Signaling Specific Skills and the Labor Market of College Graduates

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Abstract

We use census-like data and a regression discontinuity design to study the labor market impacts of a signal provided by a government-sponsored award to top-performing students on a nationwide college exit exam in Colombia. Students who can signal their high level of specific skills earn seven to ten percent more than identical students lacking such a signal. The signal allows workers to find jobs in more productive firms and sectors that better use their skills. The positive returns persist for up to five years. The signal favors workers from less advantaged groups who enter the market with weaker signals.

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JEL classifications: J20, J24, J31, J44, O15, D80.

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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 of candidates for their job openings (Spence, 1973, 1974). When searching for high-skilled workers, firms have different tools at their disposal to make decisions. Academic degrees, the reputation of the institutions granting those degrees, and diploma 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, where workers have several signaling mechanisms, a salient signal on specific skills (i.e., skills learned through the curriculum of a college major) has a positive and persistent information value. Workers who are able to use such a signal, earn higher earnings and find better job matches (in high-paying firms that better use those skills). The signal also levels the playing field, primarily benefiting workers who come from more disadvantaged backgrounds.

The signal studied in this paper is an award given to college seniors for their performance in field-specific evaluations. In Colombia, college students who are about to graduate –and to enter the labor market– are assessed by means of a college exit exam that evaluates skills *specific* to their field of study. The exam also includes a *core* component evaluating 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 virtually all graduates of every college. Thus, the national distinction award signals high skills irrespective of the college attended by a student.

We exploit the discontinuity in the assignment of the national distinction award to implement a regression discontinuity design that examines the causal 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. We use census-like longitudinal labor market data linked to college records and the universe of test scores from high school and college exit exams. We focus on the universe of students who took the college exit exam between 2006 and 2009, identifying those who received the national distinction through publicly available lists of all

[1] For articles that study the returns to academic degrees see: Hungerford and Solon (1987), Kane and Rouse (1995), Jaeger and Page (1996), Tyler, Murnane and Willett (2000), Clark and Martorell (2014), and Jepsen, Mueser and Troske (2016). For articles that estimate returns to college reputation, see: MacLeod et al. (2017), Barrera and Bayona (2019), and Bordon and Braga (2020). For articles estimating the returns to diploma characteristics (e.g., Latin Honors), see: Khoo and Ost (2018) and Freier, Schumann and Siedler (2015).

[2] Typically, graduates include the award in their resumes, and colleges frequently highlight students who have received the award as a sign of their education quality and reputation.

award recipients.

We show that the award increases recipients' initial earnings by 7 to 10 percent – equivalent to an additional year of education in Colombia. 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 or by selective attrition. In addition, we present evidence consistent with the idea that the estimated effects are not likely due to differences in general skills or additional investments in formal education. This allows us to interpret the earnings returns of the national distinction award as those that accrue exclusively from the signaling content of the award (and not from differences in skills or further educational investments).

We examine the mechanisms behind the positive effects of the award on earnings. To guide the discussion, we introduce a stylized conceptual framework that highlights the role of human capital as well as college and majors of study with heterogeneous reputations. Three mechanisms seem to be at work behind our main result.

First, we find evidence consistent with the claim that the national distinction award functions as a labor market signal. We show that the award yields larger earnings returns for those workers who enter the labor market with weaker signals. 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 earnings similar to the ones they would have obtained had they graduated from a college with a higher reputation.

Second, the signal seems to improve the allocation of talent in the economy. We build an index that assesses how good the match is between the worker's field of study and 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. Signals on the student's field-specific skills increase the likelihood of working in the same field. This effect is driven by students from lower-reputation colleges. Importantly, the return to the signal is higher for specific skills that are less transferable across industries. We also show that it is the informational content about the student's specific skills, rather than the mere fact that the student has a signal to use in the market, that seems to drive positive earnings returns. We show that the earnings returns of a different signal, one about general skills, are small and not statistically significant.

Third, we find that the signal allows high-paying, plausibly high-productivity, firms to hire higher-skilled workers. We build measures of firm pay-premiums by computing time-invariant rankings of firms (within their narrowly defined industry) according to (i) the average earnings paid to their employees and (ii) the decomposition methodology in Abowd, Kramarz and Margolis (1999). We show that the signal given by the national distinction award leads to an increase of 0.13 of a standard deviation in the ranking. Students who won the national distinction award were significantly more likely to work in better-paying firms.

The earnings effects of the national distinction award are persistent at least up to five years after graduation. This piece of evidence is in line with career-development models that highlight the role of job ladders in the career of high-skilled workers (Gibbons and Waldman, 1999*a*,*b*; Haltiwanger, Hyatt and McEntarfer, 2018). After their first job, awardees are likely to continue to be employed in higher-paying firms, creating a persistent gap compared to similar students without the signal.

Our estimated labor market returns to the signal do not seem to be explained by differences in skills. 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 who have the same level of skills (as well as other similar observable characteristics, including pre-college test score measures) who cannot provide such a signal. In addition, we show that the distinction award did not lead to a differential skill accumulation *after* the national distinction award was conferred. Awardees have a similar probability of attending graduate school after finishing college. For these reasons, we interpret our results as the earnings returns of job market signaling exclusively.

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 usually attached to them. One set of studies has 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, Murnane and Willett, 2000; Jepsen, Mueser and Troske, 2016; Clark and Martorell, 2014) or college (Hungerford and Solon, 1987; Kane and Rouse, 1995; Jaeger and Page, 1996) compared to those who had not graduated. In a study focusing on Colombia, Arteaga (2018) shows that a reform that decreased the content of human capital in a prestigious university led to a reduction in earnings after graduation.

Our paper is also 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; Heller and Kessler, 2021).

Several other 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 it is therefore positively correlated with college graduates' earnings (MacLeod et al., 2017; Barrera and Bayona, 2019; Bordon and Braga, 2020; Ge, Isaac and Miller, 2022). Second, the students' within-university ranking also has a positive wage return (e.g., Khoo and Ost (2018); Freier, Schumann and Siedler (2015); Feng and Graetz (2017) analyze the effect of Latin honors).[3] Third, the GPA and grades used as signals have positive effects in the first years after graduation (Hansen, Hvidman and Sievertsen, 2023; Tan, 2023; Pietro, 2017; Landaud et al., 2024).[4]

Finally, our paper also relates to a growing literature on occupational licensing used as signals. Previous studies have demonstrated that the imposition of license requirements for specific occupations can reduce labor market supply and, consequently, lead to increased wages (Kleiner and Soltas, 2023; Kleiner and Krueger, 2013; Gittleman, Klee and Kleiner, 2018; Blair and Chung, 2019, 2021; Chung, 2022; Blair and Fisher, 2022). However, in addition to restricting labor supply, occupational licensing allows workers to signal their skills to the market and this process seems to favor disadvantaged populations (Blair and Chung, 2022).

To the best of our knowledge, our paper is the first to contribute to the literature on returns to signaling in four alternative ways. First, we provide the only estimation of returns to signaling based on a national policy that is well recognized by employers and can potentially affect all firms and industries (and, for that reason, may have larger general equilibrium effects in the economy). Different from Latin honors and other college-specific attributes, the signal studied in this paper 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. The signal allows employers to fully and properly compare workers across schools, and, therefore, gives students who graduate from lower-ranked programs a way to signal their productivity among their peers in other schools. Our results, in general, suggest that the experimental estimates carry over to more general settings, and that high-skilled students who lack the ability to properly signal benefit from having access to alternative signaling mechanisms.

Second, we show that signals are valued in the labor market even in the context

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

[4] Some earlier literature has also indicated that awards (along with scores) can have motivational effects, prompting students to alter their behavior by influencing crucial decisions related to educational investments (Avery et al., 2018; Beuchert, Eriksen and Krægpøth, 2020; Owen, 2010; Papay, Murnane and Willett, 2016; Smith, Hurwitz and Avery, 2017). We investigate this phenomenon and find no evidence that recipients of the national distinction awards change their educational choices when compared to the counterfactual group.

of high-skilled workers where the information provided by diplomas, college reputation, and Latin Honors is already available. Even though one might expect that the information asymmetry between job applicants and employers would be fairly small in the cases of college graduates, we nonetheless find sizable earnings impacts of the signal for those in these groups.

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. Our results provide evidence of the existence of information frictions when employers try to screen candidates based on the skills acquired during college. These frictions are not lessened by other signals such as college reputation and grades, suggesting that better information about students field-specific skills are valuable in the job-matching process.

Finally, we are able to follow workers for five years after the signal was introduced to show that returns to signaling do not fade out over time. Signals usually have non-persistent effects that fade out during the first years of tenure because employers learn and update beliefs about workers (Farber and Gibbons, 1996; Khoo and Ost, 2018). We show that this is not always the case. Some labor market frictions, such as on-the-job learning and lack of efficient job-mobility, may be also at play implying that the returns to signals might not be transitory and may last across several years in the labor market.

The rest of the paper is organized as follows. In section 2 we present the institutional background. 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 present evidence aimed at validating our identifying assumptions and show our 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 7 shows that the signal has persistent effects on workers' wages. Section 8 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 in 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. We focus on professional programs, which are equivalent to a bachelor's degree in the United States. Admissions are decentralized, with students applying for admission to specific college programs (or majors). Programs may have different admission requirements across and within colleges. A key component of students' applications is the performance in a high school exit exam, which all must take to enroll in college. 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 reputation (MacLeod et al., 2017; Camacho, Messina and Uribe, 2017).

In 2003, the government introduced a college exit exam, known as *Saber Pro*, to assess the skill levels of new graduates and the quality of the instruction provided by all colleges and programs in the country. 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. 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. Test scores also matter for students because there are several benefits for high-achieving test-takers, such as scholarships, remission of graduation fees, and student loan forgiveness.

The college exit exam is comprised of two components. First, a *core component* that assesses general abilities across fields by testing reading comprehension and English proficiency. The reading section examines the capacity to read analytically, understand college-level written material, identify different perspectives, and 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 seven parts, which require knowledge of different vocabularies.

Second, the college exit exam includes a *specific component* which measures students' expertise in their 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 future careers as professionals in each area. 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.

During the period analyzed in this paper, executive decrees made the college exit exam a mandatory requirement for graduation. Thus, the vast majority of senior students in areas for which a specific exam was available took the exam. Furthermore, most students took the exam specifically designed for their major's field of study.[5]

[5] Appendix A.1 provides evidence of the legal underpinnings of the mandatory nature of the Saber Pro. It also shows that the majority of students took the exam and that the probability of taking the

Every year, students who obtain a score among the top ten scores of the *field-specific* component are given a national distinction award. (This means that in any given field-year combination there can be more than 10 awardees if multiple students share the same score among the top-ten ones.) 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.

