the percentage of students taking each specific exam across fields. These distributions are highly concentrated around 1, meaning that most students took a specific exam corresponding to the same field of study they pursue in college. For more details, refer to Appendix B.

[13] In a given field-year there can be more than 10 awardees if multiple students share the same score among the top-ten ones.

[14] This distinction was added to a long tradition of national awards based on standardized tests in Colombia. In 1976, the Ministry of Education instituted distinctions for the students with the highest test scores in the elementary and high school standardized tests. Since 1994, the well-known *Andres Bello* distinction has been awarded by the government to students with the highest scores in the high school exit exam.

[15] Appendix B discusses the distribution of awardees and the likelihood of winning the award across fields. The number of awardees vary across field-specific exams and years, with more students in popular fields (i.e., with a large student-body) receiving more awards.

skills relative to all other students in the country. Because it is based on a standardized test, students are ranked nationwide within their fields of specialization (independently of the college they attended). In that sense, the national distinction award provides information that is different from the one given by graduating with honors from college (which only allows for within-college comparisons). The distinction award is a signal that is actively used by employers and by students when looking for jobs. Employers are able to find award recipients easily, through media, on college websites, from job candidates' resumes.[16] Whereas the national distinction award is a signal actively used in the labor market, the actual test score on the specific component of the exam is likely not used because it is not readily available to students nor would it be easy to interpret by employers. Section 5 presents results of placebo tests that are consistent with this claim.[17]

3 Data

Our universe of analysis consists of the 314,090 students who were enrolled in four- and five-year programs and took the exit exam between 2006 and 2009. Using individual-level identifiers, we combine four data sources: 1) Administrative records of the universe of college exit exams, both the core exam and the specific components;[18] 2) Among these students, who were eligible to receive the award based exclusively on the field-

[16] We used public information to search online for the profiles of 59 random students who won the award in 2009. As of June 2022, all of them were still listed as awardees on their universities' websites. We found the LinkedIn profiles of 44 students; thirteen years after winning the distinction, 25 percent of this group were still mentioning the award on their LinkedIn profiles. Typically, students who won the award also know (and list) their ranking among awardees.

[17] Students who did not win the distinction award do not report their (specific) exit exam scores in their CVs. We conducted a search for 66 graduates from the Universidad del Atlántico who did not win the award. We obtained information about them using publicly available lists of graduates. Using their names, year and school of graduation, we were able to find information for 29 out of the 66, mostly in LinkedIn. None of them mention their scores in both the high school-exit exam (Saber 11) nor the college-exit exam (Saber Pro). This is not surprising for three reasons. First, students are not provided with separate overall tests scores for the core and the specific components of the exit exam. Second, test scores for the core component and the specific component are numbers that are not informative per se: the range of test scores varies from year to year and by field of specialization. (In our sample scores range from zero to 161.) Third, in the period of analysis, test administrators did not provide information on the distribution of students who fall into certain percentiles of achievement levels for any of the two components. Appendix B presents an example of a report card with a student's test scores as evidence for this last claim.

[18] 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 for which 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).

specific component of the exam, we identified all 2,690 award recipients from publicly available records published online.[19] 3) We use administrative records of the universe of students who ever registered to a higher education institution in Colombia. These data include information about the institution in which students enrolled, the field of study the student selected, the students' high school exit exam scores, and some sociodemographic information.[20] 4) We use administrative social security records from 2007 to 2015. The records include monthly earnings in the formal sector (measured in the latest observed month between the second and third quarters of every year). [21] Our main outcome of interest is the labor earnings observed when college graduates enter the labor market (which for the majority of individuals happens when they are 23 to 26 years old).[22]

In our data, about 57 percent of college graduates are women. They are, on average, 26 years old and classified as belonging to the lower-middle class of households.[23] The majority of graduates are first-generation college students: only a third have a mother who graduated from a two- or four-year college. Most students attend a private college, the majority of which are considered to be low-ranking institutions. We observe overall test scores for 41 field-specific exams, which we group into six areas of study: Health (10 fields), Engineering (10 fields), Agricultural Sciences (6 fields), Social Sciences (6 fields), Business and Economics (3 fields), and Math and Natural Sciences (6 fields).[24]

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

[20]The Ministry of Education classifies college programs into 56 fields of study so that for each student we observe both the actual field from which they graduated and the subject area in which they took the specific component of the exit college exam.

[21]We lack labor-market information for those individuals out of the labor force, unemployed, or working in the informal sector of the economy. In Colombia, 75 percent of workers with college education are employed in the formal sector.

[22]We compute the average of all observed monthly earnings of individuals when they are 23 to 26 years old. Notice that the median student graduates at age 25 while students that are +/- 1 standard deviation from the distinction award cutoff graduate on average when they are 6 months younger than that. About 35 percent of the population graduates when they are 27 years old or older. Thus, this measure allows us to maximize observations of individuals around the cutoff and, at the same time, to keep constant the age profile of students in our sample. Our results are robust to several other definitions of labor earnings, including for instance the first observed labor earning after graduation, as we show in the Online Appendix E.1.

[23]Households in Colombia are classified in six socioeconomic strata that are used to target social programs and different public subsidies. The strata range from one (very low) to six (high), and is given depending on the neighborhood where the person lives. Wealthier neighborhoods with more public amenities, better locations, and more expensive properties have a higher value of the index. Lower-middle refers to the third strata, out of the six.

[24]Appendix Table A.1 provides descriptive statistics of our main estimation sample. Further details about data construction can be found in Appendix C.

4 Empirical strategy

We use a sharp regression discontinuity design to estimate the causal effect of winning the national distinction 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.[25] 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 earnings after graduation and before students turn 27 years old (i.e. earnings observed at an early stage of the career of college graduates), but we also consider earnings one year after college graduation to show that our results are robust to an alternative measure of earnings. 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. 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 also considers a vector of control variables, X_i (Calonico et al., 2019). This vector includes age, gender, socioeconomic status, the 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 × year fixed effects; this vector captures differences across the different test editions and controls for variation across programs because the cutoffs are field specific. Standard errors are

[25] 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.

clustered by area of study and test year.

5 Results

We start by checking our identifying assumptions; we ascertain 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 of the distinction award on initial earnings after graduation, and by analyzing whether and to what degree the winning of the distinction has a persistent effect on earnings several years after students have entered the labor market.

5.1 Validity of the research design

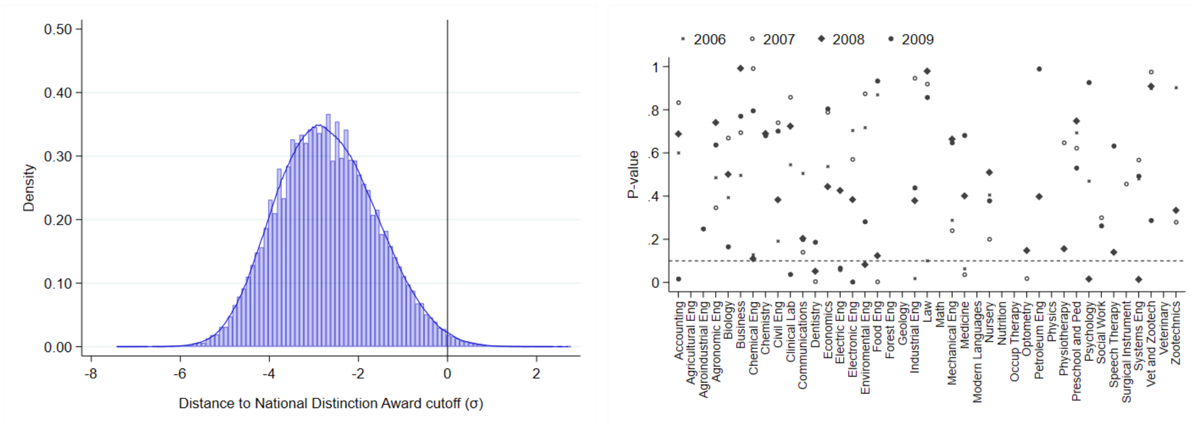
Manipulation tests. A first threat to the validity of our empirical strategy comes from the potential manipulation of the threshold used to assign the national distinction awards. Detecting a lack of smoothness in the density of the running variable (i.e., bunching) around the cutoff would be evidence of such manipulation. We consider the non-parametric test developed by Cattaneo et al. (2020), who proposed a testing procedure to check for discontinuities based on the density estimator of Cheng et al. (1997). The null hypothesis of this test is that there was no manipulation around the threshold.

The possibility of manipulation in our context is very low. The score used to determine which students received the national distinction award is the overall score computed from different subjects of the *specific* component of the college-exit exam. The threshold is not known ex ante by test takers nor by schools, and it may change from one year to another for all field exams. It is therefore unlikely that individuals could act strategically to receive (or not receive) the award.

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. The estimated density function is smooth around the cutoff. Figure 1b provides the p-values of the formal manipulation test that we implement for all field-specific exams across years. We cannot reject the null hypothesis for most exams. Furthermore, there is no field in which no manipulation is rejected consistently across years. Based on these results we rule out manipulation as a threat to the validity of the regression discontinuity estimates.

Figure 1: Density smoothness around the cutoff

(a) Running variable density (b) Manipulation tests



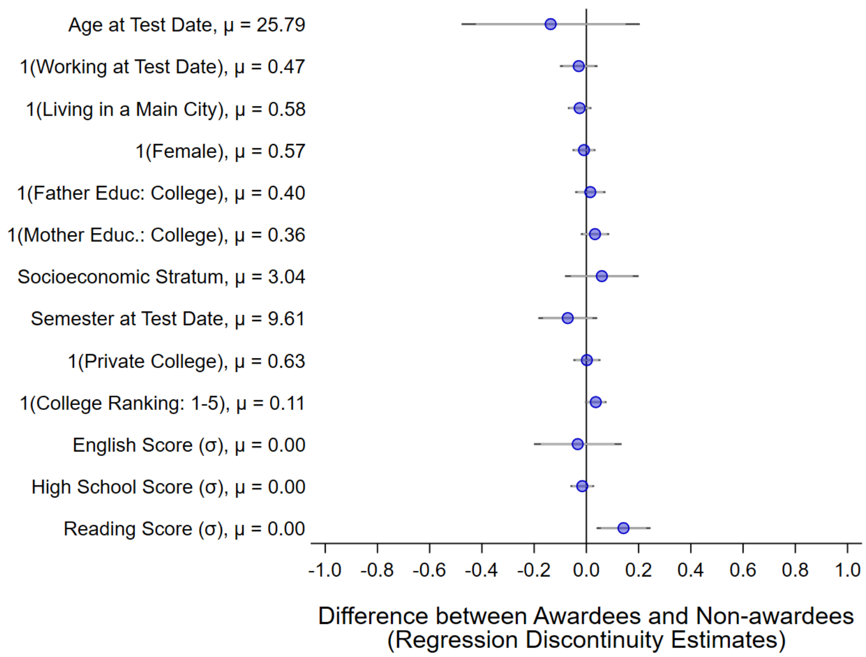
Notes. Figure 1a plots the estimated density of the running variable. Figure 1b presents the results of the manipulation test proposed by Cattaneo et al. (2020). The null hypothesis for this test is: smoothness or no manipulation in the density of the running variable around the cutoff (normalized to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

Balance tests. Our identification relies on the assumption that students around the threshold are identical. In other words, the regression discontinuity estimates could be biased if the marginal recipients of the national distinction award were systematically different from the students closer to the cutoff who were not awarded the distinction. To assess the validity of that assumption, we estimate Equation (1) – setting $\gamma = 0$ – on a set of variables determined before receiving the award, using the MSE-optimal bandwidth selected for our main outcome of interest. We plot the estimates of β and their 95 percent confidence intervals in Figure 2.

On either side close to the cutoff, individuals who received the award and those who did not receive it seem to have similar levels of general skills. We use the overall scores from the high school exit exam to proxy for general ability at the time of entering college. We rely on the reading and English test scores from the *general* component of the college exit exam to proxy for general academic skills at the time of graduating from college. In both cases, we cannot reject the null hypothesis that the average general ability of award recipient and non-recipient are equal.

A potential confounding factor would be that students from top-ranked universities were more prepared to take the *specific* component of college exit exam, or that the exam was designed to better fit the curricula in those universities. In such cases, the best test-takers would systematically be drawn from top schools, creating a discontinuity in the probability of being enrolled at top-ranked colleges. We find no evidence of such discontinuity around the award-assigning cutoff.

Figure 2: Covariate balance around the cutoff for the national distinction award



Notes. Plotted dots represent estimated differences between marginal award recipients and non-recipients along "pre-treatment" covariates. Regression discontinuity estimates use local linear regressions, an Epanechnikov kernel and MSE-optimal bandwidths. Sample means for all variables are displayed next to their names on the vertical axis. All regressions include area-of-study $\times$ year-of-exam fixed effects. Standard errors are clustered at the area $\times$ year level. Confidence intervals are provided at the 95% and 99% level.

Finally, Figure 2 shows that awardees and non-awardees close to the cutoff have similar average pre-treatment characteristics such as gender, age at the exam date, family background, the probability of being enrolled in a private colleges, and the probability of being employed on the date when they took the test.[26]

Sample selection. 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 measure educational attainment and earnings after college completion.

We estimate equation (1) letting the dependent variable, Y_{ijs}, be an indicator variable equal to one if student i was found among the universe of college graduates in year $s = 2007, ..., 2015$. Figure 3a plots the estimated coefficients δ and shows that the marginal

[26] In appendix D we provide additional evidence on the validity of our regression discontinuity design. In particular, we estimate the *specific* scores density and display all the cutoffs used by exam authorities to award the national distinction among students of every field exam between 2006 and 2009. We also show that, after normalizing the scores to make the cutoffs equal to zero, the probability of being awarded the national distinction increases sharply (i.e., all students with a field specific score equal to or above the normalized field's cutoff obtains the award, while no student below such threshold becomes an awardee). Finally, we show graphical representation of the continuity around the cutoff for "pre-treatment" variables.