The national distinction award is a signal for the labor market about students' specific 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 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 students in the labor market. Employers are able to find award recipients easily, through media, on college websites, or from job candidates' resumes. 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 neither readily available to students nor would it be easy to interpret by employers.[6]

3 Data

Our sample of analysis consists of 198,742 students who were enrolled in four- and five-year programs, took the exit exam between 2006 and 2009, and for whom we have earnings information. 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; 2) among these students, who were eligible to receive the award based exclusively on the field-specific component of the exam, we identified all award recipients from publicly available records published online; 3) administrative records of the universe of students who ever registered to a higher ed-

exam is uncorrelated with students' and diplomas' characteristics (like college reputation). In addition, it describes the core and specific components of the test and it shows a high correlation between fields of study pursued by students and the specific component of the test that was administered to them.

[6] Appendix A.2 provides further description of the award. It shows that, because of the assignment rule, more popular fields tend to have more awardees. It also shows that awardees come both from public and private universities, spanning the complete school reputation ranking. The appendix also provides evidence, based on online profiles of a small subset of awardees, that students who received the award actually use it as a signal for the labor market. It also provide evidence suggesting that students who did not receive the award are unlikely to use the test score as a signal.

ucation institution in Colombia –including information about the institution in which students enrolled, the field of study the student selected, the student's high school exit exam scores, and some sociodemographic information; 4) administrative social security records from 2008 to 2016.[7] The records include monthly earnings in the formal sector (measured in the latest observed month between the second and third quarters of every year).[8] Our main outcome of interest is the first observed labor earnings after graduation, although we consider alternative measures for robustness.[9]

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.[10] 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 45 field-specific exams, which we group into six areas of study: Health (10 fields), Engineering (10 fields), Agricultural Sciences (6 fields), Social Sciences and Humanities (9 fields), Business and Economics (3 fields), and Math and Natural Sciences (7 fields).[11]

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.[12] Additionally, we define the (running) variable Z_{ijt} as:

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

[7]The college exit exam comes from the *Saber Pro* data set. The lists of award recipients are gathered from `http://www2.icfesinteractivo.gov.co/result_ecaes/sniee_ins_mej.htm`. The higher education records come from "Sistema para la Prevención de la Deserción de la Educación Superior" (*SPADIES*). The administrative social security records come from "Observatorio Laboral para La Educación" (*OLE*).

[8]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 a college education are employed in the formal sector.

[9]We provide specific details about the data, variables, and the estimating sample in Appendix B.

[10]Households in Colombia are classified into six socioeconomic strata that are used to target social programs and different public subsidies. The strata range from one (very low) to six (very high).

[11]Appendix Table B.2 provides descriptive statistics of our main estimation sample.

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

where σ_{jt} represents the standard deviation of the specific exit college exam score computed for students in the field of study j taking the exam in year t.[13]

Using these measures, we estimate the parameters of 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 first observed earnings after graduation (i.e., earnings observed at an early stage of the career of college graduates). Our results are, however, robust to alternative measures of earnings as we discuss below. 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, Cattaneo and Farrell (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 $\times$ 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 clustered by area of study and test year.

5 Results

We start by checking our identifying assumptions; we assess whether there was manipulation of the running variable Z_{ijt}, and whether individuals around the thresh-

[13] Alternatively, we could have used the ranking in the exam for each field-year as a running variable. This can prevent that, if the distribution of Z_{ijt} is sparse around the threshold, we end up inadvertently dropping some field-years of the estimation. It has, though, two disadvantages. First, the difference between two rank points might represent different achievement gaps in the college exit exam depending on where in the distribution of test scores this difference is computed. On the contrary, the difference between Z_{ijt} and Z'_{ijt} is always interpreted as a difference in test scores measured in standard deviation. Second, using a continuous running variable allows us to more easily rely on existing methods of bandwidth selection, which are not available for discrete running variables. We provide results using the test score ranking as a running variable in our robustness analysis.

old are similar except for the fact that some received the distinction award. We then show that we are equally likely to observe the earnings of all students around the eligibility threshold. We finish the section by estimating the effect of the distinction award on initial earnings after graduation.

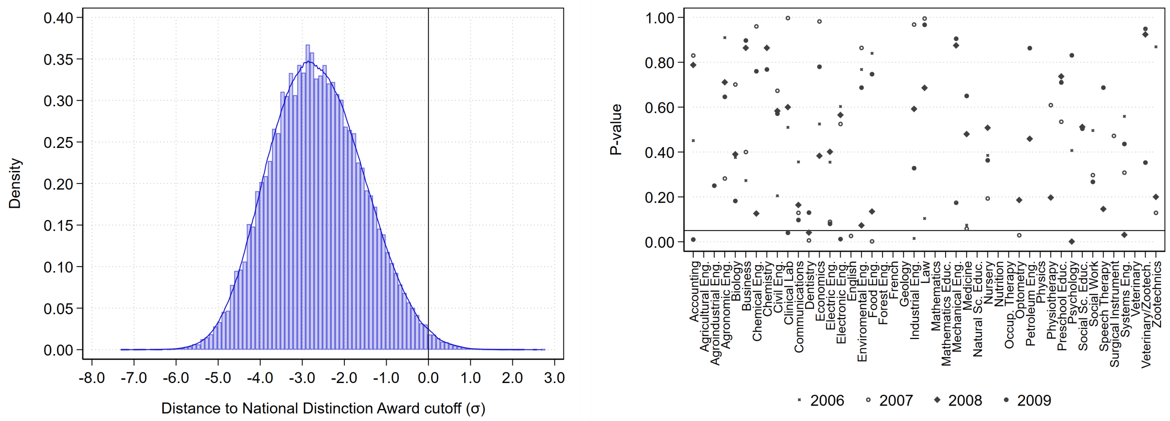
5.1 Validity of the Research Design

Manipulation tests. A first threat to the validity of our empirical strategy comes from the potential manipulation of the running variable used to assign the national distinction awards. 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 or 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.

Detecting a lack of smoothness in the density of the running variable (i.e., bunching) around the cutoff would be evidence of manipulation. We consider the non-parametric test developed by Cattaneo, Jansson and Ma (2020), who proposed a testing procedure to check for discontinuities based on the density estimator of Cheng, Fan and Maroon (1997). The null hypothesis of this test is that there was no manipulation around the threshold.

Figure 1: Density Smoothness Around the Cutoff of the National Distinction Award

(a) Running variable density (b) Manipulation tests



Notes. Panel (a) shows the estimated density of overall scores in the field-specific component of the college exit exam. Scores across field exams are normalized to set the cutoff for the national distinction award equal to zero. For interpretation and comparability, scores are re-scaled by dividing the standard deviation within fields. Panel (b) displays the results of the manipulation test based on the estimator proposed by Cattaneo, Jansson and Ma (2020). Under the null hypothesis of this test, there is no manipulation of the running variable. Therefore, under the null, the density of scores is smooth (or, there is no bunching) around the cutoff. Plotted dots correspond to p-values of the test, run for each field exam across years. The solid horizontal line represents a significance level of 5 percent.

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 we implement for all field-specific exams across years. We cannot reject the null hypothesis for most exams. We test the null hypothesis of no manipulation of the running variables for students taking the same field-specific exam. The statistical test requires more than 10 observations around the cutoff, so we can only test the hypothesis for 112 field-year combinations. We reject the null hypothesis for 11 (i.e., 9.8 percent) tests. Furthermore, there is no field where the null hypothesis of no manipulation is rejected consistently across years.[14]

Balance tests. Our identification strategy 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. We plot the estimates of β and their 95 and 99 percent confidence intervals in Figure 2.

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 college, and the probability of being employed on the date when they took the test.[15]

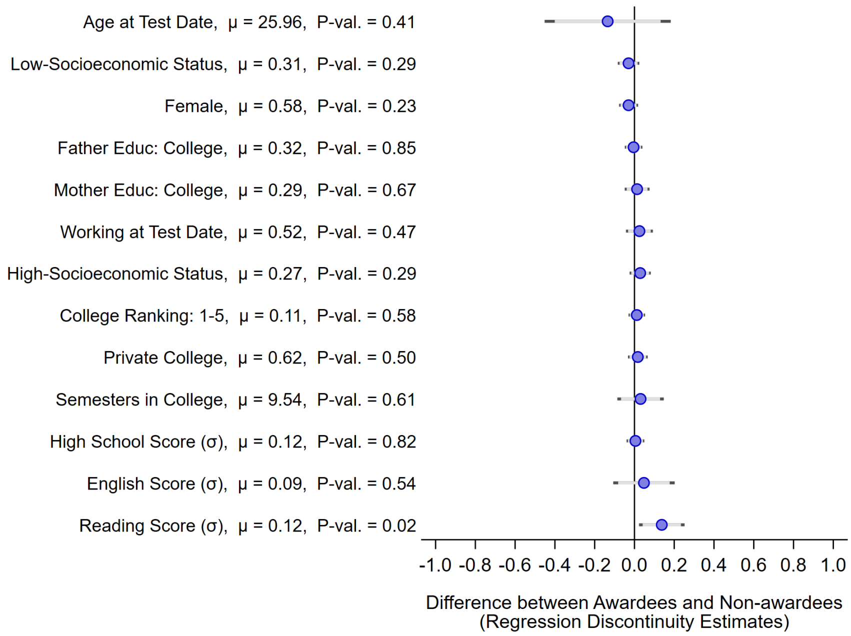
On either side close to the cutoff, individuals who received the award and those who did not receive it seem to have similar levels of general skills. We use the overall scores from the high school exit exam to proxy for general ability when entering college. We rely on the reading and English test scores from the *general* component of the college exit exam to proxy for general academic skills when graduating from college. We cannot reject the null hypothesis of equality of means in the case of the high school exit exam or the English score. However, we reject it for the average reading test score (with a small difference of 0.13 standard deviations). In our main specification, we control for the entire vector of general skills even though its inclusion does not change our results.

Finally, a potential confounding factor would be that students from top-ranked

[14] In Appendix C we provide additional evidence on the validity of our regression discontinuity design. 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 jumps sharply (i.e., all students with a field-specific score equal to or above the normalized field's cutoff obtain the award, while no student below such threshold becomes an awardee).

[15] Appendix C shows a graphical representation of the continuity around the cutoff for "pre-treatment" variables.