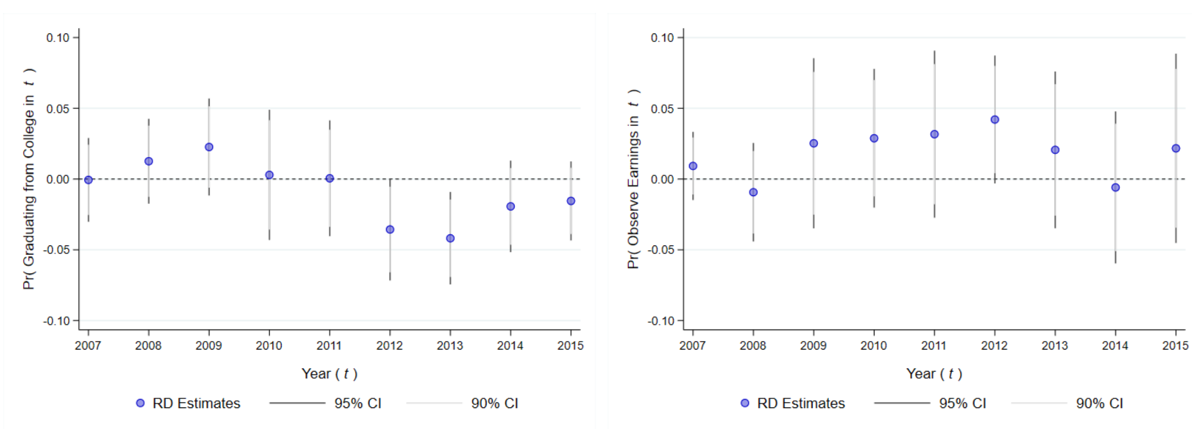
recipients of the award were not more likely to have graduated from college than non-awardees.[27]

Similarly, we estimate equation (1) letting the dependent variable, Y_{ijs}, be an indicator variable equal to one if student i was observed in the universe of college graduates with social security records in year $s = 2007, ..., 2015$. Figure 3b shows that we are equally likely to observe earning of students who did and did not receive the award.[28,29]

Taken together this evidence suggests that our results will not be affected by factors that could deferentially change the likelihood of observing earnings for award recipients (e.g., informality, students moving abroad or students attending graduate school and therefore not working).

Figure 3: Sample selection

(a) Probability of graduating from college (b) Probability of earnings being observed



Notes. Figures 3a and 3b provide evidence on non-selective attrition. Plotted dots represent differences in the likelihood of finding award recipients in administrative records of college graduates and in social security records between 2007 and 2015. Estimates are obtained through our regression discontinuity design. All regressions include area-of-study × year-of-exam fixed effects. Standard errors are clustered at the area × year level. Confidence intervals are provided at the 95% and 99% level.

5.2 Effect of the national distinction award on earnings

Main results. We use Equation (1) to estimate the effect on early career earnings of college graduates from receiving the national distinction award (the signal). Figure 4 plots the causal effect of winning the national distinction award on earnings immediately after

[27] If we estimate equation (1) pooling all the years we cannot reject that the coefficient of interest is equal to zero ($\hat{\delta}_{RD}$=-0.006, p-value=0.641).

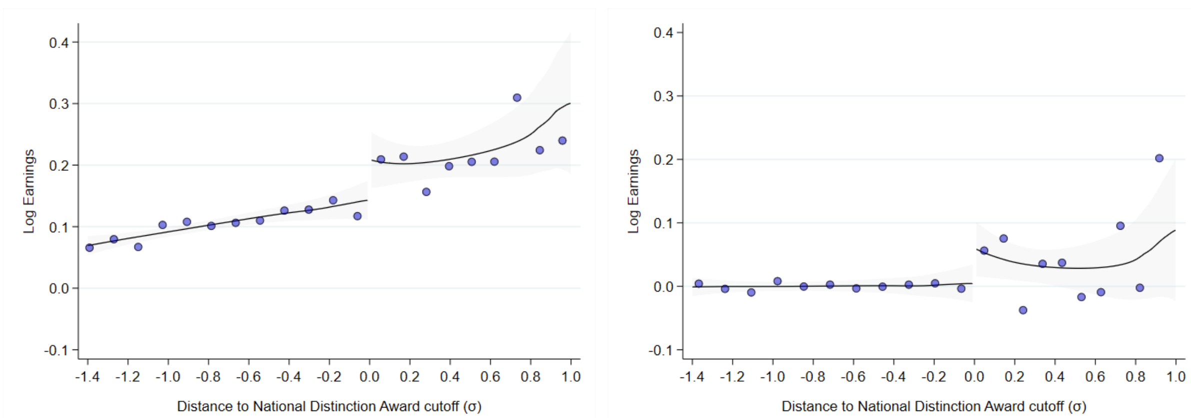
[28] In other words, Figure 3b shows that winning the national distinction award does not affect the probability of finding a formal job after graduation.

[29] If we estimate equation (1) pooling all the years we cannot reject that the coefficient of interest is equal to zero ($\hat{\delta}_{RD}$=0.021, p-value=0.248).

graduation. The effect is measured by the discontinuity observed between recipients and non-recipients around the normalized cutoff of zero. Recipients are shown to the right of the cutoff. The positive slope of the curve captures the fact that students who perform better on the specific skills part of the college exit exam tend to earn higher wages after graduation. There is also a positive and statistically significant premium on wages from being awarded the national distinction. This ranges from 7 to 12 percent.[30] In Section 7 we show that these positive effects persist even five years after students enter the labor market.

Figure 4: Effect of the national distinction award on early-career earnings

(a) Log earnings (b) Residualized log earnings



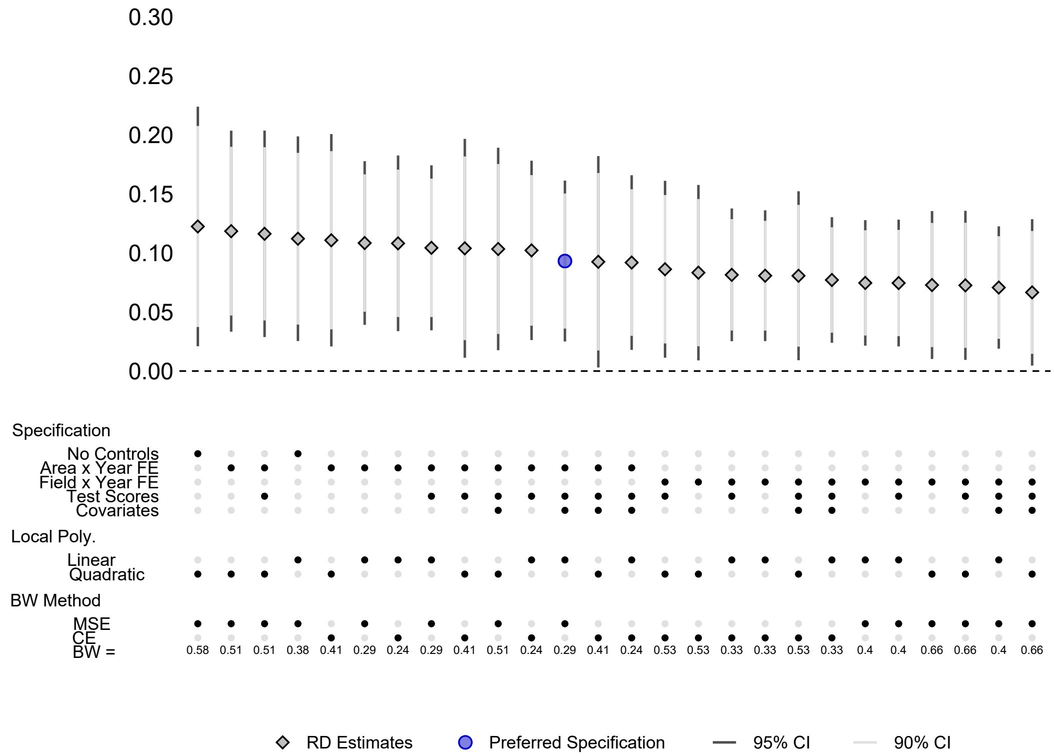
Notes. The outcome variable is the log of average monthly earnings received after graduation and before age 26. Plotted dots represent local averages of the log earnings within bins of the running variable. The running variable is the score in the college-exit exam (specific skills component) minus the cutoff value used to assign distinctions to students with the highest scores in each field of study. Data are displayed using the optimal mean square error (MSE) bandwidth of 0.291. The solid lines represent local linear regressions around the cutoff. Confidence intervals at the 90% level are displayed for each 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 level, test scores from the high school exit exam, test scores from the core component of the college exit exam and area-of-study × year-of-exam fixed effects as discussed in section 4.

This estimate could have been affected by the composition of the sample as a result of pooling students taking their field-specific exam in different years. We address such potential concerns in Figure 4b, which shows the results of estimating the discontinuity on the log of earnings conditional on initial and general skills, different baseline control variables, and areas of study × test year fixed effects, as specified in Equation (1). Results remain the same.

Robustness-. Regression discontinuity estimates might be sensitive to the choice of

[30] See Appendix Table A.2 for a full set of results.

Figure 5: Robustness of the effect of national distinction award on early-career earnings



Notes. The outcome variable is the log of average monthly earnings received after graduation and before (former) students reach 26 years of age. Plotted dots represent the regression discontinuity coefficients using linear and quadratic local regressions, an Epanechnikov kernel, and bandwidths as displayed in the bottom of the figure. The running variable is the score in the college-exit exam (specific skills component) minus the cutoff value used to assign distinctions to the best test-takers in each field of study. Field-specific exams are grouped into six areas of study: Health, Engineering, Agricultural Sciences, Social Sciences, Business and Economics, and Math and Natural Sciences. Area-of-study×Year-of-exam fixed effects are computed based on these six larger fields. Estimates including field-of-study × year-of-exam fixed effects are also provided. Test scores (controls) include: scores from the high school-exit exam and scores from the core component tests (Reading and English Proficiency) of the college-exit exam. Test scores from the core component are not used by the exam's authority to assign the national distinction award. Covariates include: indicator variables for gender and mother's education, 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 level.

tuning parameters. Figure 5 provides formal estimates of Equation (1) using alternative bandwidths and local polynomial regressions of different order. The bottom of the figure describes the specification, which we vary in three dimensions. First, we vary the control variables. 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 vary the order of the polynomial. We present estimates using a local linear regression or a local quadratic regression. Third, we present estimates obtained using MSE bandwidths or using CE bandwidths.[31]

[31] Note that CE bandwidths are commonly smaller than MSE bandwidths, which are widely used

We observe very stable point estimates between, roughly, 7 to 12 percent increase in wages for the national award recipients. This wage return is comparable to the wage premium from an additional year of education in Colombia Tenjo et al. (2017).[32]

6 Why does the signal affect labor-market outcomes?

To understand the mechanisms behind the positive effects of the national field-specific award on earnings, we first present a conceptual framework that highlights some potential channels that might be operating in the labor market. We identify and find empirical support for three channels that jointly explain why the distinction award increases earnings. We are also able to rule out one channel; we show that a difference in human capital is not a potential mechanism at play in our setting.

6.1 Labor-market valuation of signals on specific skills

Employers value workers' specific skills but do not directly observe them. Instead, when making hiring and decisions about the level of wages to offer to college graduates, they largely rely on one signal: the reputation of the college from which students graduated (Deming et al., 2016; MacLeod et al., 2017; Zimmerman, 2019; Barrera and Bayona, 2019; Bordon and Braga, 2020). The national distinction award introduces a second signal about people's specific skills.

Signals for the labor market. Following MacLeod et al. (2017), consider a continuum of students endowed with pre-college skills $\theta_i^0 \sim F$ and initial wealth $I_i^0 \sim G$. θ_i^0 is not directly observable. Instead, a proxy measure is a *high school* exit exam,

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

in regression discontinuity applications. As mentioned by Calonico et al. (2020), estimates based on MSE bandwidths require robust-biased-corrected methods to make a valid statistical inference, although confidence intervals would remain suboptimal regarding coverage error. CE bandwidths correct such lack of optimality by yielding inference-optimal choices.

[32]We provide alternative robustness checks in Appendix E. Specifically, we show 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. We find that the effects remain robust although somewhat more imprecise due to a smaller sample size. Finally, we show in Appendix Figure A.1 that the results do not exist in any other part of the test score distribution. The national distinction award is given to, roughly, the top 1 percent of test takers. We expect that the difference exists only between awardees and non-awardees, and not in any other given percentile. Thus, we conduct a placebo test by varying the regression discontinuity cutoffs to each percentile of the distribution. As expected, we do not observe any jump across the distribution.

which is a function of the pre-college skills and a random variable, $\epsilon_i \sim N(0, \sigma_\epsilon^2)$.

Colleges admit applicants based on their high school exit test scores and their ability to pay for tuition. This leads to colleges having a student body of different initial skills. We define college reputation as:

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

the expected (high school) admission scores of the graduating class from college s.

For simplicity, we assume that colleges have either a high reputation, R_s^+, or a low reputation, R_s^-. The probability of attending a college with a high- or a low- reputation is given by,

$$\begin{aligned} P[R_i = R_s^+] &= P[T_i > \bar{T} | I_i^0 > \bar{I}_s] \\ P[R_i = R_s^-] &= P[T_i \leq \bar{T}] + \underbrace{P[T_i > \bar{T} | I_i^0 \leq \bar{I}_s]}_{\text{Income-constrained}}, \end{aligned} \tag{2}$$

where $\bar{I}_s$ is the tuition cost of college s and $\bar{T}$ is the minimum high school test-score threshold for admission. Only highly skilled students who have the means to pay for tuition attend high-reputation colleges; students in colleges with a low-reputation are a combination of students who are either lower skilled or income constrained.[33]

After college graduation, students' skills include additional attributes that are heterogeneous and depend on the college s they attended and their field of specialization j. We assume that college inputs increase students' skills. The post-college level of skills is:

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

where v_s and v_j correspond to college- and field-specific attributes, which are also not observable.

A college's reputation is a signal about the initial skills of the student who enrolls at that college, and about the value added by the college; however, this reputation does not signal field-related skills. We assume that the college-specific component satisfies that:

$$\begin{aligned} E[\theta_i^0 + v_s | R_s] &= P[R_i = R_s^+] R_s^+ + P[R_i = R_s^-] R_s^- \\ E[v_j | R_s] &= 0 \end{aligned}$$

[33]We assume that everyone attends college. Table A.3 provides evidence that students from high-income families are more likely to attend prestigious colleges (suggesting that credit constraints might be at play in our setting).

Graduation from R_s is observable to employers and constitutes a signal of θ_i^0 and of v_s. Students that attend colleges with a high reputation send a signal R_s^+, whereas students who attend colleges with a low reputation schools send a signal $R_s^- < R_s^+$. The precision of the signal is governed by the inverse of the noise parameter, $1/\sigma_R$, which depends on σ_ϵ and on the degree of financial constraints that limit the ability to pay tuition among those students with high admission test scores.