Figure 2: Covariate Balance Around the Cutoff of the National Distinction Award



Notes. Plotted dots represent regression discontinuity estimates using covariates measured at the date of the exam as outcomes. Sample means, represented by μ, are displayed on the vertical axis along with the p-value for each estimate. All regressions include area-year (of exam) fixed effects. The running variable is the distance of scores (measured in standard deviations) from the cutoff for the national distinction award. Estimates use linear local regressions, an Epanechnikov kernel, and MSE-optimal bandwidths. 90 and 95 percent confidence intervals, based on robust standard errors clustered at the area-year level, are displayed around coefficients.

universities were more prepared to take the *specific* component of the 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.

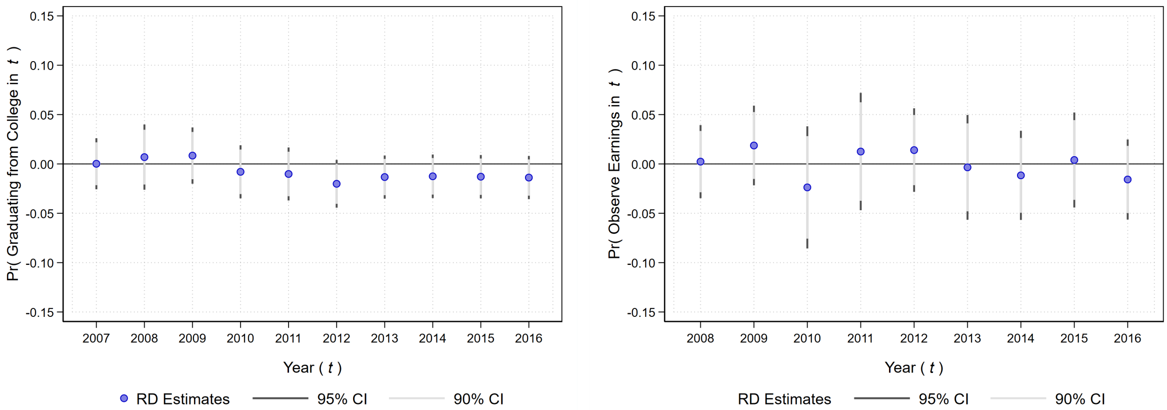
Sample selection. A potential threat to the validity of our results is related to the possibility that national awardees are more likely to be found in the administrative records used to measure educational attainment and earnings after college completion.

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 $s = 2007, ..., 2016$. Figure 3a plots the estimated coefficients $\hat{\delta}$ and shows that the marginal recipients of the award were not more likely to have graduated from college than non-awardees.[16] 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 $s = 2008, ..., 2016$. Figure 3b shows that we are equally likely to observe the earnings of students who did and

[16] If we estimate equation (1) pooling all the years, we cannot reject that the coefficient of interest is equal to zero ($\hat{\delta}_{RD}$=-0.004, p-value=0.758).

Figure 3: Sample Selection Around the Cutoff of the National Distinction Award

(a) Probability of Graduating from College (b) Probability of Observing Earnings



Notes. This figure presents evidence of non-selective attrition. Panel (a) displays regression discontinuity estimates of the difference in the likelihood that marginal award recipients and non-recipients graduate from college after taking the exam. Panel (b) displays regression discontinuity estimates of the difference in the likelihood of observing formal sector earnings for marginal award recipients and non-recipients. All regressions include area-year (of-exam) fixed effects. The running variable is the distance of scores (in standard deviations) from the cutoff for the national distinction award. Estimates use linear local regressions, an Epanechnikov kernel, and MSE-optimal bandwidths. 90 and 95 percent confidence intervals, based on robust standard errors clustered at the area-year level, are displayed around coefficients.

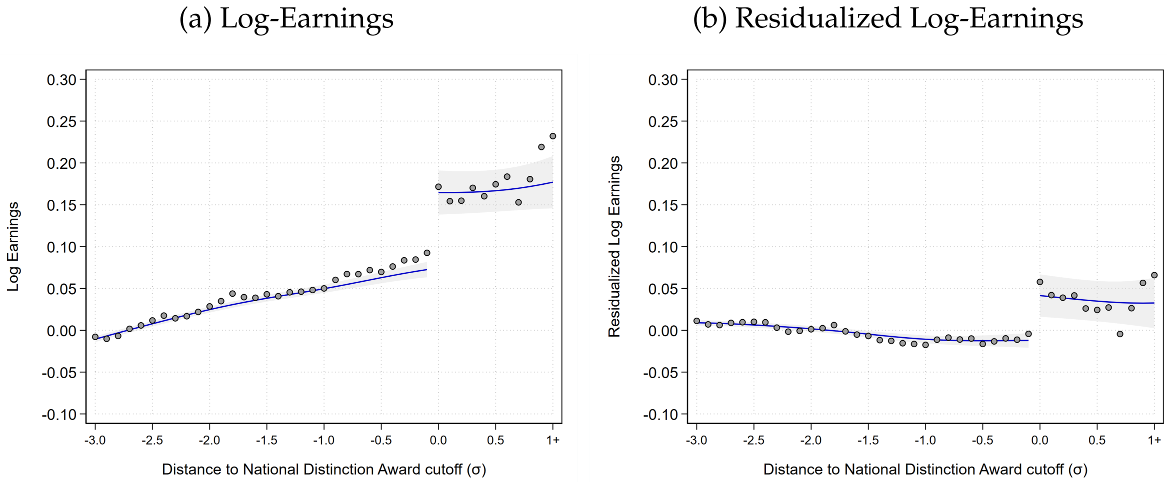
did not receive the award.[17] Taken together these results suggest that our main treatment effects estimates are not likely affected by factors that could differentially change the probability of observing earnings for award recipients (e.g., informality, students moving abroad, or students attending graduate school and therefore not working).

5.2 Effect of the National Distinction Award on Earnings

Main results. We use equation (1) to estimate the effect of receiving the national distinction award on the first observed earnings of college graduates.

[17] If we estimate equation (1) pooling all the years we cannot reject that the coefficient of interest is equal to zero ($\hat{\delta}_{RD}$=-0.001, p-value=0.937).

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



Notes. This figure plots early-career earnings as a function of the distance of scores (in standard deviations) from the cutoff for the national distinction award. Early-career earnings are defined as the first observed earnings after graduating college. Panel (a) represents the regression discontinuity in log earnings without including any controls. Log earnings are rescaled by subtracting the mean to facilitate interpretation. Panel (b) represents the regression discontinuity in log earnings after controlling for area-year (of exam) fixed effects, test scores, and other covariates. Test scores include scores from the high school exit exam and scores from the core component tests (Reading and English Proficiency) of the college exit exam. Scores from the core component tests are not used by exam authorities to confer the national distinction award. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. Plotted dots represent local averages of log earnings within equidistant bins of the running variable. A width of 0.2 is used to compute local averages. Solid lines represent linear local regressions using a bandwidth equal to 0.449 and an Epanechnikov kernel. 95 percent confidence intervals are displayed around the local regressions on both sides of the cutoff.

Figure 4a plots the causal effect which 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 earnings after graduation. There is also a positive and statistically significant premium on earnings from being awarded the national distinction of around 8 percent.

In principle, this estimate could have been affected by the composition of the sample as a result of pooling students taking their field-specific exams in different years. Figure 4b plots the results of estimating the discontinuity on the log of first observed earnings after graduation conditional on several variables including initial and general skills, baseline sociodemographic variables, and areas of study $\times$ test year fixed effects, as specified in equation (1). Results remain the same. The slope of the curve, however, shrinks; which suggests that the control variables absorb most of the predictive power of the field-specific test score on earnings.

Table 1: Effect of National Distinction Award on Early-Career Earnings

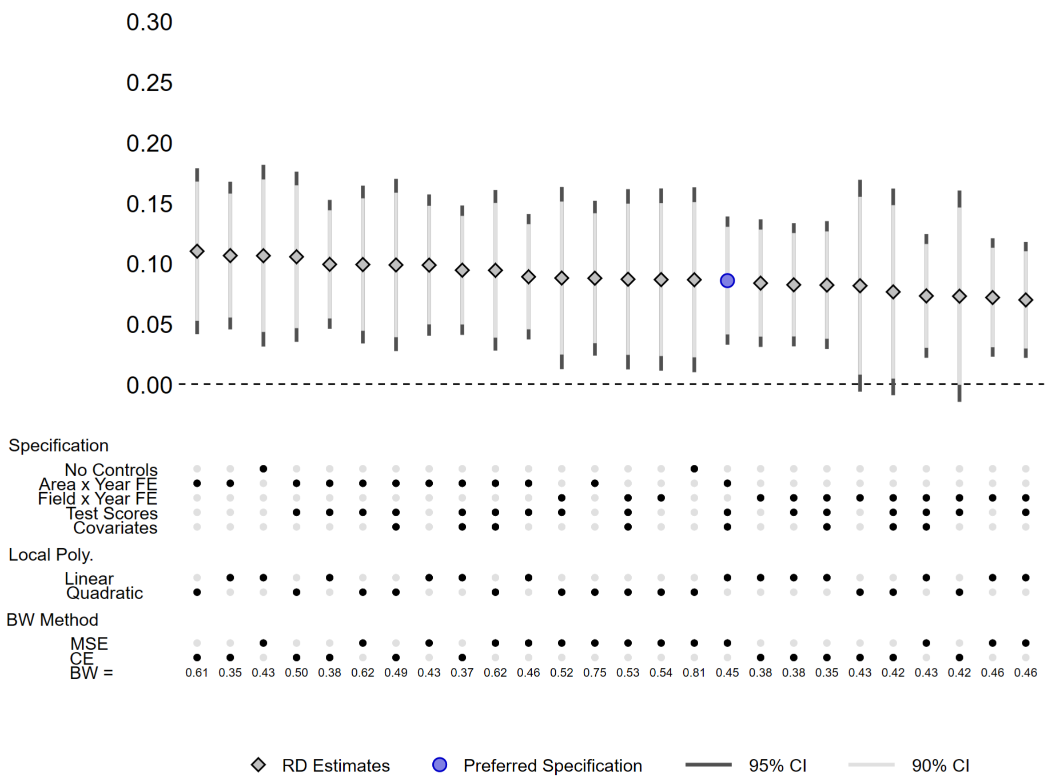
	Dependent Variable : Log Earnings					
	(1)	(2)	(3)	(4)	(5)	(6)
National Award	0.095***	0.090***	0.086***	0.072***	0.071***	0.071***
	[0.029]	[0.026]	[0.027]	[0.025]	[0.025]	[0.026]
Observations	198,742	198,742	198,742	198,742	198,742	198,742
Bandwidth	0.449	0.449	0.449	0.449	0.449	0.449
Control Obs.	3807	3807	3807	3807	3807	3807
Treatment Obs.	1538	1538	1538	1538	1538	1538
Area x Year FE	Yes	Yes	Yes			
Field x Year FE				Yes	Yes	Yes
Test Scores		Yes	Yes		Yes	Yes
Covariates			Yes			Yes

Notes. This table presents regression discontinuity estimates of the effect of the national distinction award on early-career earnings. The outcome variable is the log of early-career earnings, defined as the first observed earnings after graduating college. The running variable is the distance of scores (measured in standard deviations) from the cutoff for the national distinction award. 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. Scores from the core component tests are not used by the exam authorities to confer the national distinction award. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. Estimates use linear local regressions and an Epanechnikov kernel. The common bandwidth across columns corresponds to the MSE-optimal bandwidth computed using the specification in column (3). Robust standard errors are clustered at the area-year level and displayed in squared brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Table 1 shows the full set of results –again, using the first observed earnings after graduation as the outcome variable. Our preferred specification, shown in Column 3, controls for the area of study by year of the exam, a full set of baseline sociodemographic characteristics, and a rich set of measures of skills. To facilitate the comparison of estimates across columns we fix the bandwidth to the MSE-optimal bandwidth determined for the specification shown in Column 3. The effect of the national distinction award on early career earnings ranges from 7 to 10 percent. These estimated returns are comparable, for instance, to the 9 percent wage increase of an increase in GPA found by Hansen, Hvidman and Sievertsen (2023), but smaller than the 13 percent effect found by Arteaga (2018) when analyzing the effect of reducing the coursework required for college graduation. Their magnitude is large, similar to the 11 percent earnings premium from an additional year of education in Colombia (Tenjo et al., 2017).

Robustness. Regression discontinuity estimates might be sensitive to the choice of tuning parameters. Figure 5 provides formal estimates of equation (1) using alternative bandwidths and local polynomial regressions of a different order. The bottom of the figure describes the specification, which we vary in three dimensions.

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



Notes. This figure shows that our estimates of the effect of the national distinction award on earnings are robust to changes in the tuning parameters of the research design and to different control variables. The outcome variable is the log of early-career earnings, defined as the first observed earnings after graduating college. Plotted dots represent regression discontinuity estimates using local polynomial regressions of different order and an Epanechnikov kernel. The MSE-optimal bandwidth used for each estimate is displayed at the bottom of the specification. The running variable is the distance of scores (measured in standard deviations) from the cutoff for the national distinction award. 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. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. 90 and 95 percent confidence intervals, based on robust standard errors clustered at the area-year level, are displayed around coefficients.

First, we vary the control variables. We present estimations with no controls, with field-year fixed effects, conditioning on 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 CE bandwidths.[18]

We observe very stable point estimates between, roughly, a 7 to 12 percent increase in earnings for the national award recipients. We provide additional robustness checks in Appendix D. Specifically, we show that the estimated effect is robust to: (i) a large

[18]Note that CE bandwidths are commonly smaller than MSE bandwidths, which are widely used in regression discontinuity applications. As mentioned by Calonico, Cattaneo and Farrell (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.

set of bandwidths; (ii) alternative definitions of the outcome variable that take into consideration that students might take different amounts of time to enter the formal labor market after graduation (we thus estimate the effect of the signal on the log earnings one year after graduation and on the average log earnings between the ages of 23 and 28); (iii) dropping smaller fields from the estimation (to assess whether awardees from smaller fields are different from those of more popular fields); and (iv) using the ranking of the field-specific scores as running variable instead of the score.[19]

5.3 Who benefits more from the signal?

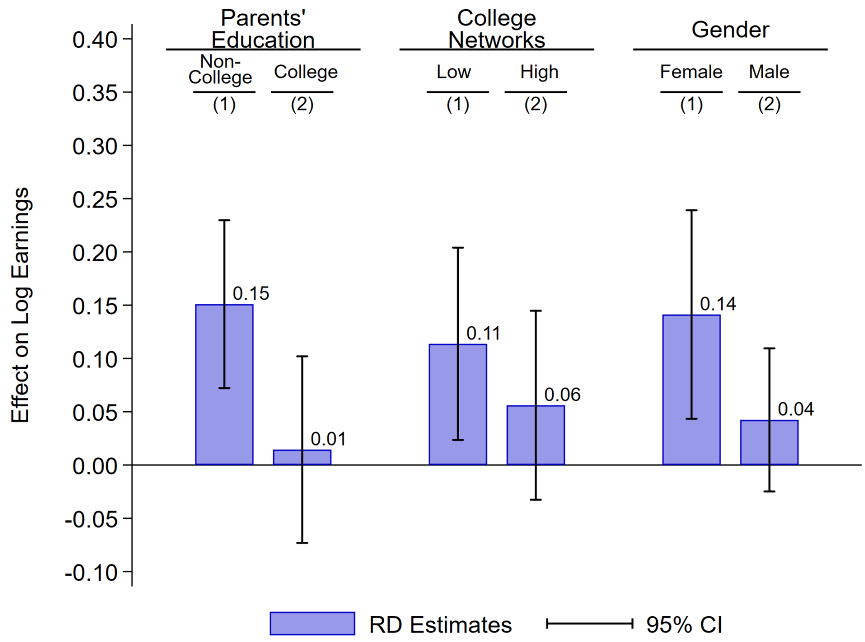
The average high-achieving graduate benefits from signaling their specific skills when entering the labor market. To better understand the effect of the signal for people with different background characteristics, we estimate the regression discontinuity model described in equation (1) for the subsamples of students with different levels of parent's education, gender, and different access to job search networks. This measure captures the number of firms that are in a college-program's network. To compute it we proceed as follows. 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 top quartile of programs in j's field with the largest number of firms that belong to j's networking.[20]

Figure 6 plots the regression discontinuity estimates of the award for each group (described in the top part of the figure). Columns marked as (1) in the plot display the effect for the group of students who usually display lower earnings in the data and that, for the sake of simplicity, we label as "disadvantaged" (i.e., students with parents without college education, students with weaker college networks, and women), whereas columns marked as (2) display the effect within the group that can be ex-ante considered "advantaged" (i.e., students whose parents have college education, students with a stronger networks, and men). Being able to signal specific skills tends to benefit the set of workers who come from a disadvantaged background. The signal has an earnings return of 15 percent for students whose parents do not have a college education, 11 percent for students with lower access to networks, and 14 percent for female workers. By contrast, we observe positive but not statistically significant effects for workers who come from more advantaged backgrounds.

[19] In Appendix Figure A.6 we show that the estimated effects of the award on earnings are not positive and statistically significant almost anywhere else in the test score distribution. The national distinction award is given to, roughly, the top one percent of test takers. We expect that the difference exists only between awardees and non-awardees. Indeed, we do not observe any other jump across the distribution.

[20] We estimated equation (1) using the index of the college's network as the dependent variable and found no significant effect of winning the national distinction award.

Figure 6: Heterogeneous Effects of the National Distinction Award



Notes. The outcome variable is the log of early-career earnings, defined as the first observed earnings after graduating college. Bars represent regression discontinuity estimates using linear local regressions, an Epanechnikov kernel, and MSE-optimal bandwidths. Estimates are computed within the subsample defined by the characteristic displayed at the top of each bar. All specifications control for area-year (of exam) fixed effects and test scores. Test scores include scores from the high school exit exam and scores from the core component tests (Reading and English Proficiency) of the college exit exam. 95 percent confidence intervals, based on robust standard errors clustered at the area-year level, are displayed around estimates.

Are the heterogeneous effects of signaling specific skills enough to close the earnings gap between workers from advantaged and disadvantaged backgrounds? Our data and research design do not allow us to unequivocally answer this question. We can use our results to provide some guidance, however, noting that doing so requires extrapolating our local treatment effect estimates to a larger population.

We compute some back-of-the-envelope calculations analyzing hypothetical cases in which the advantaged and/or disadvantaged groups can signal their skills. We present the complete analysis in Appendix E. One important result to highlight is that the ability to signal specific skills can potentially decrease the average earnings gaps of those students born to parents with less/more years of schooling by three percentage points. A similar result is observed for the gender wage gap, which shrinks when both men and women can signal their skills. These results are closely related to the effects that occupational licenses have on reducing racial earnings gaps in the United States (Blair and Chung, 2022).

This result implicitly suggests that selective college admission processes may be inefficient. Students who are sufficiently skilled but are credit-constrained are less likely to attend high-reputation universities. The distinction award is able to correct some of the negative consequences of this inefficient allocation of students, but it has a limited scope. 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, Rodríguez and Sánchez (2020) and Solis (2017) evaluate two national policies, in Colombia and Chile respectively, that 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. Furthermore, Londoño-Vélez et al. (2023) show that, in the Colombian case, the policy increased the earnings of financial aid recipients.

6 How Does the Signal Affect Labor-Market Outcomes?

To guide the discussion of some of the mechanisms behind the positive effects of the national field-specific award on earnings, we first present a conceptual framework that highlights potential channels that might be operating in the labor market.

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 wage-offer decisions of 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,

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

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,

$$P[R_i = R_s^+] = P[T_i > \bar{T} | I_i^0 > \bar{I}_s]$$
$$P[R_i = R_s^-] = P[T_i \leq \bar{T}] + \underbrace{P[T_i > \bar{T} | I_i^0 \leq \bar{I}_s]}_{\text{Income-constrained}}, \quad (2)$$

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 (e.g., those from less advantaged backgrounds).[21]

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 to the employer.

A college's reputation is a signal about the initial skills of the student who enrolls at that college, about the value added by the college, and potentially about field-related skills. We assume that the college-specific component satisfies that:

$$E[\theta_i^0 + v_s + v_j | R_s] = P[R_i = R_s^+]R_s^+ + P[R_i = R_s^-]R_s^-.$$

Graduation from a college with reputation level R_s is observable to employers and constitutes a signal of θ_{ijs}^1. Students who attend colleges with a high reputation send a signal R_s^+, whereas students who attend colleges with a low reputation send a signal $R_s^- < R_s^+$. The precision of the signal is determined 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.[22]

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

[21] We assume that everyone attends college. In our setting, students from high-income families are more likely to attend prestigious colleges (suggesting that credit constraints might be at play in our setting).

[22] Following, MacLeod et al. (2017) the post-college ability signal follows: $\theta_{ijs}^1 \sim N(R_s, \sigma_R)$, where $\rho_R = 1/\sigma_R$ is the noise parameter.

exam, such that:

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

where $1(\cdot)$ is an indicator function and k_j is an unknown threshold used to assign the national distinction award.[23] 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^0_i. 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., $E[\theta^1_{ijs}|A_{ij}] > E[\theta^1_{ijs}|R_s]$). We also assume that the former signal is more precise than the latter ($1/\sigma_A > 1/\sigma_R$).