The national distinction award is a second signal in the labor market. The field-specific component v_j is not observable. It is signaled for those who obtain the national distinction award (A_{ij}) which is based on the *specific*-component of the college exit exam, such that:

$$A_{ij} = 1(\theta_{ijs}^1 > k_j),$$

where $1(\cdot)$ is an indicator function and k_j is an unknown threshold used to assign the national distinction award.[34] Note that the distinction not only reveals information about the field-specific skills v_j, but also information about the school-specific component v_s, and the pre-college ability θ_i^0. We assume that winning the national distinction award sends a stronger signal about the post-college skills than the signal sent by the reputation of the college (i.e., $E[\theta_{ijs}^1|A_{ij}] > E[\theta_{ijs}^1|R_s]$). We also assume that the former signal is more precise than the latter ($1/\sigma_A > 1/\sigma_R$).[35]

Signals and wage setting. There are two types of employers that differ on their level of productivity, ω_h for a high type and ω_l for a low type (with $\omega_h > \omega_l$). Each employer is also either specialized or non-specialized. Specialized firms require specific skills from a subset K of all possible skills. Workers with specific skills $j \in K$ are more productive than workers without those skills when they are hired in a specialized firm. We denote this productivity as $\kappa_j > 1$ if $j \in K$. Non-specialized firms, on the contrary, demand all types of skills. Worker i, who graduated from college s in field j, has a productivity at time t in firm type f given by,

$$y_{ifjst} = \omega^f \kappa_j \theta_{ijs}^1 + \rho y_{ijs,t-1} + \varepsilon_{ifjst}.$$

We follow MacLeod et al. (2017) and assume that the contemporaneous productivity depends on its lagged value. Workers learn from previous experience, making them more productive. Thus, an initial match with a better employer, and in an industry that

[34] We could include a noise parameter that captures the fact that A_{ij} is a measure of latent human capital. Including this parameter yields similar predictions but with expected rather than deterministic conditions.

[35] For simplicity, we normalize $E[\theta_{ijs}^1|A_{ij}] = 1$.

matches the workers' skills, induces the worker to enter a learning and promotion trajectory that gives space to job-ladders.

Firms, however, cannot directly observe workers' productivity, but they have access to a time-changing vector of information, $\mathbb{I}_{it} = (R_i, A_{ij}, y_{i,0}, ..., y_{i,t-1})$ (Farber and Gibbons, 1996), which allows them to compute an expected performance measure of the form:

$$\begin{aligned} p_{ifjst} &= \omega_f \kappa_j E[\theta^1_{ijs} | R_i, A_{ij}] + y_{ijf,t-1} + u_{it} \\ &= A_{ij}\kappa_j\omega_f + (1 - A_{ij})\omega_f \left[E[\theta^0_i + v_s | R_s] \right] + y_{ijs,t-1} + u_{it}. \end{aligned} \tag{3}$$

Conditional on the signals, firms offer recent graduates an equilibrium *entry* wage equivalent to the expected performance measure:[36]

$$w_{ifjst} = \beta_a A_{ij} + \beta_r 1(R_i = R^+_s | A_{ij} = 0), \tag{4}$$

where β_a and β_r are functions of ω_f and κ_j, which are unobserved.

This conceptual framework highlights some potential mechanisms behind the results found in Section 5. First, the signal is a valuable screening device to infer specific skills. Second, the performance of workers in high-productivity firms is higher than worker performance in low-productivity firms. High-productivity firms are able to pay higher wages and therefore to attract workers with higher skills. Third, workers that won the national distinction award have a higher expected performance and wages when employed in specialized industries that better use their specific skills. We next provide empirical evidence that suggests that these mechanisms are operating in our setting.

6.2 The signal is a valuable screening device to infer specific skills

Following Equation (4), the salary for an awardee is given by the performance that the firm expects from her, which depends on having received the award (and not on the reputation on the college she attended), $w^a_{ifjst} = \beta_a$. The firm infers the performance of those workers who have not received the national distinction award based on the reputation of the college they attended, $w^{na}_{ifjst} = \beta_r 1(R_i = R^+_s)$. This implies:

Proposition 1. *The wage premium for college reputation is zero among awardees; by contrast, the premium for college reputation is positive for non-awardees.*

We provide evidence consistent with Proposition 1 by estimating a linear regression

[36] We normalize $w_{ifjst} = 0$ for graduates of low-reputation colleges who did not win award.

model using wages as the dependent variable and college reputation as the independent variable for awardees and non-awardees, separately. We compute college reputation for individual i entering college s in year t as the average high school exit exam score of the class of students graduating in t from college s. We include high school exit test scores in this specification trying to fully control for pre-college individual skills.

The first two columns of Table 1 show the results. Column (1) presents results for the sample of awardees. Column (2) presents results for the sample of non-awardees. College reputation predicts wages only for those workers who did not receive the national distinction award. By contrast, it has less predictive power when considering individuals who received the distinction. These results also suggests that more information about a college graduate's productivity comes from the signal given by the distinction than from the reputation of the college she attended.

A second indirect implication that arises from the conceptual framework is that the signal given by the national distinction award should be more valuable when firms are trying to infer the expected productivity of workers that had graduated from colleges with low reputations. In other words,

Proposition 2. *The wage premium associated with the distinction award (i.e.,* $w^{a}_{ifjst} - w^{na}_{ifjst}$*) is larger for students graduating from schools with lower reputations (i.e.,* $\Delta\hat{w}^{-}_{ifjst} = \beta_a > \Delta\hat{w}^{+}_{ifsjt} = \beta_a - \beta_r$*).*

Table 1: National Distinction Award and College Reputation

	Dependent Variable : Log Earnings						
	Distinction Status :		School Ranking :			Cross-sample Comparison : Top 5 Non-awardees vs.	
	Awardees	Non-Awardees	Top 5	Top 6-20	Below 20	Top 6-20 Awardees	Below 20 Awardees
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
College Reputation (σ)	0.042	0.064***					
	[0.027]	[0.009]					
1(National Distinction)			0.037	0.141**	0.169**	0.034	0.029
			[0.046]	[0.060]	[0.066]	[0.055]	[0.062]
Observations	1,691	103,018	20,083	18,102	70,750	19,693	19,599
Model	OLS	OLS	RD	RD	RD	RD	RD
Bandwidth			0.461	0.427	0.411	0.481	0.394
Effect. obs. control			1248	653	787	1314	997
Effect. obs. treat			595	320	264	338	262

Notes. The outcome variable is the log of average monthly earnings received after graduation and before (former) students are 26 years of age. Columns (1) and (2) display OLS estimates within subsamples defined by status of the national distinction award (i.e. awardees or non-awardees). College reputation is the average score of a college graduating cohort in the high school exit exam (see MacLeod et al. (2017) for more details). Columns (3) to (7) display regression discontinuity estimates of Equation (1) using linear local regressions, an Epanechnikov kernel, and bandwidths optimally computed to minimize the MSE. The running variable is the overall score in the college exit exam (specific skills component) minus the cutoff value used to assign distinctions to the highest scorers in each field of study. Columns (3) to (5) use subsamples defined by the ranking of colleges divided into 3 groups: top 5 schools (the top tier), top 6-20 schools (the middle tier), and schools below the top 20 (the bottom tier). Columns (6) and (7) restrict the sample to awardees from colleges in middle and bottom tiers and non-awardees from the top-tier colleges (control group). 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 area-of-study × year-of-exam fixed effects. Errors clustered by area × year and displayed in brackets. * p<0.10, ** p<0.05, *** p<0.01.

We test Proposition 2 by directly computing regression discontinuity estimates using Equation (1), and splitting the sample between workers who graduated from universities with different reputations.[37] Columns (3)-(5) of Table 1 show the results. We observe that students who graduated from top-five universities do not benefit from the distinction when compared to other graduates from the same universities. However, awardees who graduated from universities with lower reputations had a large increase in earnings compared to those that graduated from the same universities.

What explains the absence of wage returns for award winners from high-reputation colleges (i.e., top-five colleges)? According to our conceptual framework this can only happen if the returns to the award are similar to the returns of graduating from a high-reputation college, $\beta_a = \beta_r$ (i.e., $\Delta^+_{ifjst} = 0$ in Proposition 2). We test this directly by estimating the regression discontinuity model in Equation (1) but modifying the subsamples. We compare wages earned by award winners in low-reputation colleges (to obtain an estimate of β_a) with those earned by non-awardees in high-reputation colleges (to obtain an estimate of β_r). This comparison yields an estimate of Δ^+_{ifjst} which we use to test the

[37]We use the QS University Rankings to classify colleges between the top 5, top 6-20, and below the top 20.

null hypothesis that it is equal to zero. We do this for awardees graduating from colleges in the middle and bottom tiers.

Columns (6)-(7) of Table 1 show the results. The wage return for awardees who graduated from a low-reputation college is equivalent to the return obtained from graduating from a high-reputation college (without winning the award). We conclude that the return to winning the national distinction award is comparable in magnitude to that of attending a high reputation college.

This evidence suggests that the national distinction award works as a signal in the labor market. It allows workers graduating from lower reputation colleges to signal their skills. This is consistent with the results of Deming et al. (2016) who, using a resume audit study design, find that college students who graduate from for-profit colleges are less likely to receive job callbacks than those graduating from non-selective public institutions. Our result is also in line with the existing experimental evidence that finds that individuals whose educational backgrounds are less favored in the labor market drive the positive effects of skill signaling on labor-market outcomes (Abebe et al., 2021). Our theoretical framework suggests that, in the absence of the award, employers could make erroneous inferences about a young worker's skills based on observable group membership, specifically, college reputation. Thus, the signal helps firms update their priors about highly skilled graduates from low-reputation schools; thus, these students experience a wage premium with respect to their peers. Our findings are similar to those of Carranza et al. (2022) and Pallais (2014) in that we provide evidence showing that job seekers, who lack ways to communicate their skills to employers, experience larger labor market returns to a signal on abilities.

6.3 Signals help firms in specialized industries find workers with the right skills

In our conceptual framework, employers that value college graduates' specific skills offer higher wages because those workers have a better expected performance. There is a positive wage premium associated with working in a specialized firm that requires a specific set of skills (i.e., wages offered to an individual with skills $j \in K$ are $\Delta W^{s}_{ifjst} = \omega_f(\kappa_j - 1) > 0$). For example, the signal given by the distinction is not the same for a business firm that hires multiple people across majors as it is for a firm in chemicals production that hires people with specific knowledge in chemistry. The signal A_{ij} has information about the individual's skills acquired in program j (i.e. v_j) and for that reason,

Proposition 3. *The signal allows specialized industries to pay higher wages to workers with specific skills (by identifying those workers with the required skills for the job).*

We provide direct and indirect empirical evidence for Proposition 3. Direct evidence comes by assessing whether awardees from field of study j are more likely to work in industries that demand skills acquired from field of study j. For example, we evaluate whether graduates from chemistry go to pharmaceutical firms, or if veterinarians work in firms that deal with animals. To test for this we construct an indicator variable that takes the value of one if the fields of study match the industry codes that represent the firm where the individual works, and zero if not.[38] We then estimate Equation (1) using this indicator variable as the outcome. Column (1) of Table 2 shows the results.

Table 2: Effects on Allocation of Skills

	Dependent Variable :					
	1(Field-Industry Match)				Log Earnings	
		by School Ranking :			by Type of Skills :	
	Full Sample	Top 5	Top 6-20	Below 20	Specific	Transferable
	(1)	(2)	(3)	(4)	(5)	(6)
1(National Distinction)	0.073**	-0.003	0.091*	0.143**	0.110***	-0.010
	[0.029]	[0.041]	[0.055]	[0.073]	[0.039]	[0.077]
Observations	179,474	27,630	27,242	124,602	58,788	50,147
Bandwidth	0.276	0.388	0.311	0.330	0.293	0.250
Effect. obs. control	1767	1244	506	710	1140	282
Effect. obs. treat	1049	628	293	281	693	199

Notes. Regression discontinuity estimates of Equation (1) using linear local regressions, an Epanechnikov kernel, and bandwidths optimally computed to minimize the MSE. The outcome variable in columns (1) to (4) is an indicator variable that takes the value of one if a worker's industry matches the skills taught in the worker's college major (program). The outcome in columns (5) and (6) is the log of the average monthly earnings received after a student's graduation and before she reaches age 26. The running variable is the score in the college exit exam (specific skills component) minus the cutoff value used to assign distinctions to the highest scorers in each field of study. 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 area-of-study × year-of-exam fixed effects. Errors clustered by area × year and displayed in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

We find that winning the national distinction award increases the likelihood of working in an industry that better matches the competencies of a given graduate's field of study. In other words, the information provided by the award regarding specific skills allows

[38] To create this indicator variable we evaluate whether the skills that a major or college program provides to its students match the description of the economic activity of an industry. For such a purpose we use the brochures provided online by universities in Colombia. These brochures describe the economic sectors in which their graduates' abilities fit better, and detail where their alumni are currently working (These brochures are commonly referred to as "alumni professional profiles."). Appendix E.4 provides more details on the construction of this variable.

firms across industries to identify candidates with the specific set of qualifications needed for the positions they want to fill.

The increase in the probability of matching students' field of study and firms' industry is mainly driven by students graduating from low-reputation colleges. As shown in columns (2)-(4) of Table 2, high-ability workers from low-reputation colleges obtain the most considerable improvement in the labor-matching process. This helps explain why the biggest benefits of obtaining the national distinction award are observed among students in lower-reputation colleges; these were the students who were not able to signal their skills in other ways.

We also obtain indirect evidence for Proposition 3 by analyzing two additional results. First, we compare the returns to the national distinction award across fields of study with different degrees of specialization. We calculate a specialization index that captures the level of transferability of skills for each field of study j by adding up the number of four-digit SIC codes in which graduates from j find jobs after graduation.[39] We find that "Business" is the field of study demanded by the largest number of industries (387 in total). We interpret this as meaning that business students have a set of specific skills that are the most transferable across industries. On the other end of the spectrum, "Modern Languages" is used by 28 industries. We classify fields of study into two groups depending if they are above or below the median of this index. Firms below the median are considered to be in fields requiring specific skills, and those above the median are considered to be in fields requiring transferable skills. We estimate Equation (1) in subsamples defined by these two groups.