Signals and wage setting. Consider two types of employers that differ in 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 $j \in K$, which we assume is more likely to be revealed for those who win the national distinction award (i.e., $P(j \in K|A_{ij}) > P(j \in K|R_i)$). 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,

$$y_{ifjst} = \omega_f \kappa_{j \in K} \theta^1_{ijs} + \rho y_{ijs,t-1} + \varepsilon_{ifjst}.$$

Following MacLeod et al. (2017), we assume that current productivity depends on its lagged value (i.e., $\rho \in (0, 1)$). Workers learn from previous experience and this on-the-job learning makes them more productive. Thus, an initial job with a better employer, and in an industry that better utilizes the workers' skills, can put the worker in a learning and promotion trajectory (potentially allowing them to stay up the job ladder).

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:

$$\begin{aligned} p_{ifjst} &= E[\omega_f \kappa_j \theta^1_{ijs}|R_i, A_{ij}] + \rho y_{ijf,t-1} + u_{it} \\ &= A_{ij} \left\{ \omega_A \kappa_A E[\theta^1_{ijs}|A_{ij}] \right\} + (1 - A_{ij}) \left\{ \omega_R \kappa_R E[\theta^1_{ijs}|R_s] \right\} + \rho y_{ijs,t-1} + u_{it}, \end{aligned} \quad (3)$$

[23] This conceptual framework can also accommodate a noise parameter that captures the fact that A_{ij} is a measure of latent skills. Including such a parameter would yield similar predictions but with expected –rather than deterministic– conditions.

where $\omega_S = p(h|S)\omega_h + (1 - p(h|S))\omega_l$, $\kappa_S = p(j \in K|S)\kappa_j$, for $S \in (A_{ij}, R_i)$.[24]

Conditional on the signals, firms offer recent graduates an equilibrium *entry* wage equivalent to the expected performance measure:[25]

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

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

Wage premium. Following equation (4), the wage of awardees is given by the performance that the firm expects from them, which depends on having received the award (and not on the reputation on the college they 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, $w^{na}_{ifjst} = \beta_r 1(R_i = R_s^+)$. The wage premium of the signal can, therefore, be expressed as

$$\delta = \beta_a - \beta_r 1(R_i = R_s^+ | A_{ij} = 0).$$

From this expression, it follows:

Mechanism 1. *The distinction award is a signal with valuable informational content. The wage premium associated with the award (i.e., $\delta = w^a_{ifjst} - w^{na}_{ifjst}$) is positive and larger for students graduating from schools with lower reputation (i.e., $\beta_a = \hat{\delta}^-_{ifjst} > \hat{\delta}^+_{ifsjt} = \beta_a - \beta_r$).*

In other words, the signal is a valuable screening device to infer workers' skills; especially those who lack a stronger signal when entering the labor market (i.e., those who had not graduated from a more prestigious college).

The conceptual framework also highlights that the signal has market value because it changes the types of matches between employers and employees. First, employers that value college graduates' specific skills will offer higher wages to those who have those skills –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: $W^s_{ifjst} - W^{ns}_{ifjst} = \omega_f(\kappa_j - 1) > 0$, where s stands for specialized and ns for non-specialized). 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,

[24] For simplicity, we assume that firms' productivity (ω_f), the likelihood of matching a specialized firm (κ_S), and unobserved post-tertiary education ability (θ_i) are uncorrelated.

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

Mechanism 2. *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).*

Second, in the conceptual framework, the performance of workers in high-productivity firms is higher than worker performance in low-productivity firms. 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,

Mechanism 3. *The signal allows high-productivity firms to attract high-skill workers (i.e., the recipients of the national distinction award).*

We next provide evidence that suggests that these mechanisms are likely operating in our setting.[26]

6.2 The Signal is a Valuable Screening Device to Infer Worker's Skills

We provide evidence that the signal is a valuable screening device to infer workers' skills, particularly for those who lack a stronger signal (Mechanism 1). We do this by estimating Equation (1) using our regression discontinuity design on subsamples of workers who graduated from universities with different reputations. We rely on the QS University Rankings to classify colleges into top 5 schools, schools ranked 6 to 20, and schools below the top 20. Column (1) of Table 2 shows our main results. Columns (2)-(4) show the results by subsample. We observe that students who graduated from the top-five universities do not benefit from the distinction compared to other graduates from the same schools. However, award recipients who graduated from universities with lower reputations had a large increase in earnings compared to those who graduated from similar, less prestigious institutions.

What explains the smaller, statistically insignificant earnings returns for award winners from high-reputation (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 Mechanism 1). We test this directly by estimating the regression discontinuity model in equation (1) but modifying the subsamples. We compare earnings obtained 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 null hypothesis that it is equal to zero. We do this for award recipients graduating from colleges ranked 6 to 20 and from colleges

[26]The results presented throughout Section 6 allow the MSE-optimal bandwidth to vary depending on the sample and outcome of interest. This implies that the effective sample across regression discontinuity estimates is not necessarily the same as that used to estimate our main results in Table 1. We provide estimations with a fixed bandwidth equivalent to the main estimation sample in Appendix F. Results are robust to either fixing the bandwidth or letting it vary.

Table 2: National Distinction Award and College Reputation

	Dependent Variable : Log Earnings					
		College Ranking :			Cross-sample Comparison : Top 5 Non-awardees vs.	
	Full Sample	Top 5	Top 6-20	Below 20	Top 6-20 Awardees	Below 20 Awardees
	(1)	(2)	(3)	(4)	(5)	(6)
National Award	0.086***	0.022	0.107	0.158**	0.083	–0.008
	[0.027]	[0.044]	[0.076]	[0.063]	[0.057]	[0.055]
Observations	198,742	26,577	30,278	141,887	26,074	26,094
Bandwidth	0.449	0.411	0.324	0.290	0.292	0.321
Control Obs.	3807	1401	593	684	848	1003
Treatment Obs.	1538	668	342	317	324	340
Mean Control	14.17	14.22	14.22	14.06	14.22	14.23

Notes. The outcome variable is the log of early-career earnings, defined as the first observed earnings after graduating college. Column (1) replicates the main results (Column 3 of Table 1). Regression discontinuity estimates within samples defined by college ranking are displayed in columns (2) to (6). Columns (2) to (4) show estimates for students in schools within the same tier of the college ranking. Colleges are divided into three categories: top tier (schools in the top 5), middle tier (schools ranked 6th to 20th), and bottom tier (schools below the top 20). Columns (5) and (6) display estimates for award recipients in middle- and bottom-tier colleges with respect to non-recipients in top-tier schools. Estimates across columns control for area-year (of exam) fixed effects, test scores, and covariates. Test scores include scores from the high school exit exam and scores from the core component tests (Reading and English Proficiency) of the college exit exam. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. Regression discontinuity estimates use linear local regressions, an Epanechnikov kernel, and MSE-optimal bandwidths. Robust standard errors are clustered at the area-year level and displayed in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

below the top 20. Columns (5)-(6) of Table 2 show the results. The earnings return for awardees who graduated from a low-reputation college is equivalent to the return they would have obtained had they graduated from a high-reputation college (but without holding the award).

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 high 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 results also align with the existing experimental evidence, which documents that individuals from less favored educational backgrounds drive the positive effects of skills 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. Instead, introducing a signal of skills given across colleges – such as the national distinction award– can help firms update their priors about highly skilled graduates from low-reputation schools. This can explain the documented earnings premium for graduates from low-reputation colleges 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.[27]

6.3 The Signal Helps Firms in Specialized Industries to Find Workers with the Right Skills

We provide direct and indirect evidence that the signal seems to allow firms in specialized industries to find workers with the right skills (Mechanism 2). Direct evidence comes from 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 this, we construct an indicator variable equal to one if a graduate's field of study matches the industry code where the individual works and zero otherwise.[28] We then estimate equation (1) using this indicator variable as the outcome. Column (1) of Table 3 shows the results.

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 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' fields of study and firms' industries is mainly driven by students graduating from low-reputation colleges. As shown in columns (2)-(4) of Table 3, high-ability workers from low-reputation colleges obtain the most considerable improvement in the labor-matching process. This helps to explain why the largest

[27] Graetz (2021) argue that if innate talent directly influences labor productivity, beyond the impact of knowledge acquired through formal education, then a positive regression discontinuity estimate of diplomas on wages can be considered as evidence of information frictions in the labor market. However, in his model, it remains challenging to identify the relative importance of acquired knowledge and innate talent in the production function. It is worth noting that in our specific context, this concern appears to be of lesser significance for two key reasons. Firstly, observable characteristics, including various test score measures, are well-balanced, suggesting that unobserved innate talent is also likely to be balanced around the discontinuity threshold. In other words, there is no evidence that individuals who received the award and those who narrowly missed it by a few test-score points possess significantly different levels of innate talent. Secondly, our robustness exercises indicate that even when controlling for proxy measures of innate talent, such as a comprehensive set of pre-college test scores, there is no impact on our regression discontinuity estimates.

[28] 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 that universities post online to advertise the majors they offer. 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 G.1 offers more details regarding the construction of this variable and shows that the results are robust when using alternative outcome measures

Table 3: Effects on the Allocation of Skills

	Dependent Variable :					
	Field-Industry Match				Log Earnings	
	Full Sample	College Ranking :			Type of Skills :	
		Top 5	Top 6-20	Below 20	Specific	Transferable
	(1)	(2)	(3)	(4)	(5)	(6)
National Award	0.049*	0.015	0.025	0.134*	0.082***	0.042
	[0.026]	[0.041]	[0.071]	[0.069]	[0.031]	[0.060]
Observations	187,331	25,664	29,314	132,353	122,779	75,963
Bandwidth	0.385	0.475	0.395	0.297	0.519	0.357
Control Obs.	2916	1631	770	676	3828	540
Treatment Obs.	1333	702	363	297	1334	259
Mean Control	0.411	0.437	0.405	0.396	14.14	14.28

Notes. This table presents regression discontinuity estimates of the effect of the national distinction award on the likelihood of being employed in an industry related to the student's field of study (columns 1 to 4), and on early-career earnings by type of field (columns 5 and 6). The outcome variable in columns (1) to (4) is an indicator equal to one if a worker's industry matches the worker's field (college major). For details about the field-industry match indicator see Appendix G. The outcome variable in columns (5) and (6) is the log of early-career earnings, defined as the first observed earnings after graduating college. Estimates across columns control for area-year (of exam) fixed effects, test scores, and covariates. Test scores include scores from the high school exit exam and scores from the core component tests (Reading and English Proficiency) of the college exit exam. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. All estimates use linear local regressions, an Epanechnikov kernel, and MSE-optimal bandwidths. Robust standard errors are clustered at the area-year level and displayed in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

benefits of obtaining the national distinction award are observed among students in lower-reputation colleges.