Columns (5)-(6) of Table 2 show the results. The national distinction award has a positive wage return for students graduating from fields that are more specific but a negligible effect in fields that demand skills that are more transferable across industries. This is consistent with a labor market in which firms in more specialized industries use the signal given by the national distinction award to hire workers with a set of specific skills that better match their needs.

Second, we evaluate if a similar signal with different informational content (i.e. no information about field-specific skills) has also positive earnings returns. Starting in 2010, top-scorers in the *core* components of the college-exit exam were also eligible to obtain an award for their performance in problem solving, critical thinking, English proficiency, and personal understanding.[40] We rely on data for students who took the college-exit exam

[39] We compute the number of four-digit industries in which graduates of each of the 41 fields of study are employed each year. We then compute the average number of industries that employed graduates of a given field from 2007 to 2015.

[40] Students who took the exam between 2003 and 2009 were only eligible for the distinction in the

in 2010 to estimate a regression discontinuity model that tests for the existence of returns to signaling generic skills, and present the results in Table 3.[41]

Table 3: Effect of Generic Skills Distinctions on Early-Career Earnings

	Dependent Variable : Log Earnings				
Generic Test :	Personal Understanding	English Proficiency	Critical Thinking	Problem Solving	Stacked
	(1)	(2)	(3)	(4)	(5)
1(Generic Distinction)	0.012	0.008	0.024	-0.083	0.000
	[0.076]	[0.058]	[0.081]	[0.104]	[0.033]
Observations	10,653	10,028	10,653	10,654	41,988
Bandwidth	1.089	1.272	0.668	0.533	1.040
Effect. obs. control	1,280	1,939	578	443	5,627
Effect. obs. treat	269	819	294	448	1,940

Notes. The outcome variable is the log of the average monthly earnings received after graduation and before students are 26 years of age. Regression discontinuity estimates of Equation (1) using linear local regressions, an Epanechnikov kernel, and bandwidths optimally computed to minimize the MSE. The running variable is the score in the generic test (displayed in the top of each column) minus the cutoff value used to assign distinctions within each area of study. Column (5) stacks all students taking the four generic tests. All specifications control by gender, socioeconomic status, mother's education, test scores from the high school exit exam, scores from the reading test evaluated in the core component of the college exit exam, and area-of-study × year-of-exam fixed effects. Robust standard errors displayed in brackets from columns (1) to (4). Errors in column (5) are clustered at the individual level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

We do not observe sizable nor significant point estimates, indicating that the field-specific content, embedded in the national distinction award on specific skills, is what our analysed labor market truly matters. The information about field-specific skills seems to be, therefore, an important driver of the return to the signal.

The introduction of the national distinction award, as a signal for the labor market, improves the allocation of talent in the economy. The award corrects part of the allocation inefficiencies that arise when relying on a noisier signal (i.e., college reputation) to assign workers to firms. These results are similar to recent experimental evidence that shows that signaling of skills can increase workers' earnings by improving the efficiency of job allocations (Abebe et al., 2021; Bassi and Nansamba, 2022; Carranza et al., 2022), which in turn can explain why the returns to the award are persistent in the long run (Abebe et al., 2021).

field-specific component of the college-exit exam.

[41] We merge these data with the same data sets described in Section 3. Unfortunately, for 2010 we do not have information about test scores in the specific component of the college exit exam. We do observe test scores in the core component and whether or not they received a distinction award for their performance in that core component.

6.4 Signals allow high-productivity firms to find high-skilled workers

The signal from the national distinction award provides high-productivity firms with the ability to identify and attract more workers with higher skills. Given the performance measure in Equation (3), high-productivity firms are able to offer higher wages to awardees (i.e., $\beta_a(\omega_h) > \beta_a(\omega_l)$). In other words,

Proposition 4. *The signal allows high-productivity firms to attract high-skill workers (i.e., the recipients of the national distinction award).*

We test Proposition 4 by estimating Equation (1) using as an outcome a measure of firm productivity that we construct as follows: Firms are sorted according to the average wages they pay to their employees. We then compute a time-invariant ranking of firms in the economy. Finally, to accommodate the fact that some workers change jobs, we compute the average firm ranking in which each worker was employed throughout the period under analysis.[42]

Table 4: Effects on the Probability of Switching Jobs and on Employers Wage Premia

	Dependent Variable :						
	Employers' Premia (σ)		1(Mover)	Employers' Wage Premia Across Time (t)			
	Unconditional Ranking	AKM Ranking		$t = 1$	$t = 2$	$t = 3$	$t = 4$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1(National Distinction)	0.180***	0.175**	0.071**	0.158***	0.182**	0.205**	0.174*
	[0.054]	[0.074]	[0.033]	[0.061]	[0.086]	[0.085]	[0.094]
Observations	197,627	205,155	112,945	112,945	112,945	112,945	83,484
Bandwidth	0.457	0.286	0.420	0.365	0.302	0.265	0.266
Effect. obs. control	3664	1926	2142	1719	1322	1131	859
Effect. obs. treat	1466	1137	916	860	765	713	534

Notes. Regression discontinuity estimates of Equation (1) using linear local regressions, an Epanechnikov kernel, and bandwidths optimally computed to minimize the MSE. The outcome variable in column (1) is the earnings ranking computed for all firms within an industry based on the average earnings they paid to college graduates between 2009 and 2015. In column (2), the outcome is the firms' earnings ranking in the period 2009-2015 based on firm fixed effects from a regression of earnings that also controls for individual fixed effects, as in Abowd et al. (1999). Both dependent variables in columns (1) and (2) are standardized. The outcome in column (3) is an indicator if the student is observed in more than one firm in the six years following their graduation. Columns (4) to (7) use as an outcome the AKM-ranking of the first ($f = 1$) to fourth ($f = 4$) firm f in which the student was employed post-graduation. 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 area-of-study$\times$year-of-exam fixed effects. Standard errors displayed in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Columns (1) and (2) of Table 4 show the results. Column (1) uses an unconditional ranking as outcome, whereas column (2) uses a ranking computed using the methodology

[42] We construct two different wage ranking of firms for individual i. The first is an unconditional ranking built by: (i) computing the average wages paid at the firm and year level; (ii) computing the percentile of the distribution within an industry by using three-digit standardized industrial classification (SIC) codes for each year; and (iii) the average of the percentiles across years. The second wage ranking estimates the firm fix effect (firm wage premia) using the methodology by Abowd et al. (1999).

in Abowd et al. (1999) (i.e., with individual and firm fixed effects). We observe that obtaining the distinction induces hiring of college graduates by high-productivity firms. Our estimates suggest that being granted the national distinction award is associated with being hired by firms that on average are 18 percent of a standard deviation higher in the productivity ranking within their industries.

This result complements the evidence from the previous literature showing that signaling skills increases the degree of positive assortative matching in the labor market. Bassi and Nansamba (2022) find that employment between managers at more profitable firms (i.e., high-ability managers) and workers with higher non-cognitive skills increases when the workers' grades on a questionnaire measuring such skills are revealed during job interviews. Moreover, Abebe et al. (2021) find that information about workers' general skills has short-run effects on the probability of being employed with an open-ended contract, which serves as a proxy for employment in formal firms. This evidence is related to labor-market models stressing the effects of information frictions and employers' learning. The national distinction award is able to reduce such information frictions and boost employers' learning – thereby leading to the sorting of higher-skilled workers into more-productive firms.

6.5 Signaling or human capital?

The wage premium of the national distinction award estimated using Equation (1) compares students with the same levels of human capital (as measured by their high school exit exam scores, their general and specific college exit exam scores). However, the national distinction award could have induced students to further accumulate human capital. We rule out this mechanism.

Table 5 presents regression discontinuity estimates using multiple outcomes that measure human capital accumulation. Column (1) uses as outcome the number of months taken to graduate since the moment when the person took the college exit exam. Column (2) includes the total number of subjects taken by students as of their graduation time. Column (3) estimates the probability of graduating from a graduate program within five years of college graduation. The distinction award does not have any impact on any of these outcomes. In columns (4) to (6) we split the result by college ranking, and we cannot reject a null effect for any of the groups. These results rule out that human capital accumulation is a potential driver of the effect.

Table 5: Effects on Human Capital Accumulation

	Dependent Variable :					
	Months to College Grad. Date	Subjects by College Grad. Date	1(Graduate Education)			
			Full Sample	by School Ranking :		
				Top 5	Top6-20	Below 20
	(1)	(2)	(3)	(4)	(5)	(6)
1(National Distinction)	-0.180	0.472	0.004	0.011	-0.036	-0.017
	[0.594]	[1.165]	[0.028]	[0.045]	[0.058]	[0.046]
Observations	221,236	239,917	255,027	33,427	34,415	187,185
Bandwidth	0.400	0.420	0.393	0.352	0.390	0.341
Effect. obs. control	3599	3829	3563	1352	840	992
Effect. obs. treat	1572	1557	1623	744	426	379

Notes. Regression discontinuity estimates of Equation (1) using linear local regressions, an Epanechnikov kernel, and bandwidths optimally computed to minimize the MSE. The outcome variable is an indicator variable that takes the value of one if a student completed a graduate program (i.e. one-year master's degree, two-year master's degree, or a doctorate) between 2010 and 2015. The running variable is the overall score in the field-specific component of the college exit exam minus the cutoff used to assign distinctions to the highest scorers in each field of study. 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 area-of-study×year-of-exam fixed effects. Errors clustered by field-exam × year-of-exam and displayed in brackets. * p<0.10, ** p<0.05, *** p<0.01.

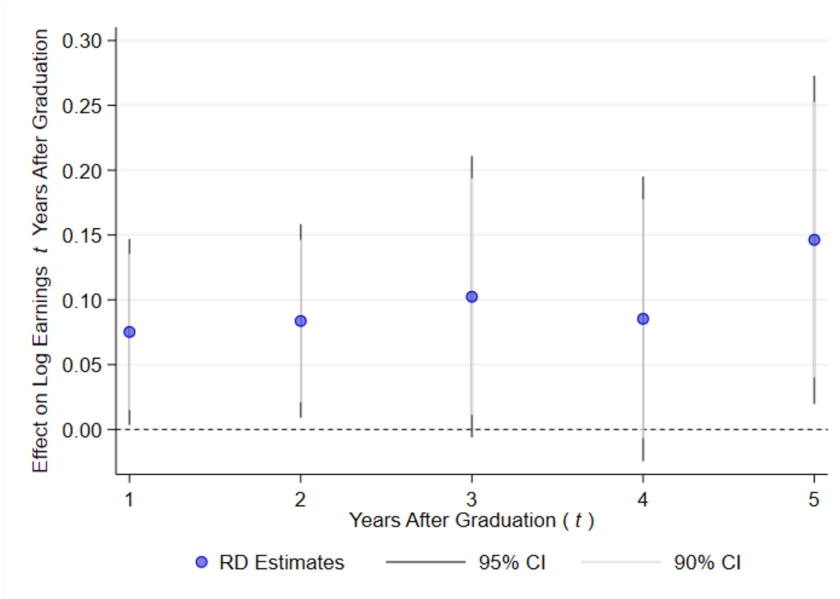
This is not to say that human capital does not have a return for those who received the national distinction award. It certainly does. In a linear regression of earnings on an indicator variable equal to one for those that received the award, without conditioning for any kind of human capital, the premium of being awarded the distinction is $\hat{\beta}_{ols} =$ 14%. This premium is due to the fact that award recipients have higher human capital than the average worker, and that they have a signal (i.e., $\beta_{ols} = \delta_{signal} + \delta_{hk}$, where δ_{signal} is the signaling effect on earnings and δ_{hk} is the effect due to human capital). Our regression discontinuity identifies the *pure* signaling effect on earnings (i.e., $\delta_{RD} = \delta_{signal}$), with $\hat{\delta}_{RD} = 8.1\%$. We can use these estimates to compute a back-of-the-envelope estimate of the percent wage difference between recipients of the national distinctions awards and the average college-graduate worker that is explained by the signal vis-a-vis differences in human capital: the effect on earnings explained by the signal is about 58% of the difference in earnings (i.e., $\hat{\delta}_{RD}/\hat{\beta}_{ols} = 0.58$).

7 Job ladders and signal's persistent effect

Section 5.2 showed a positive and statistically significant premium on initial labor earnings from being awarded the national distinction. The effect ranged from 7 to 12 percent. These estimates captures the effect of the distinction when students enter the labor market. We investigate how persistent this effect is by using a sample of individuals for whom we observe earnings for at least the first three years after graduation. We estimate the parameter of interest in equation (1) letting the dependent variable be the log of earnings one to five years after entering the labor market.

Figure 6 shows that the effect of winning the national award does not fade out, even after the market has had time to learn about a given worker's specific skills.[43] The national distinction awardees' wages are 10 percent higher than similar workers even five years after entering the labor market.

Figure 6: Persistence of the effect of national distinction award on early-career 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 bandwidths. The running variable is the score in the college exit exam (specific skills component) minus the cutoff value used to assign distinctions to the highest scorers in each field of study. To maintain a consistent sample across specifications, the analysis is restricted to a "balanced" panel of individuals for whom we observe earnings during the first three years after graduation. Confidence intervals at the 90% and 95% levels are displayed for each coefficient, and computed using standard errors clustered by area × year level.

This result contrasts with those of Khoo and Ost (2018) and Freier et al. (2015), who find that the wage returns to graduating with honors dissipate three years after graduation. This could be explained by the different nature of the awards. Receiving an honors diploma depends on a within program-college ranking, which provides firms with a noisy signal of the students' ability. Such a ranking is a signal that mixes the student's own abilities with the composition of the student body at his or her program and college. As firms learn about workers' specific skills, the value of a noisy signal given

[43] We lose some precision in our estimate of the effect in fourth and fifth years due to a smaller sample size. However, we cannot reject the null hypothesis that these coefficients are equal to those estimated for years one to three.

by the honors award diminishes. Employer-learning models predict that as employers learn about workers' unobserved skills/productivity the effects of signaling would dissipate over time (Farber and Gibbons, 1996; Altonji and Pierret, 2001). This learning process can potentially be accumulated even if workers change jobs as prospective employers either bid by offering higher wages (Pinkston, 2009) or use job promotions as signals (DeVaro and Waldman, 2012). This learning process, however, can take longer than our data allow us to test (Lange, 2007).

The conceptual framework discussed in Section 6.1 suggests that the productivity of a given worker in a year t depends on its lagged value productivity, implying the potential existence of job ladders. The persistent effect of the national distinction award is consistent with career-development models which suggest that when higher-ability workers are assigned to higher positions on the job ladder, workers acquire specific human capital as they accumulate experience (Gibbons and Waldman, 1999a,b, 2006), a process that might be more relevant for skilled labor (Altonji et al., 2016). Thus, having an early experience at a job with greater training and promotion opportunities can put workers on a career path that both better uses and further develops their task-specific skills – ultimately leading to long-run earnings gains.[44] Recent evidence has shown that signals on workers' skills may help firms have a more effective screening process to fill their vacancies, improving the quality of the match between workers and firms – translating in turn into long-run effects on wages (Abebe et al., 2021; Bassi and Nansamba, 2022; Carranza et al., 2022).

We indirectly test the job ladder hypothesis by estimating Equation 1 using as dependent variable an indicator variable that takes the value of one if the worker changes jobs after graduation. We present the results in column (1) of Table 4. Obtaining the award increases the likelihood of switching employers after graduation in around 12 percentage points. Awardees, nonetheless, seem to move to firms that have a high AKM-fixed effect (i.e., high-productivity firms). We evaluate this by, again, estimating Equation 1 but using the ranking of the firm (estimated using Abowd et al. (1999) methodology) where the worker is employed one to four years after graduation as dependent variables. We present the results in columns (2) to (5). The effect on the firm ranking is non-decreasing in time, until three years after graduation, implying that switchers are more likely to move to more productive, better paying firms. The national distinction award induces awardees to be employed in better paying firms which allows them to later switch jobs to other

[44] The effects of getting off to a poor start also appear to linger. For example, evidence in the context of economic downturns has shown that college graduates who find their first job at low-paying firms with unattractive career opportunities have lower earnings even 10 or 15 years later (Beaudry and DiNardo, 1991; Oreopoulos et al., 2012; Schwandt and von Wachter, 2019).

Table 6: Effects on the Probability of Switching Jobs and on Employers Wage Premia

	Dependent Variable :						
	Employers' Premia (σ)		1(Mover)	Employers' Wage Premia Across Time (t)			
	Unconditional Ranking	AKM Ranking		$t = 1$	$t = 2$	$t = 3$	$t = 4$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1(National Distinction)	0.180***	0.175**	0.071**	0.158***	0.182**	0.205**	0.174*
	[0.054]	[0.074]	[0.033]	[0.061]	[0.086]	[0.085]	[0.094]
Observations	197,627	205,155	112,945	112,945	112,945	112,945	83,484
Bandwidth	0.457	0.286	0.420	0.365	0.302	0.265	0.266
Effect. obs. control	3664	1926	2142	1719	1322	1131	859
Effect. obs. treat	1466	1137	916	860	765	713	534

Notes. Regression discontinuity estimates of Equation (1) using linear local regressions, an Epanechnikov kernel, and bandwidths optimally computed to minimize the MSE. The outcome variable in column (1) is the earnings ranking computed for all firms within an industry based on the average earnings they paid to college graduates between 2009 and 2015. In column (2), the outcome is the firms' earnings ranking in the period 2009-2015 based on firm fixed effects from a regression of earnings that also controls for individual fixed effects, as in Abowd et al. (1999). Both dependent variables in columns (1) and (2) are standardized. The outcome in column (3) is an indicator if the student is observed in more than one firm in the six years following their graduation. Columns (4) to (7) use as an outcome the AKM-ranking of the first ($f = 1$) to fourth ($f = 4$) firm f in which the student was employed post-graduation. 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 area-of-study×year-of-exam fixed effects. Standard errors displayed in brackets. * p<0.10, ** p<0.05, *** p<0.01.

high-paying firms (climbing up the job ladder).

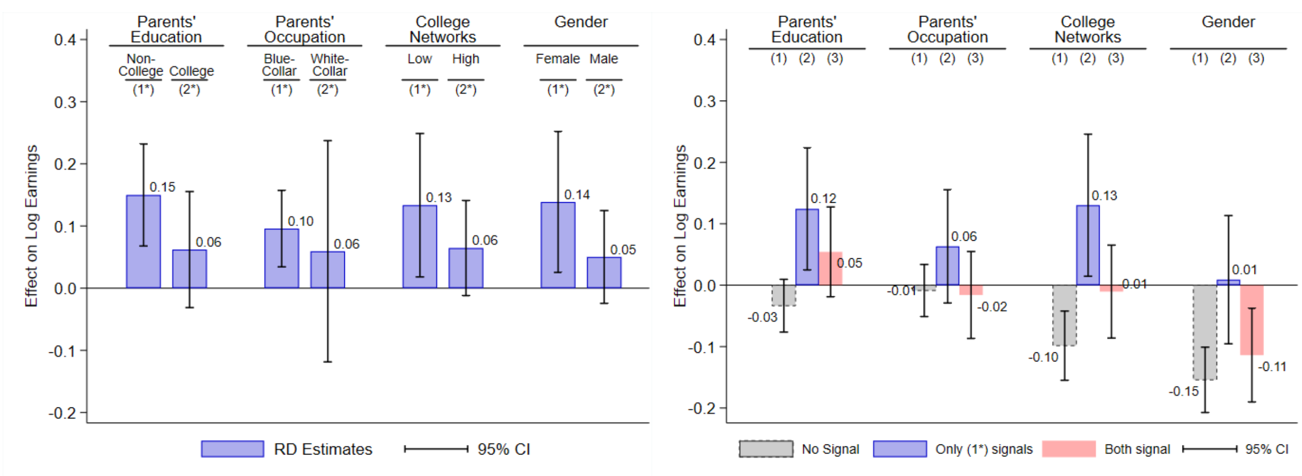
8 Signals and equality of opportunities

The national distinction award benefits more the set of high-skilled college graduates who are not able to attend highly prestigious schools. In our setting, this occurs because of income constraints: among the group of award recipients, attending a top school is associated with having higher income levels rather than with having higher skills.[45] This means that the signal can partially offset the wage gap between workers that come from more versus less advantaged backgrounds.

We estimate the regression discontinuity model described in Equation (1) for the subsamples of students with different socioeconomic status, parent's education, parent's occupation, access to job search networks, and sex.[46,47]

Figure 7: Heterogeneous Effects of the Signal and Earnings Gaps

(a) Heterogeneous effects (b) Effects on earnings gaps



Notes. The outcome variable is the log of average monthly earnings received after graduation and before students turn 27 years of age. Panel A of Figure 7 plots regression discontinuity estimates within subsamples defined by different characteristics, shown at the top of each bar. Estimates based on linear local regressions, an Epanechnikov kernel, and bandwidths selected to minimize MSE. Panel (b) displays estimates of the earnings gap around the cutoff used to award the national distinction (i.e. the signal). For each category at the top of panel B of Figure 7, the gap is equivalent to the difference in earnings of group (1*) in Panel (a) with respect to group (2*). Estimates with "No signal" refer to OLS estimates of the gap among non-awardees whose test scores are close to the cutoff. Estimates when "Both signal" refer to OLS estimates among awardees whose scores are close to the cutoff. Estimates when "Only (1*) signals" refers to regression discontinuity estimates when the national distinction is awarded among individuals of group (1*) in Panel (a), but not among individuals of group (2*). Whiskers represent 95 percent confidence intervals computed using standard errors clustered by field-exam × year-of-exam.

[45] See Appendix Table A.3.

[46] Our measure of job-search network captures the number of firms that are in a college-program's network. First, we consider a firm k as part of college program j's network if the share of graduates from j working at k lies in the top quartile of the distribution of shares within j's field. Second, we consider that a college-program j has a highly developed network if it ranks among the first 20 programs in j's field with the largest number of firms that belong to j's networking.

[47] We additionally estimate Equation (1) using the networks index as dependent variable and we find no significant effect of winning the national distinction award.

Panel A of Figure 7 plots the regression discontinuity estimates of the award for each group (described in the top part of the figure).[48] Columns marked as (1) in the plot display the effect for the group of students who usually display lower wages in the data and that, for the sake of simplicity, we label as "disadvantaged" (i.e. students with parents with no education, parents with blue collar jobs, students with not strong college networks, and women.), whereas columns marked as (2) display the effect within the group that can be ex-ante considered "advantaged" (i.e. men, students whose parents have college education or work at white collar occupations, and among students with a high level of networks).

Being able to signal specific skills benefits more the set of workers that come from a disadvantaged background. The signal has a wage return of 15 percent for students whose parents do not have college education, of 10 percent for students whose parent have jobs in blue collar occupations, of 13 percent for students with lower access to networks, and of 14 percent for female workers. By contrast, we observe positive but not statistically significant effects for workers that come from more advantaged backgrounds.

Are the heterogeneous effects of signaling specific skills enough to close the wage gap between workers from advantaged and disadvantaged background? We attempt to answer this question by providing a back-of-the-envelope calculation that compares earnings gaps with and without the signal. We calculate three wage gaps:

1. Wage gap without signal: we compute a local estimator of the earnings gap without the signal by comparing both groups immediately to the left of the cutoff (i.e. among those who did not obtain the award but are close to the cutoff). This gap takes the form: $Gap_{NS} = \log(\tilde{W}_a) - \log(\tilde{W}_d)$, where $\tilde{W}_a$ and $\tilde{W}_d$ correspond to the wages of the advantaged and disadvantaged group, without the signal.

2. Wage gap with one-sided signal: we compare earnings of the "disadvantaged" group marginally to the right (those who won the award but are close to the cutoff) with the "advantaged" group marginally to the left. This comparison yields a local estimator of the earnings gap with a *one-side* signal sent only by workers that belong to the disadvantaged group, and takes the form: $Gap_{One-Side} = \log(\tilde{W}_a) - (\log(\tilde{W}_d) + \beta_d)$, where β_d represents the return of the signal among the disadvantaged group.

3. Wage gap with signal: we compare wages of both groups slightly to the right of the cutoff (i.e. among award winners). This gap takes the following form: $Gap_S =$

[48] Group classifications are likely correlated. For instance, a similar group of students have parents with non-college education and parents working in blue-collar jobs. Correlation, however, is not perfect which leads to different treatment effects of the award of the different subgroups.

$(\log(\tilde{W}_a) + \beta_a) - (\log(\tilde{W}_d) + \beta_d)$, where β_a corresponds to the return of the signal to the advantaged group.

Panel B of Figure 7 shows the results. The gray bars represent earnings gaps *without* the signal, purple bars with *one-side* signal, and pink bars *with* the signal. We observe that being able to signal specific skills decreases earnings gaps across all groups. The gap between students whose parents have and do not have college closes entirely, from 3 percent to a positive but not statistically significant point estimate when all students can use the signal. Similarly, signaling closes the gap almost entirely between individuals with a low and high level of networks. This last result is in line with the signal benefiting individuals who could not signal using college reputation. The gender earnings gap also decreases from 15 percent, in favor of men, to 12 percent (20 percent reduction) when males and females signal their specific skills to the market, even though these coefficients might not be statistically different. Taken together this evidence suggests that better information in the labor market level the playing field for workers coming from more disadvantaged backgrounds.

9 Conclusion

This paper studies the labor market effects of signaling field-specific skills to potential employers. The signal comes in the form of a salient and well-known national distinction award given to the best student of each field (based on a mandatory exit exam test score). We rely on census-like data and a regression discontinuity design to estimate that the signal has an earnings return of 7 to 12 percent. This positive return is observed even five years after graduation. We show that workers who graduated from low-reputation colleges benefit the most from being able to signal their specific skills to employers. The signal allows workers to find jobs in more productive firms and in sectors that better use their skills. We rule out that the signal is associated with higher levels of human capital.

Our results suggests that policies that provide information about workers' skills are likely to improve the allocation efficiency in the economy by allowing high-skilled workers to find jobs where their talents are more productively used. In addition, such policies could benefit more those workers from disadvantaged backgrounds, who lack access to other credible signals, and therefore partially offset preexisting inequalities of opportunities. Public systems of skills or competencies certification and standards could be effective if they provide measures that are credible and easy to be observed and understood by employers. However, more research is needed since there is very little credible of their effectiveness.

This paper also highlights that selective college-admission processes may lead to inefficient allocations of students – especially for those who have limited financial resources to pursue higher education. Students who are sufficiently skilled but who lack the necessary economic means are less likely to attend high reputation universities. The national distinction award is a policy measure that is able to correct some of the negative consequences of this inefficient allocations of students, but it has a limited scope and therefore a limited capacity to correct all the potential negative consequences of the educational mismatches. Information policies that correct information frictions when students enter the labor market could be accompanied by policies that tackle the problem before students enter college. Londoño-Vélez et al. (2020) evaluate a policy in Colombia which provided financial aid to high-achieving and low-income students to attend high-quality colleges. Their results suggest that the policy closed the enrollment gap in access to college between low- and high-income students.

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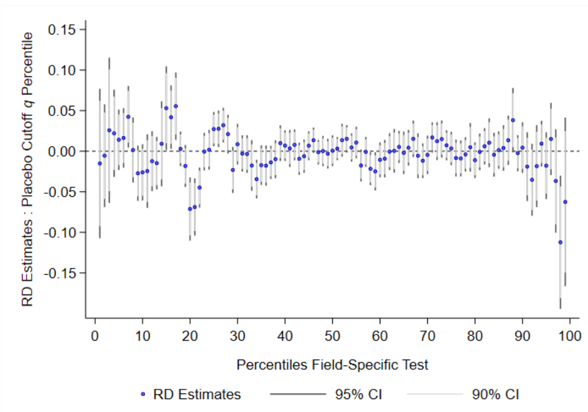
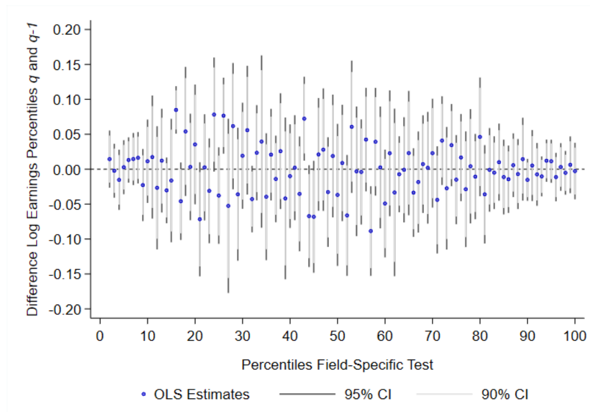
A Appendix Figures and Tables

Figure A.1: Placebo tests and differences in earnings between contiguous percentiles

(a) Placebo test



(b) Earnings differences



Notes. The outcome variable is the log of average monthly earnings after graduation and before students are 26 years old. Panel (a) displays RD estimates of equation (1) among non-awardees and using cutoffs defined by each percentile of the running variable as shown in the horizontal axis. Panel (b) presents OLS estimates of the earnings difference among non-awardees in percentiles q and $q-1$ of the running variable. 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 area-of-study×year-of-exam fixed effects. Errors clustered by field-exam × year-of-exam.