Next, we show two pieces of indirect evidence that are consistent with Mechanism 2. 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 quantifies the level of transferability of skills by computing the number of industries (four-digit codes) where students in each field find jobs after graduation.[29] For instance, 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

[29] 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 2008 to 2016.

Table 3 show the results. The national distinction award has a positive earnings 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 it is the award or its informational content that matters for wages. We rely on a similar signal that has no information about field-specific skills. Starting in 2010, an award was introduced for top scores in problem-solving, critical thinking, socio-emotional abilities, and English proficiency.[30] We estimate a regression discontinuity model, similar to the one described in equation (1), to obtain an estimate of the earnings return to a generic skills signal.[31] Results are shown in Table 4. The small and not statistically significant effects of the signal on generic skills on earnings contrasts with the positive earnings return to a signal on specific skills. This suggests that it is the information about the field-specific skills of awardees that matters for the labor market.

The introduction of the national distinction award, as a signal for the labor market, seems to improve 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).

6.4 The Signal Allows High-Productivity Firms to find High-Skilled Workers

We test the hypothesis that the signal allows high-productivity firms to find high-skilled workers (Mechanism 3) by estimating equation (1) using as an outcome a proxy measure of firm productivity that we construct as follows: Firms are sorted according to the average salaries they pay to their employees. We then compute a time-invariant

[30]Students taking these general-skills tests were enrolled in fields lacking a specific exam before 2010. Between 2003 and 2009, test-takers were only eligible to obtain a distinction in the *field-specific* component of the college exit exam.

[31]The information on the 2010 distinction award comes from publicly available records (available online). For this cohort of students, we observe test scores in the core component and whether or not they received a distinction award for their performance in that core component. We merge this information to the social security records described in Section 3. For 2010, we lack information about test scores related to the specific component of the college exit exam (which prevents us from estimating a regression discontinuity model like the one we can estimate for the period 2006-2009).

Table 4: 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)
National Award	–0.012	0.018	–0.040	–0.004	–0.010
	[0.035]	[0.023]	[0.030]	[0.023]	[0.023]
Observations	17,854	17,854	17,854	17,854	71,416
Bandwidth	1.430	0.547	1.392	1.065	0.638
Control Obs.	6371	2239	7119	5419	8404
Treatment Obs.	682	1436	1174	1765	4307
Mean Control	14.05	14.07	14.05	14.06	14.09

Notes. This table presents estimates of the effect of distinctions awarded to top performers in four generic skills tests on early-career earnings. The outcome variable is the log of early-career earnings, defined as the first observed earnings after graduating college. Estimates across columns control for area-year (of exam) fixed effects, test scores, and covariates. Test scores include scores from the high school exit exam and scores from the writing and reading comprehension tests of the college exit exam. Exam authorities do not grant distinctions to top scores in the writing and reading tests. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. The specification in column (5) stacks the scores of students in the four generic tests. Robust standard errors are clustered at the area-year level and displayed in brackets, except for column (5) where errors are clustered at the individual level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

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.

Table 5 shows the results. Column (1) uses an unconditional ranking as outcome, whereas column (2) uses a ranking computed using the methodology in Abowd, Kramarz and Margolis (1999) (i.e., with individual and firm fixed effects).[32] The signal allows workers to find jobs in 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

[32]We construct two different earnings rankings of firms for individual i. The first is an unconditional ranking built by: (i) computing the average earnings 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 earnings ranking estimates the firm fixed effect (firm earnings-premium) using the methodology by Abowd, Kramarz and Margolis (1999). See Appendix Section G.2 for a description of the model used to estimate the AKM-model. In addition, we show that our results are robust when estimating the treatment effect of the signal on other productivity measures and in the subsample of individuals used to obtain our main earnings results.

Table 5: Effects on the Match Probability with High-Productivity Firms

	Dependent Variable : Employer's Wage Premium			
	First Employer		Avg. Across Employers	
	Unconditional Ranking	AKM Ranking	Unconditional Ranking	AKM Ranking
	(1)	(2)	(3)	(4)
National Award	0.083**	0.133***	0.076**	0.149***
	[0.034]	[0.041]	[0.036]	[0.047]
Observations	188,566	188,609	188,566	188,609
Bandwidth	0.477	0.397	0.532	0.297
Control Obs.	3990	3051	4649	1983
Treatment Obs.	1505	1354	1593	1147
Mean Control	0.712	0.551	0.803	0.635

Notes. This table presents regression discontinuity estimates of the effect of the national distinction award on the likelihood of working at higher-productivity firms. Two time-invariant measures of firm productivity are considered: (i) *Unconditional ranking* : within-industry ranking based on the firm's average earnings, and (ii) *AKM ranking* : ranking based on the firm effects from a regression of earnings that also controls for individual fixed effects, year fixed effects, a graduate education indicator, and a degree two polynomial of age and potential experience (see Abowd, Kramarz and Margolis (1999) for details on the estimator). Both measures are rescaled to facilitate interpretation. First, both rankings are inverted to display an ascending order (from the least to the most productive firm). Second, we divide the position of the most productive firm, so both rankings are expressed in percentile terms. Finally, we standardize these measures by subtracting the mean and dividing the standard deviation. For additional details about these measures see Appendix G. Columns (1) and (2) present estimates of the effect on the productivity of the first observed employer. Columns (3) and (4) show estimates of the effect on the average productivity of all observed employers. Estimates across columns control for area-year (of exam) fixed effects, test scores, and covariates. Test scores include scores from the high school exit exam and scores from the core component tests (Reading and English Proficiency) of the college exit exam. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. All estimates use linear local regressions, an Epanechnikov kernel, and MSE-optimal bandwidths. Robust standard errors are clustered at the area-year level and displayed in brackets. * p<0.10, ** p<0.05, *** p<0.01.

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 Skills?

The earnings premium of the national distinction award estimated using equation (1) compares students with the same levels of skills –measured by the student's set of *general* and *specific* skills that are assessed by the high school exit exam scores and the general and major-specific scores from the college exit exam. However, the national distinction award could have induced students to change their educational decisions. In particular, awardees could have had a motivational effect that induced them to accumulate additional education, increasing their level of skills. We do not find evidence that supports this mechanism.

Table 6 presents regression discontinuity estimates using multiple outcomes aimed to measure skill accumulation. Column (1) presents the effect of the signal on the number of months taken to graduate since the moment when the person took the college exit exam. Column (2) shows the treatment effect on the total number of subjects taken by students as of their graduation time. Columns (3) and (4) show impacts on the number of subjects a student registered and approved, respectively. Column (5) 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.

Table 6: Effects on Additional Accumulation of Skills

	Dependent Variable :				
	Months to College Grad. Date	Number of Subjects by Graduation			Graduate Education
		Total Registered	Registered After Exam: Total	Registered After Exam: Passed	
	(1)	(2)	(3)	(4)	(5)
National Award	–0.001	–0.498	0.001	–0.005	0.017
	[0.499]	[0.949]	[0.270]	[0.262]	[0.032]
Observations	198,742	146,764	146,764	146,764	198,742
Bandwidth	0.525	0.368	0.476	0.458	0.351
Control Obs.	4837	2403	3452	3241	2705
Treatment Obs.	1651	1175	1336	1318	1347
Mean Control	11.33	59.83	6.590	6.228	0.253

Notes. This table presents regression discontinuity estimates of the effect of the national distinction award on different measures of skill accumulation. The outcome variable in column (1) is the number of months from the date of the exam to the student's graduation date. In column (2), the outcome is the number of subjects in a student's academic history by the time she graduates. In columns (3) and (4), the outcomes correspond to the number of subjects a student registered for and successfully passed after taking the college exit exam. The outcome in columns (5) is an indicator equal to one if a student completes a graduate program within five years from the date of the exam. Estimates in all columns control for area-year (of exam) fixed effects, test scores, and covariates. Test scores include scores from the high school exit exam and scores from the core component tests (Reading and English Proficiency) of the college exit exam. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. All estimates use linear local regressions, an Epanechnikov kernel, and MSE-optimal bandwidths. Robust standard errors are clustered at the area-year level and displayed in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

This is not to say that skills do not have a return for those who received the national distinction award. They certainly do. In a linear regression of earnings on an indicator variable equal to one for those who received the award, without conditioning on any kind of measure of pre-award skills, the premium of being awarded the distinction is $\hat{\beta}_{ols} = 12.6\%$. This premium is due to the fact that award recipients have higher measured skills than the average worker and that they have a signal (i.e., $\beta_{ols} = \delta_{signal} + \delta_{skills}$, where δ_{signal} is the signaling effect on earnings and δ_{skills} is the effect due to differences in skills). Our regression discontinuity estimates identify the signaling effect on earnings (i.e., $\delta_{RD} = \delta_{signal}$), with $\hat{\delta}_{RD} = 8.6\%$. We can use these estimates to compute a back-of-the-envelope calculation of the percent earnings difference between recipients of the national distinctions awards and the average college-graduate worker explained by the signal vis-a-vis differences in skills. The effect on earnings explained by the signal is about 68% of the difference in earnings (i.e., $\hat{\delta}_{RD}/\hat{\beta}_{ols} = 0.68$).

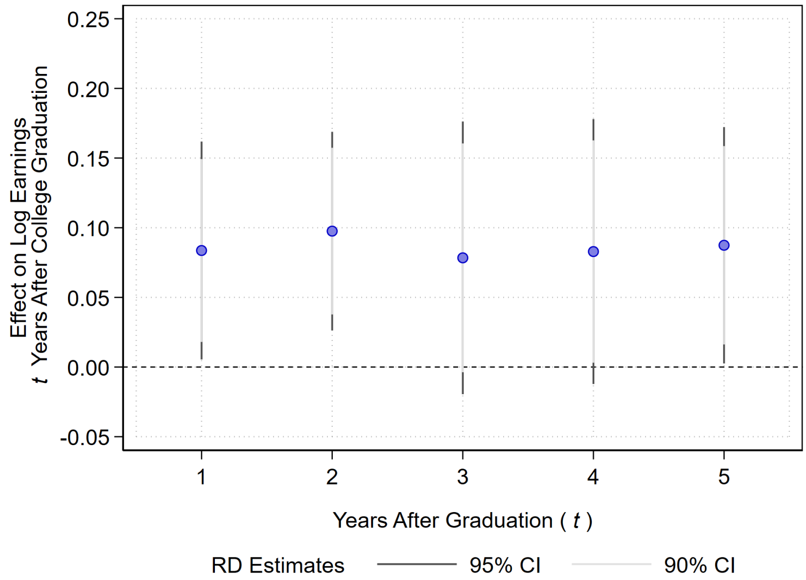
7 Job-Ladders and the Persistence of the Signal's Effect

Section 5.2 showed a 7 to 10 percent to being awarded the national distinction. 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 7 plots the results. 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. The national distinction awardees' earnings are around 8 percent higher than similar workers, and this effect is constant during, at least, the first five years after entering the labor market.