Table A.1: Summary Statistics of College Exit Exam Test-Takers, 2006-2009

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

Notes. $N = 313,363$. Summary statistics pooling all students taking the college exit 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.

Table A.2: Effect of national distinction award on early-career earnings

	Dependent Variable : Log Earnings						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1(National Distinction)	0.115*	0.108***	0.104***	0.093***	0.085**	0.086**	0.081**
	[0.060]	[0.035]	[0.036]	[0.035]	[0.033]	[0.034]	[0.032]
Observations	108,935	108,935	108,935	108,935	108,935	108,935	108,935
Bandwidth	0.291	0.291	0.291	0.291	0.291	0.291	0.291
Effect. obs. control	1478	1478	1478	1478	1478	1478	1478
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 Field of Study × Year level and in squared brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table A.3: Family Income and Pre-college Skills Difference Among Awardees from Top- and Low-ranked Schools

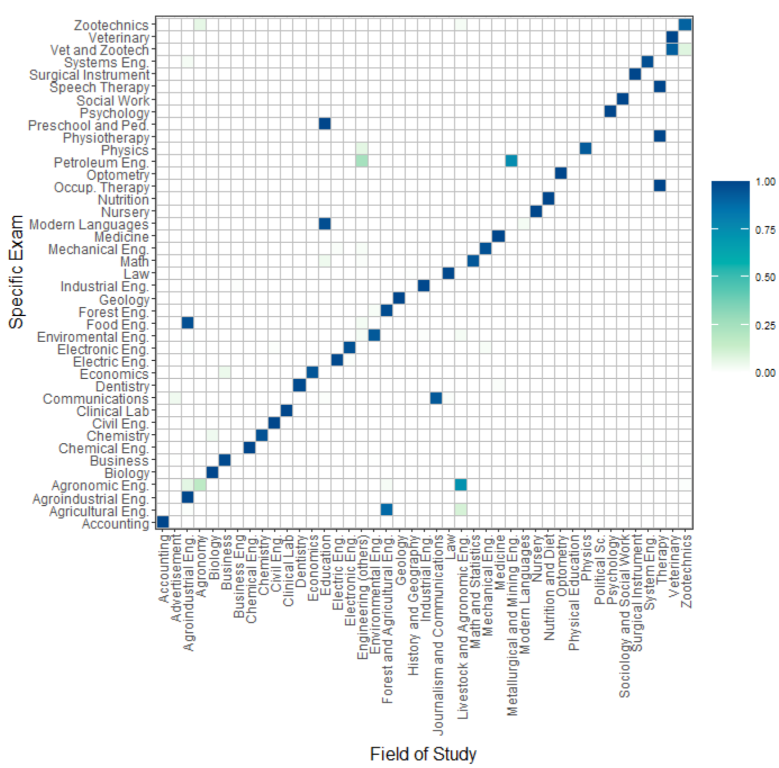
	Dep. Var. : 1(Top 5 College)		
	(1)	(2)	(3)
1(High Stratum)	0.069***		0.067***
	[0.024]		[0.024]
High School Exam Score (σ)		0.029	0.027
		[0.032]	[0.032]
Observations	2,680	2,680	2,680
R-squared	0.285	0.283	0.286
Field×Year FE	Yes	Yes	Yes

Notes. Ordinary least squares estimates. The dependent variable is an indicator variable that takes the value of one if the student is enrolled at a college ranked among the top five schools, and zero otherwise. 1(High Income) is an indicator variable that takes the value of one if a student's family belongs to socioeconomic stratum 4, 5, or 6. High School Exam Score corresponds to the student's percentile computed from the overall performance in the Saber 11 exam (i.e., the high school exit exam). All regression include area of study × year fixed effects. Errors clustered by Field×Year-of-exam and displayed in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

B 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 B.1 shows that each specific exam was mainly taken by the students from the field of study for which it was designed.[49]

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

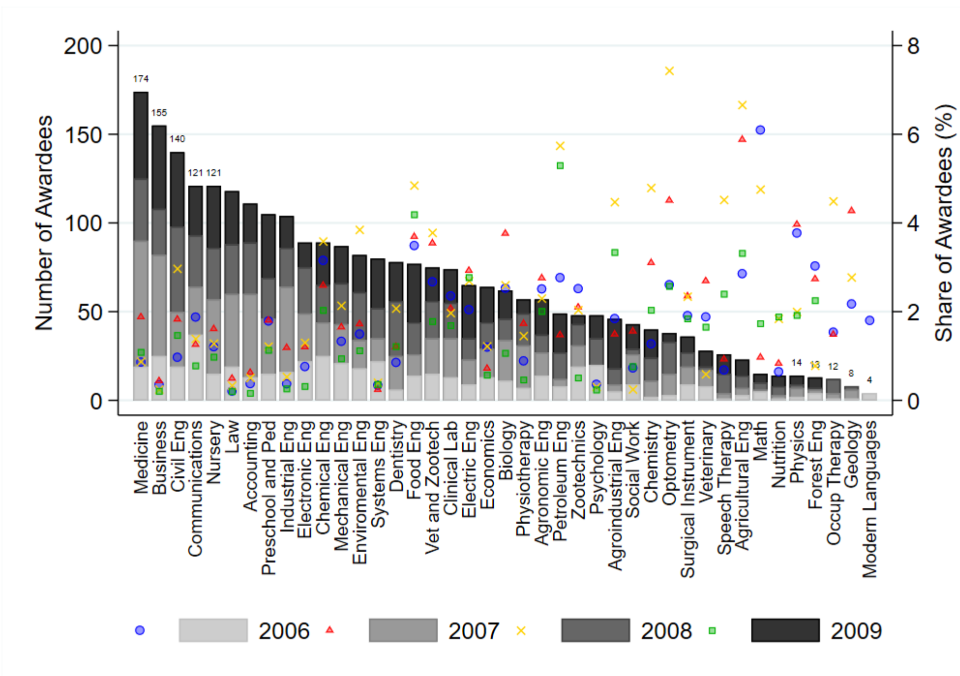


Notes. College students from 43 fields of study (as classified by the Colombian Ministry of Education) took the exam between 2006 and 2009. The graph plots the share of students from different fields who were registered to take each of the available specific exams. Rows add up to one.

[49]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 B.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.

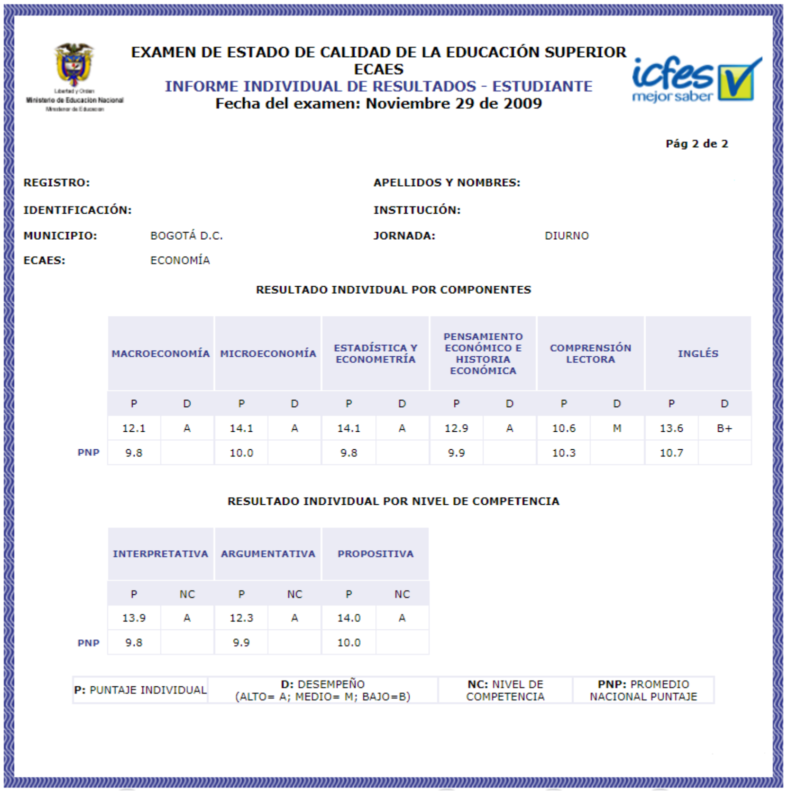
Figure B.2: Distinction Recipients by Field of Study and Exam Year



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.

Figure B.3 shows a sample report of a student's performance in the college exit exam. Scores at every subject test in the *specific* component of the exam are displayed, as well as scores in the *core* component. Neither overall scores nor order statistics for the field-specific exam are provided to students. The only relative performance measure provided to students in this report categorize subject scores into three groups: i) low, ii) medium, and iii) high. Even though the national average for each subject is included, it is still hard to interpret the scale and performance of a student, especially since the standard deviation of scores is not displayed.

Figure B.3: Sample Report of Performance in the College Exit Exam



EXAMEN DE ESTADO DE CALIDAD DE LA EDUCACIÓN SUPERIOR
ECAES
INFORME INDIVIDUAL DE RESULTADOS - ESTUDIANTE
Fecha del examen: Noviembre 29 de 2009

Pág 2 de 2

REGISTRO: | APELLIDOS Y NOMBRES:
IDENTIFICACIÓN: | INSTITUCIÓN:
MUNICIPIO: BOGOTÁ D.C. | JORNADA: DIURNO
ECAES: ECONOMÍA

RESULTADO INDIVIDUAL POR COMPONENTES

	MACROECONOMÍA		MICROECONOMÍA		ESTADÍSTICA Y ECONOMETRÍA		PENSAMIENTO ECONÓMICO E HISTORIA ECONÓMICA		COMPRENSIÓN LECTORA		INGLÉS	
	P	D	P	D	P	D	P	D	P	D	P	D
	12.1	A	14.1	A	14.1	A	12.9	A	10.6	M	13.6	B+
PNP	9.8		10.0		9.8		9.9		10.3		10.7	

RESULTADO INDIVIDUAL POR NIVEL DE COMPETENCIA

	INTERPRETATIVA		ARGUMENTATIVA		PROPOSITIVA	
	P	NC	P	NC	P	NC
	13.9	A	12.3	A	14.0	A
PNP	9.8		9.9		10.0	

P: PUNTAJE INDIVIDUAL	D: DESEMPEÑO (ALTO= A; MEDIO= M; BAJO=B)	NC: NIVEL DE COMPETENCIA	PNP: PROMEDIO NACIONAL PUNTAJE

Notes. Report of an economics student's performance in the college exit exam in 2009. Individual results for tests in macroeconomics, microeconomics, statistics and econometrics, and economic thinking and economics history are displayed in this report. Scores in reading comprehension and English proficiency, which are part of the *core* component of the exam, are also included. Scores are categorized into three performance groups: low (bajo), medium (medio), and high (alto). Neither overall scores, nor order statistics, in the specific component of the exam are provided.

C Appendix: Data Construction

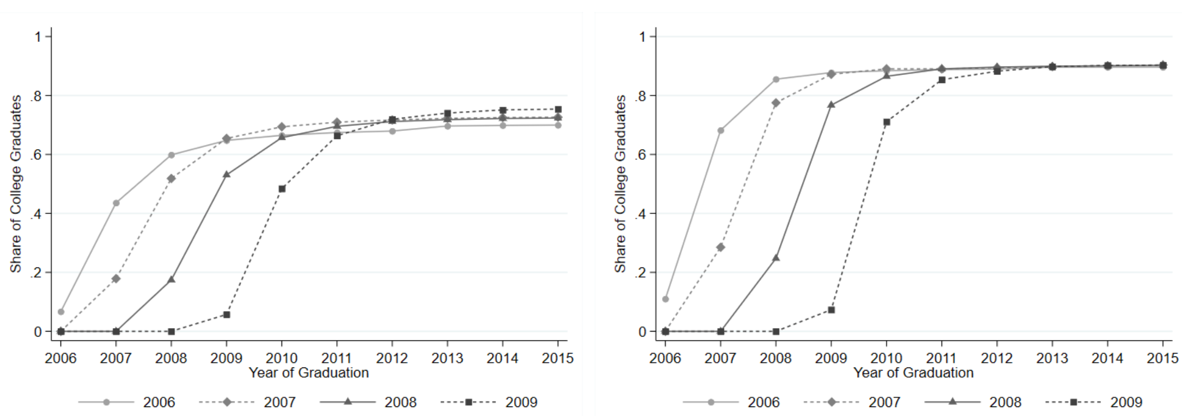
In this appendix we describe the process that we followed to assemble our sample. We first downloaded the public information of students who received the national academic award from the web page of the Colombian Institute For the Assessment of Education (ICFES, by its acronym in Spanish). Using the 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.

Table C.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.

Note that the labor market data we use in our analysis cover only college graduates. Figure C.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 C.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.