This result contrasts with those of Khoo and Ost (2018) and Freier, Schumann and Siedler (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 students' abilities. 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 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).

The conceptual framework discussed in Section 6.1 suggests that the productivity of a given worker in year t depends positively on the lagged value productivity, implying the potential existence of a (non-decreasing) wage profile. This persistence is consistent with career-development models in which workers acquire specific skills as they accumulate on-the-job experience which, in turn, allows them to stay ahead on the job ladder (Gibbons and Waldman, 1999*a*,*b*, 2006). This process might be more relevant for skilled labor (Altonji, Kahn and Speer, 2016). Haltiwanger, Hyatt and

Figure 7: Persistence of the Effect on Earnings



Notes. This figure presents regression discontinuity estimates of the effect of the national distinction award on earnings over time. Plotted dots correspond to independent regressions. The outcome variable is the log of earnings observed one to five years after a student graduates from college. Each coefficient is estimated using a "balanced" sample of students for whom earnings are observed all three years after graduation. All regressions control for area-year (of exam) fixed effects, test scores, and covariates. Test scores include scores from the high school exit exam and scores from the core component tests (Reading and English Proficiency) of the college exit exam. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. All estimates use linear local regressions, an Epanechnikov kernel, and MSE-optimal bandwidths. 90 and 95 percent confidence intervals, based on robust standard errors clustered at the area-yer level, are displayed around coefficients.

McEntarfer (2018) show that in the reallocation of workers across firms more educated workers are more likely to work in more productive firms and less likely to separate from them. Thus, having an early job in a more productive firm can put higher-ability workers on a career path that allows them to have permanent earnings gains.[33]

We indirectly test this "job-ladder hypothesis" by estimating equation 1 using as a dependent variable an indicator variable that takes the value of one if the worker changes jobs and looking at the types of firms that employ workers with a signal. On average, about 36 and 13 percent of individuals change jobs once or twice, respectively, in the six year period after graduation. Columns (1) and (2) of Table 7 show that obtaining the award does not directly affect the likelihood of switching employers after graduation.

In columns (3)-(7) we investigate if the award affects the job trajectory of students by analyzing the type of firms where awardees are employed after the first firm. The outcome in column (3) is the earnings/AKM-ranking of the first firm of employment

[33] 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, von Wachter and Heisz, 2012; Schwandt and von Wachter, 2019).

Table 7: Effects on the Probability of Switching Jobs and Job Characteristics After Switching

	Dependent Variable :						
	Worker Switch Employers		Employer's Wage Premium Across Time, τ				
			First Employer			Δ Future Employers	
	Once	Twice	$\tau = 1$			$\tau = 2$	$\tau = 3$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Linear Polynomial							
National Award	–0.015	0.005	0.133***	0.096**	0.079*	–0.039	–0.066
	[0.034]	[0.023]	[0.041]	[0.041]	[0.046]	[0.051]	[0.053]
Quadratic Polynomial							
National Award	–0.018	0.010	0.188***	0.193***	0.153**	–0.021	–0.029
	[0.053]	[0.039]	[0.057]	[0.067]	[0.076]	[0.068]	[0.072]
Observations	165,768	141,619	188,609	165,768	141,619	165,768	141,619
Bandwidth	0.397	0.397	0.397	0.397	0.397	0.397	0.397
Control Obs.	2692	2298	3051	2692	2298	2692	2298
Treatment Obs.	1184	1015	1354	1184	1015	1184	1015
Mean Control	0.358	0.133	0.551	0.570	0.594	0.0816	0.150

Notes. This table presents regression discontinuity estimates of the effect of the national distinction award on the probability of switching employers (columns 1 and 2) and on a measure of employer's productivity over time (columns 3 to 7). In columns (1) and (2), the outcome is an indicator equal to one if the worker switches employers once or twice after they graduate from college. The outcome in columns (3) to (5) corresponds to the productivity of the first observed employer. In columns (6) and (7), the outcome is the difference between the first employer's productivity and the second and third employer's. A sample of graduates for whom we observe two firms over time is used in columns (1), (4), and (6). A sample for which we observe three firms over time is used in columns (2), (5), and (7). The measure of productivity in this table corresponds to the *AKM ranking* of firms (see Table 5 for more details on this measure). Estimates across columns control for area-year (of exam) fixed effects, test scores, and covariates. Test scores include scores from the high school exit exam and scores from the core component tests (Reading and English Proficiency) of the college exit exam. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. Estimates use local regressions of different degrees and an Epanechnikov kernel. Bandwidths across columns are computed by minimizing the Mean Square Errors (MSE) of the linear specification. Robust standard errors are clustered at the area-year level and displayed in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

($\tau = 1$). It matches the results displayed in column (2) of Table 5. Columns (4) and (5) show the treatment effect on the same outcome but restrict the sample to workers for whom we observe firm transitions two and three times, respectively, in the first six years after graduation.[34] For all three samples, there is a positive effect of the signal on the productivity-ranking of the first firm in which the worker is employed.

Columns (5) and (6) evaluate if the job trajectory –after that first job– followed by awardees differs from that followed by non-awardees. We compute the difference in the productivity ranking between the first and the second employer ($\tau = 2$ in Column (6)) and between the first and the third employer ($\tau = 3$ in Column (7)). We cannot reject the null hypothesis that the coefficients are zero. This suggests that the signal allows workers to initially match with higher-productivity firms and continue to stay employed in similarly high-productivity firms in subsequent jobs. In other words, the signal induces a parallel upward shift of the wage profile which could explain why

[34] We lack firm identifiers for a subgroup of workers in our data. These mainly correspond to workers who moved to unemployment or informality, or workers observed only in the last available year of data for whom is impossible to observe a second firm.

the wage effect of the national distinction award persists in the first five years after graduation.

8 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 in 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 10 percent. This positive return is observed even five years after graduation. The signal allows workers to find jobs in more productive firms and sectors that better use their skills. We do not find evidence that the signal is associated with higher skill levels or with additional investments in education. These results suggest that policies that provide information about workers' skills are likely to improve the allocative efficiency of the economy by allowing high-skilled workers to find jobs where their talents are more productively used.

We also show that workers who graduated from low-reputation colleges benefit the most from being able to signal their specific skills to employers. Implicitly, this result 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 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 allocation of students, but it has a limited scope and therefore a limited capacity to correct all the potential negative consequences of 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.

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Appendices

A Saber Pro Exam and the National Award

This appendix describes in detail the Saber Pro exam, its legal background, its implementation, and how it is used as a signal. We also detail several aspects of the national distinction award.

A.1 Saber Pro

Legal Background.– In 2002 the Colombian Congress enacted Law 749 which organized the tertiary education system in the country. This law was intended to make Colombian education more competitive by regulating the different programs in tertiary education and categorizing them into "technical", technological", or "professional" (Diaz, 2003). The Law 749 also introduced evaluation methods for students nearing college graduation. Specifically, Article 8 stipulated that the national government was responsible for regulating exams for tertiary education students as a means of assessing the quality of tertiary education.

Following the passing of Law 749 in 2002, the Colombian Ministry of Education formally established a college exit exam under Decree 1781 of 2003. This decree introduced the National Exam of the Quality of Higher Education (ECAES, as per its Spanish acronym) as a tool for assessing the quality of colleges and, additionally, as a source of information for making education policy decisions.

Article 8 of Law 749 was declared unconstitutional in 2007 by a ruling of the Colombian Constitutional Court.[35] The ruling determined that Law 749 was not sufficiently clear, and it compelled the Colombian government to regulate Law 749 before 2009 by clarifying the implementation issues identified in the 2002 text.[36]

Consequently, in 2009, the Colombian Congress passed Law 1324, which replaced Law 749 of 2002 by addressing the issues related to Article 8. In accordance with this newer law, the government enacted Decree 3963 of 2009, which regulated the college exit exam under the name *Saber Pro*, as it is currently known, and provided a clear description of the exam's implementation.

On the Mandatory Nature of the Exam.– Decree 1781 of 2003 declared the college exit exam to be mandatory and held colleges accountable for ensuring their senior students' compulsory participation in the exam. The decree outlined administrative actions in case colleges failed to register students (Articles 1 and 5). However, since

[35]Two rulings declared the Law unconstitutional: the C-852 of 2005 and the C-782 of 2007.

[36]Details about this can be found at: https://www.eltiempo.com/archivo/documento/MAM-2671730.

exams for different fields of study were introduced gradually over the years, compliance was limited to areas with available tests. As a result, not every student nearing graduation took the exam.

In the last quarter of 2007, the law that established the college exit exam was declared unconstitutional. It also gave the government a timeline: Congress had a year and a half to amend Law 749. Until then, students wishing to graduate from college (in programs where an exam existed) were still required to take the exam.[37] In the first semester of 2009, the Colombian government offered the college exit exams, which remained mandatory for the first semester of the year.[38]

By the second semester of 2009, Law 1324 and Decree 3963 had been passed making the exam mandatory for all fields. However, for the edition of the exam administered in the second semester of the year, it was determined by the Ministry of Education that those students who had completed all their graduation requisites by October 14^{th} were exempt from taking the test. The announcement was made only two weeks before the date of the exam, and therefore, a large number of students who were supposed to graduate took it.[39] After 2009, the college exit exam became a graduation requirement for all college students. In the case of those students graduating from a field with no specific component of the exam, they were still mandated to take the general component.

Sample of Test-Takers.– A large share of eligible students took the college exit exam –which is evidence of the compulsory nature of the exam. Appendix Table A.1 provides information about the share of students who were eligible and took the exam. University programs in Colombia typically last four to five years, implying that eligible students correspond to those who enrolled in a university between 2002 and 2005.[40] We provide information about students who enrolled in 2006 and 2007 to include those students who took less to finish their degrees and as a reference.

The college exit exam was taken by the majority of eligible students. Around 80 percent of the students about to graduate from a field with an established field-specific exam took the college exit exam. This validates the fact that, despite the confusing institutional setting, the college exit exam was considered compulsory for most students who wished to graduate from fields for which an exam was available.

Taking the test is also uncorrelated with observable characteristics that could induce selection into the sample of test takers. We estimate a linear probability model

[37] Details can be found at: https://www.eltiempo.com/archivo/documento/MAM-267173.

[38] Details available at: https://www.semana.com/si-habra-ecaes-2009/72997/.

[39] Details can be found in https://www.eltiempo.com/archivo/documento/MAM-3698752.