Table C.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

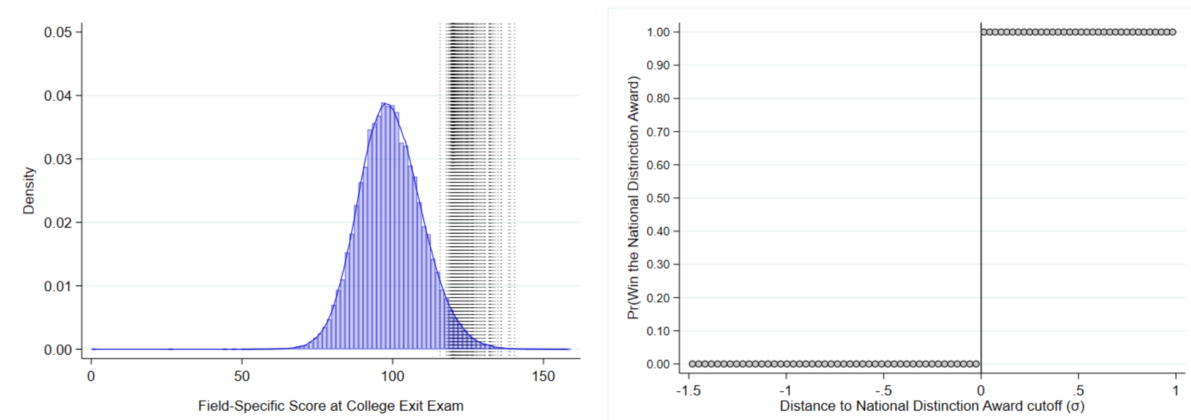
Notes. Count of college students taking the Saber Pro exam between 2006 and 2009. Earnings post-graduation refer to the number of years after a students graduation date (e.g. $t = 1$ means 1 year after college graduation). The number of schools and college programs evaluated during these years is displayed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

D Appendix: Additional Evidence on the RD Validity

In this appendix, we present complementary evidence regarding the identifying assumptions of our regression discontinuity strategy. Figure D.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 D.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 D.1: Field-Specific Exam Scores and RD First Stage

(a) Field-Specific Scores Density (b) Probability of Winning the National Award

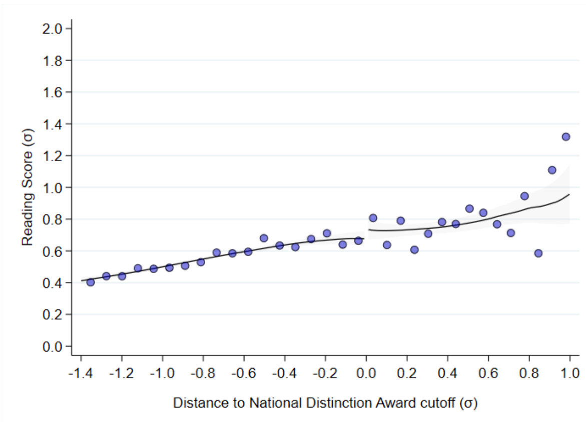


Notes. Panel (a) displays the estimated density of the scores from the field-specific component of the Saber Pro exam. Individuals from different fields taking the exam between 2006 and 2009 are pooled to estimate the scores density. The cutoffs used to assign the national award to all fields across 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.

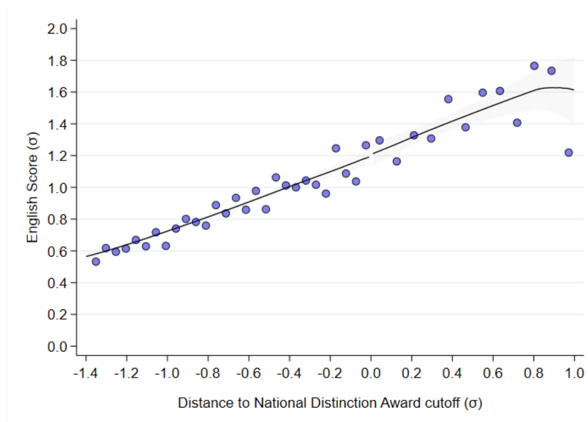
Figures D.2 and D.3 complements the evidence presented in Figure 2 regarding the comparability between award recipients and non-recipients around the cutoff. The empirical literature using sharp RD designs describes this assumption as continuity in pretreatment covariates. Graphical inspection of these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

Figure D.2: Continuity in Pretreatment Covariates

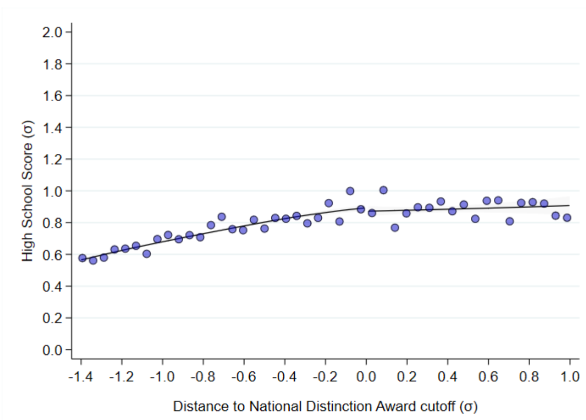
(a) Reading Score (sd)



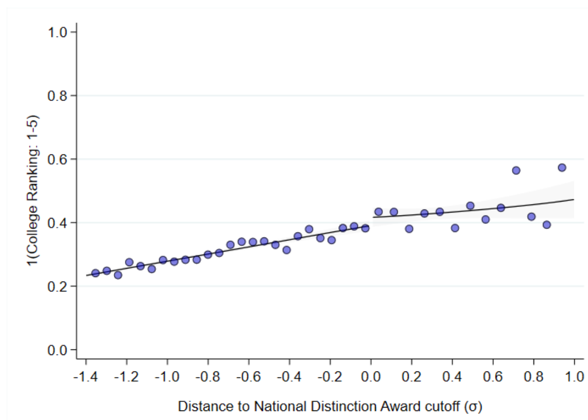
(b) English Score (sd)



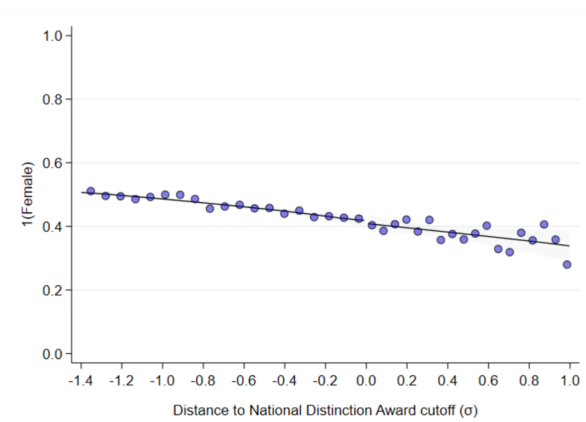
(c) High School Exit Exam (sd)



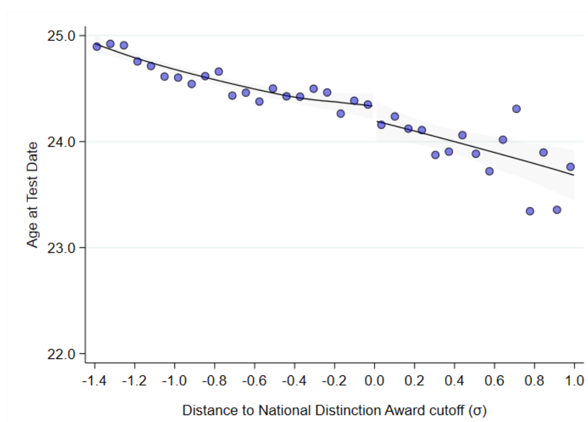
(d) Enrolled at a Top 5 University



(e) Female



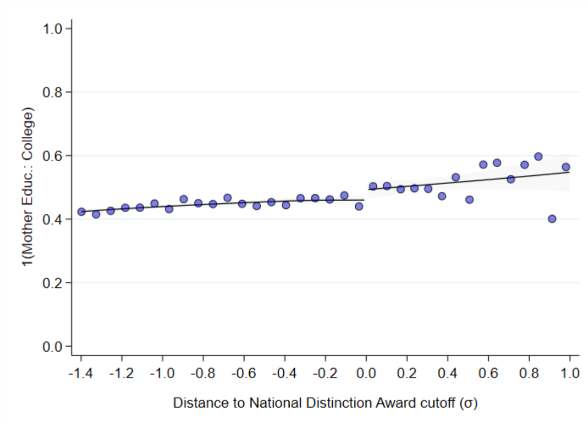
(f) Age at Test Date



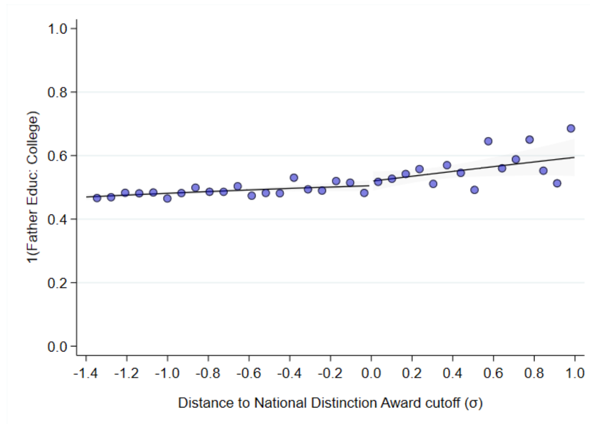
Notes. Evidence on covariate continuity or smoothness around the cutoff used to award the Saber Pro distinction to the best test-takers. The running variable is the score in the Saber Pro specific exam minus the threshold defined for each major to award the distinction to the best test-takers. All subfigures display data using a fixed bandwidth of 0.617. 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 D.3: Continuity in Pretreatment Covariates

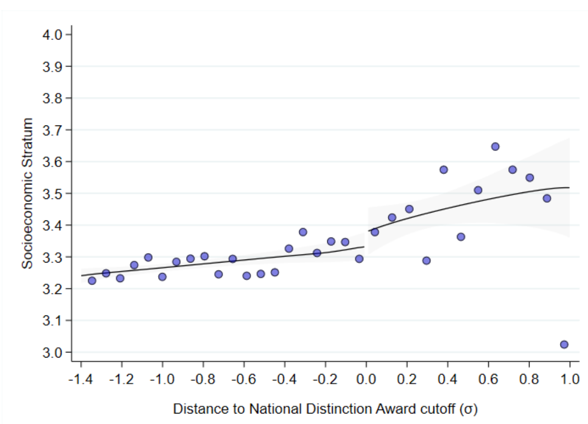
(a) Mother's Education: 4-year College



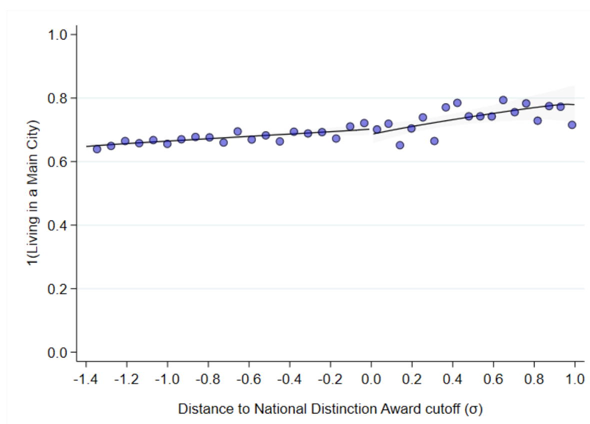
(b) Father's Education: 4-year College



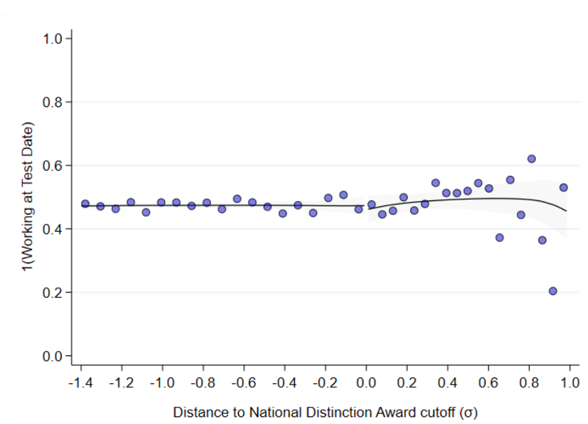
(c) Socioeconomic Stratum



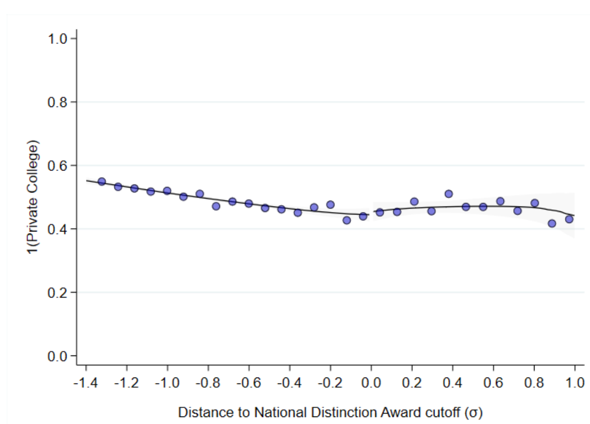
(d) Living at a Principal City



(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.

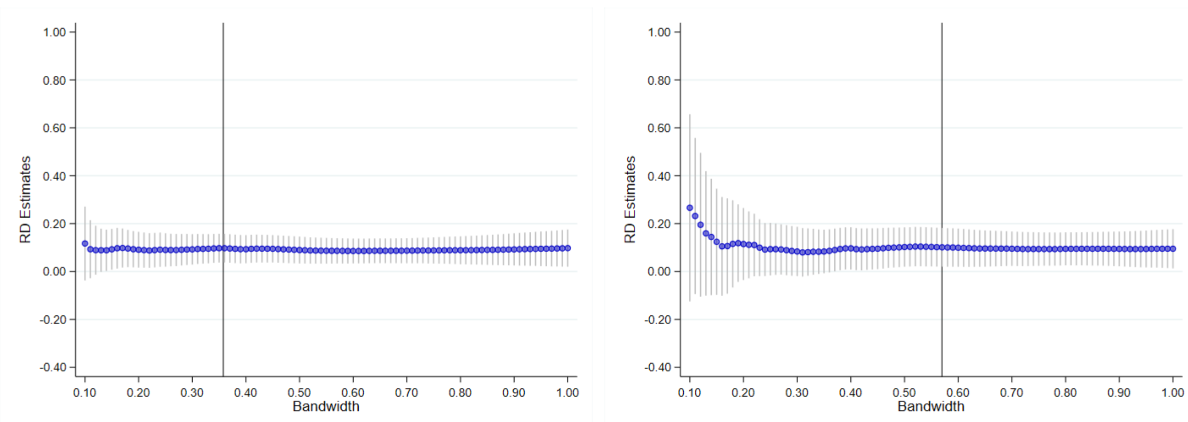
E Appendix: Additional Robustness Checks

E.1 Robustness to tuning parameters

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 E.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 E.1: RD Estimates as Function of the Bandwidth

(a) Linear Polynomial (b) Quadratic Polynomial

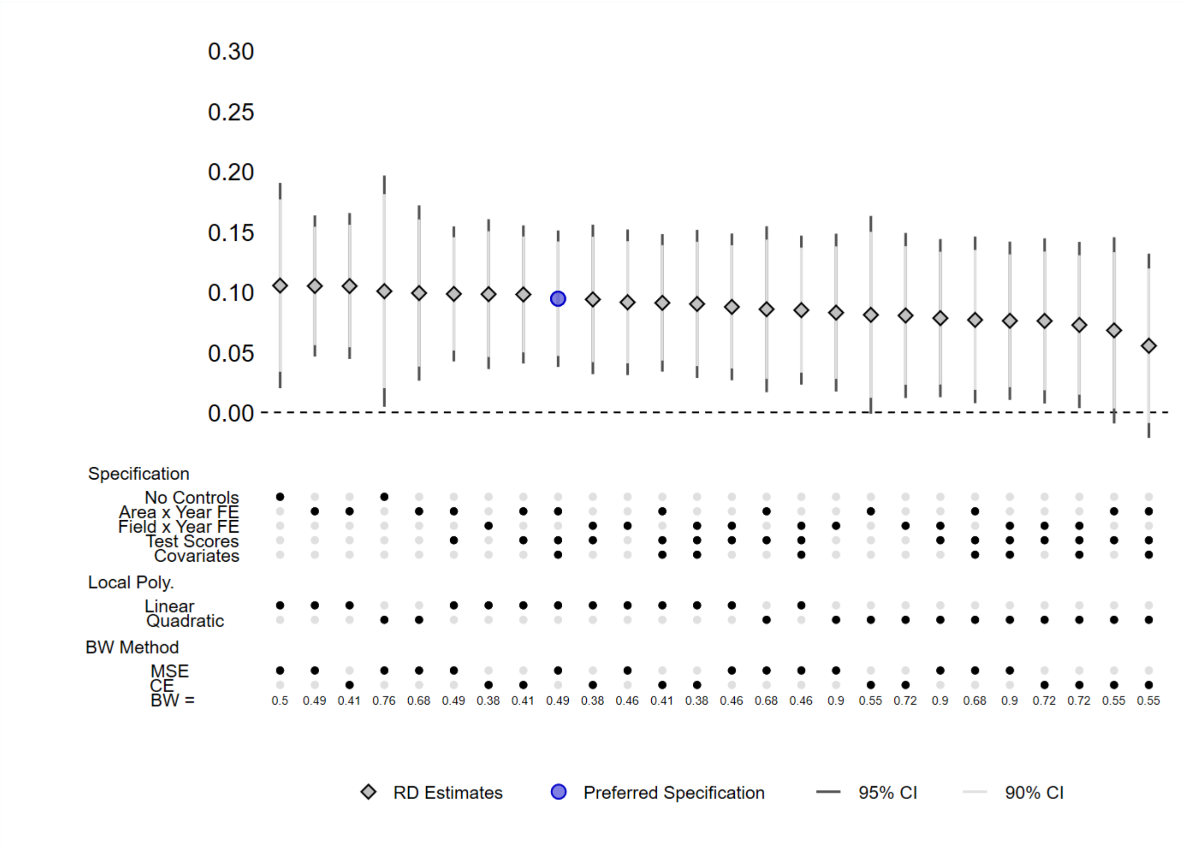


Notes. Panels (a) and (b) presents the RD estimates as a function the chosen bandwidth. Plotted dots represent the estimates around the cutoff using our preferred specification. Estimates in Panel (a) use a linear local regression model, while estimates in Panel (b) use a quadratic local regression model. 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.

E.2 Robustness to an alternative definition of early career earnings

Our estimates are also robust to an alternative measure of initial earnings, namely wages observed one year post college graduation. Figure E.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 A.2, 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 E.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.

E.3 Robustness of the evidence on mechanisms

Table E.1: Effects on Allocation of Skills

	Dependent Variable :					
	1(Field-Industry Match)				Log Earnings	
	Full Sample	by School Ranking :			by Type of Skills :	
		Top 5	Top 6-20	Below 20	Specific	Transferable
	(1)	(2)	(3)	(4)	(5)	(6)
1(National Distinction)	0.019	-0.028	-0.005	0.165*	0.110***	-0.010
	[0.039]	[0.062]	[0.065]	[0.095]	[0.039]	[0.077]
Observations	83,688	17,456	14,917	51,315	58,769	50,132
Bandwidth	0.357	0.385	0.361	0.328	0.293	0.250
Effect. obs. control	1671	835	413	452	1140	285
Effect. obs. treat	883	452	243	196	693	199

Notes. Regression discontinuity estimates of Equation (1) using linear local regressions, an Epanechnikov kernel, and bandwidths optimally computed to minimize the MSE. The outcome variable in columns (1) to (4) is an indicator variable that takes the value of one if a worker's industry matches the skills taught in the worker's college major (program). The outcome in columns (5) and (6) is the log of the average monthly earnings received after a student's graduation and before she reaches age 26. The running variable is the score in the college exit exam (specific skills component) minus the cutoff value used to assign distinctions to the highest scorers in each field of study. 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 area-of-study × year-of-exam fixed effects. Errors clustered by area × year and displayed in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Table E.2: Effects on the Probability of Switching Jobs and on Employers Wage Premia

	Dependent Variable :						
	Employers' Premia (σ)		1(Mover)	Employers' Wage Premia Across Time (t)			
	Unconditional Ranking	AKM Ranking		$t = 1$	$t = 2$	$t = 3$	$t = 4$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
1(National Distinction)	0.146**	0.175**	0.060*	0.175***	0.160**	0.183**	0.143
	[0.067]	[0.079]	[0.035]	[0.066]	[0.078]	[0.091]	[0.103]
Observations	95,708	95,708	63,579	63,579	63,579	63,579	48,541
Bandwidth	0.383	0.366	0.408	0.422	0.402	0.315	0.311
Effect. obs. control	1922	1828	1582	1649	1537	1079	821
Effect. obs. treat	971	948	704	723	702	619	465

Notes. Regression discontinuity estimates of Equation (1) using linear local regressions, an Epanechnikov kernel, and bandwidths optimally computed to minimize the MSE. The outcome variable in column (1) is the earnings ranking computed for all firms within an industry based on the average earnings they paid to college graduates between 2009 and 2015. In column (2), the outcome is the firms' earnings ranking in the period 2009-2015 based on firm fixed effects from a regression of earnings that also controls for individual fixed effects, as in Abowd et al. (1999). Both dependent variables in columns (1) and (2) are standardized. The outcome in column (3) is an indicator if the student is observed in more than one firm in the six years following their graduation. Columns (4) to (7) use as an outcome the AKM-ranking of the first ($f = 1$) to fourth ($f = 4$) firm f in which the student was employed post-graduation. 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 area-of-study×year-of-exam fixed effects. Standard errors displayed in brackets. * p<0.10, ** p<0.05, *** p<0.01.

Table E.3: Effects on Human Capital Accumulation

	Dependent Variable :					
	Months to College Grad. Date	Subjects by College Grad. Date	1(Graduate Education)			
			Full Sample	by School Ranking :		
				Top 5	Top6-20	Below 20
	(1)	(2)	(3)	(4)	(5)	(6)
1(National Distinction)	0.450	0.844	0.007	0.045	-0.075	-0.047
	[0.471]	[1.379]	[0.036]	[0.061]	[0.070]	[0.058]
Observations	96,048	93,053	106,712	19,982	17,770	68,960
Bandwidth	0.380	0.427	0.358	0.322	0.329	0.365
Effect. obs. control	2080	2320	1984	761	433	637
Effect. obs. treat	1039	1004	1045	472	271	248

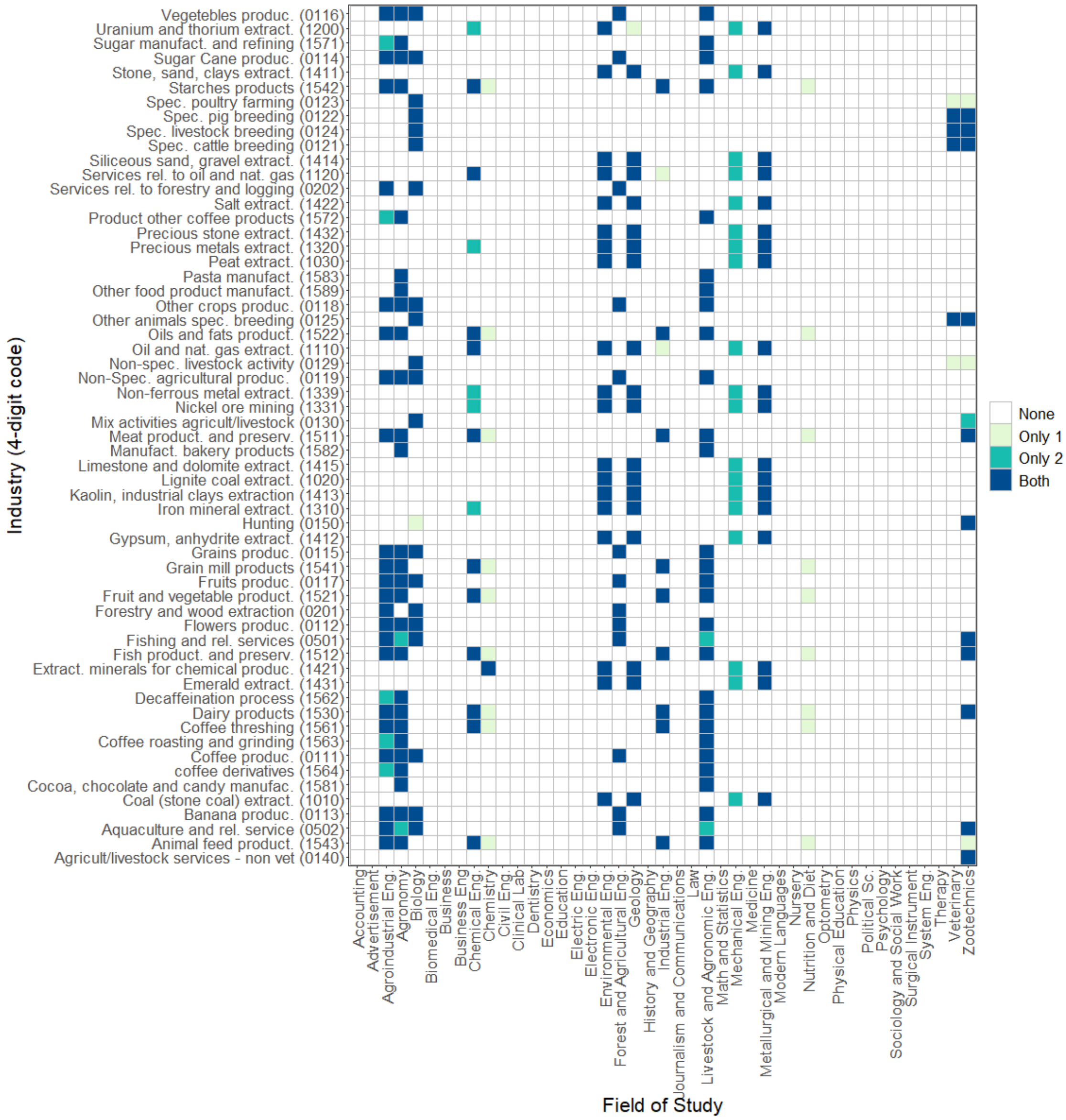
Notes. Regression discontinuity estimates of Equation (1) using linear local regressions, an Epanechnikov kernel, and bandwidths optimally computed to minimize the MSE. The outcome variable is an indicator variable that takes the value of one if a student completed a graduate program (i.e. one-year master's degree, two-year master's degree, or a doctorate) between 2010 and 2015. The running variable is the overall score in the field-specific component of the college exit exam minus the cutoff used to assign distinctions to the highest scorers in each field of study. 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 area-of-study×year-of-exam fixed effects. Errors clustered by field-exam × year-of-exam and displayed in brackets. * p<0.10, ** p<0.05, *** p<0.01.

E.4 Field-Industry match measure and robustness

Section 6.3 provides evidence that college graduates awarded the national distinction are more likely to work in industries where their specific skills play an essential role in the production process. To compute the direct measure of match quality used in this section, we collected information posted online by universities in Colombia regarding their "alumni profiles," where they describe the industries in which the skills learned by the students who successfully graduate from each of their majors will better fit, as well as relevant industries where some of their graduates are currently working. Based on this information, we asked two researchers to independently determine whether or not the description of each four-digit industry codes matches the skills of graduates from a field of study. The exercise of both researchers was then recorded as indicator variables, each of which takes the value of one if the production process of an industry was deemed to require the skills of graduates from a specific field. Figures E.3 and E.4 show samples of the exercise carried out by both independent researchers over the fields of study contained in our data. Researchers coincide in 70 percent of the industry-field pairs they deemed to be a good match between a worker's specific skills and an industry's production process requirements.

Table E.4 shows the effect of being awarded the national distinction on the direct measure of match quality. Results show significant positive estimates that are qualitatively similar regardless if we use the measure of one researcher or the other, or we use the overlap or the union between their industry-field pairs.

Figure E.3: Direct Measure of Match Quality between Field of Study and Industry



Notes. This figure displays a sample of the exercise carried out by two independent researchers to determine whether the specific skills of a college graduate match the skills required in the production process of different industries. Four-digit industry codes were used to determine industry-field pairs.

Figure E.4: Direct Measure of Match Quality between Field of Study and Industry

Notes. This figure displays a sample of the exercise carried out by two independent researchers to determine whether the specific skills of a college graduate match the skills required in the production process of different industries. Four-digit industry codes were used to determine industry-field pairs.

Table E.4: Effects on Allocation of Skills

	Dependent Variable : 1(Field-Industry Match of Skills)			
	Researcher 1	Researcher 2	Overlap	Union
	(1)	(2)	(3)	(4)
1(National Distinction)	0.071***	0.080***	0.079***	0.076***
	[0.027]	[0.024]	[0.026]	[0.024]
Observations	179,474	179,474	179,474	179,474
Mean control	0.284	0.281	0.206	0.344
Bandwidth	0.244	0.278	0.258	0.268
Effect. obs. control	1537	1768	1676	1717
Effect. obs. treat	967	1054	1013	1027

Notes. RD estimates of equation (1) using linear local regressions, an Epanechnikov kernel and bandwidths optimally computed to minimize the MSE. The outcome is an indicator variable that takes the value of one if a worker's industry matches the skills learned during a worker's college major (program). Column (1) shows the results using the measure using Researcher 1's answers, Column (2) use Researcher 2's answers, Columns (3) and (4) respectively use the overlap and the union of answers given by both researchers 1 and 2. The running variable is the score in the college exit exam (specific skills component) minus the cutoff value used to assign distinctions to the best test-takers in each field of study. 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 area-of-study×year-of-exam fixed effects. Errors clustered by field-exam × year-of-exam and displayed in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.