[40] Recall that the main requisite for taking the test was to be enrolled in the last year of the program (or have finished three-quarters of the coursework) so we consider as eligible students enrolled four years before 2006 and registered in programs where a specific exam existed at the time.

using a dummy variable for whether the student took the test as a function of several student-level characteristics and show the results in Appendix Table A.2. The vector of characteristics does not explain the probability of taking the exam. We only observe significant point estimates for enrollment age, but the point estimates are very close to zero. We provide additional evidence in Appendix Figure A.1, where we correlate the likelihood of taking the exam and the measure of college reputation. These two seem not to be correlated, which suggests that there is no selection in the sample of test-takers.

Appendix Table A.1: Eligibility to Take the College Exit Exam by Cohort

		Students Taking College Exit Exam:			
Cohort of Enrollment	Eligible Students	From 2006 to 2009	%	Overall	%
	(1)	(2)	(3)	(4)	(5)
2002	62,524	41,499	66.37	43,213	69.11
2003	65,602	44,564	67.93	48,115	73.34
2004	62,830	41,351	65.81	48,897	77.82
2005	63,381	38,529	60.79	56,328	88.87
2006	56,794	10,875	19.15	50,731	89.32
2007	43,139	6,172	14.31	37,358	86.60
Total	354,270	182,990	51.65	284,642	80.35

Notes. This table presents the percentage of students eligible to take the college exit exam, computed among all students enrolled in four- and five-year programs between 2002 and 2007. A student is identified as being eligible if she graduated between 2006 and 2012. Column (1) displays the number of eligible students from each cohort. Column (2) presents the number of eligible students who took the exam between 2006 and 2009. Column (4) shows the number of eligible students who took the college exit exam before graduating college.

Test Description.– The college exit exam, known as *Ecaes* (before 2009) or *Saber Pro* (after 2009), assesses students knowledge and the quality of the instruction provided by colleges. It is administered twice per year on a common date for all exam takers. 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.[41]

The college exit exam is comprised of two components. First, a *core component* that 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 seven parts, which require knowledge of different vocabularies.

[41]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.

Appendix Table A.2: Probability of Taking the College Exit Exam

	Dependent Variable : Took College Exit Exam					
	(1)	(2)	(3)	(4)	(5)	(6)
High School Exam Scores	0.000	0.000	0.000	0.000	0.000	0.000
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Top 5 College		–0.004	0.003		0.017	0.011
		[0.017]	[0.019]		[0.017]	[0.019]
Top 6–20 College		–0.010	–0.007		0.010	0.006
		[0.021]	[0.021]		[0.017]	[0.017]
Private College			0.018			–0.018
			[0.023]			[0.018]
Female				0.001	0.001	0.001
				[0.003]	[0.003]	[0.003]
Age at Enrollment				–0.004***	–0.004***	–0.004***
				[0.001]	[0.001]	[0.001]
High SES				0.004	0.002	0.007
				[0.010]	[0.009]	[0.009]
Observations	354,270	354,270	354,270	354,270	354,270	354,270
R-squared	0.003	0.003	0.004	0.093	0.094	0.094
Cohort FE				Yes	Yes	Yes
Field of Study FE				Yes	Yes	Yes

Notes. This table presents Ordinary Least Squares estimates of the probability of taking the college exit exam among eligible students. The outcome is an indicator variable equal to one if a student takes the exam before graduating college. The sample corresponds to all college students who enrolled in four- and five-year programs between 2002 and 2007, and graduated between 2006 and 2012. High SES is an indicator variable equal to one if the student is classified as stratum 3 or higher. Socioeconomic stratum is a variable with six categories based on the assessment of a household's living conditions. Households classified by the Colombian government in stratum 1 correspond to the poorest families. Standard errors are displayed in brackets and clustered at the college level. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

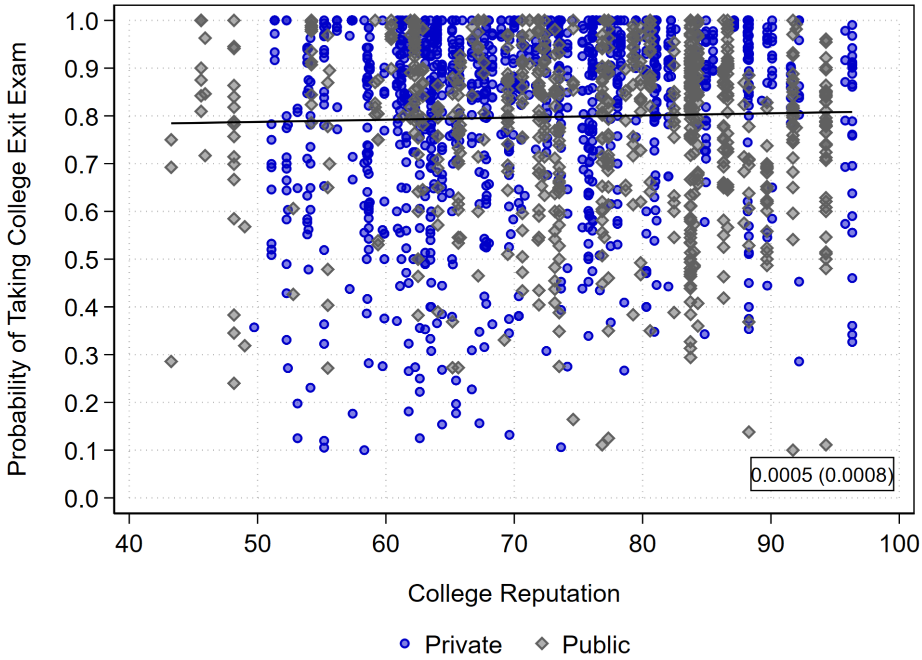
Second, the college exit exam includes a *specific component* which measures students' expertise in their program's field of study. Depending on the field, students take between four and twelve sub-tests on subjects deemed fundamental for their future careers as professionals in each area. Questions are designed by experts in each field and follow well-defined standards so that test scores are comparable across years.

The results of the exam matter for students and colleges. Students benefit because there are several advantages for high-achieving test-takers, such as scholarships, remission of graduation fees, and study loan forgiveness. 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.

Students can prepare for the exam in two ways. First, the exam's authority – the Colombian Institute for the Evaluation of Education (ICFES in Spanish) – makes preparation material available online. Second, some schools provide internal incentives and tools to prepare and motivate students to perform well.

Test Match with Field of Study.– During these initial years of the exam, students were allowed to register to take any field-specific exam, and there was no formal system to assign students from different programs to a field-specific exam. Using the Ministry of

Appendix Figure A.1: Probability of Taking the College Exit Exam as a Function of College Reputation

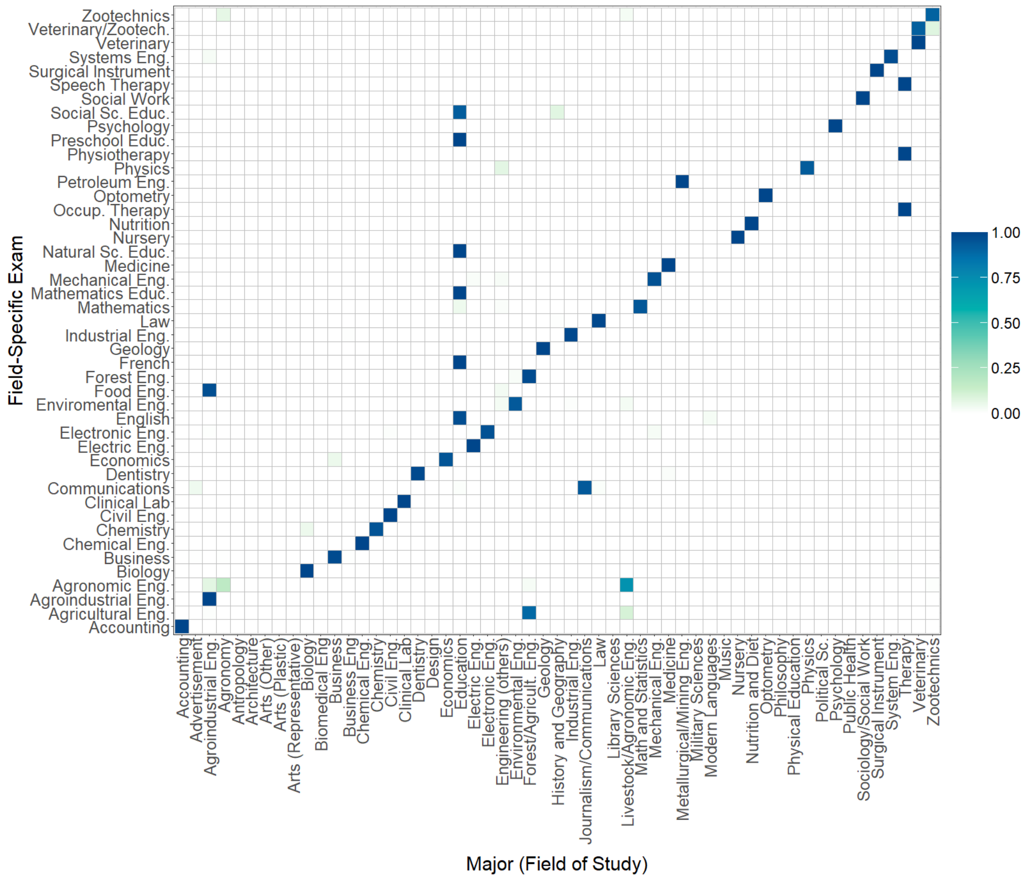


Notes. This figure presents the probability of taking the college exit exam as a function of college reputation. Plotted dots represent the share of students who took the college exit exam among eligible enrollees in four- and five-year college programs. The sample used for this figure corresponds to all college students who enrolled between 2002 and 2007 and graduated between 2006 and 2012. College reputation is defined as the average pre-college test scores of college graduates (see MacLeod et al. (2017) for details on this measure of reputation).

Education's classification of all college programs into fields of study, we determine the share of students that took the exam specific to their field and plot them in Appendix Figure A.2. The distribution of the shares is highly concentrated around one, meaning that most students took a specific exam corresponding to the same field of study they pursued in college.[42]

[42] 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 the names "Economics" and "Economics and Finance", these might belong to the same field (MacLeod et al., 2017).

Appendix Figure A.2: Relationship Between Students' Fields of Study and Specific Exams



Notes. This figure plots the share of students across all majors that took the same field-specific exam between 2006 and 2009. The Colombian Ministry of Education classifies all college programs nationwide into 55 majors or fields of study (horizontal axis). Rows add up to one.

A.2 National Distinction Award

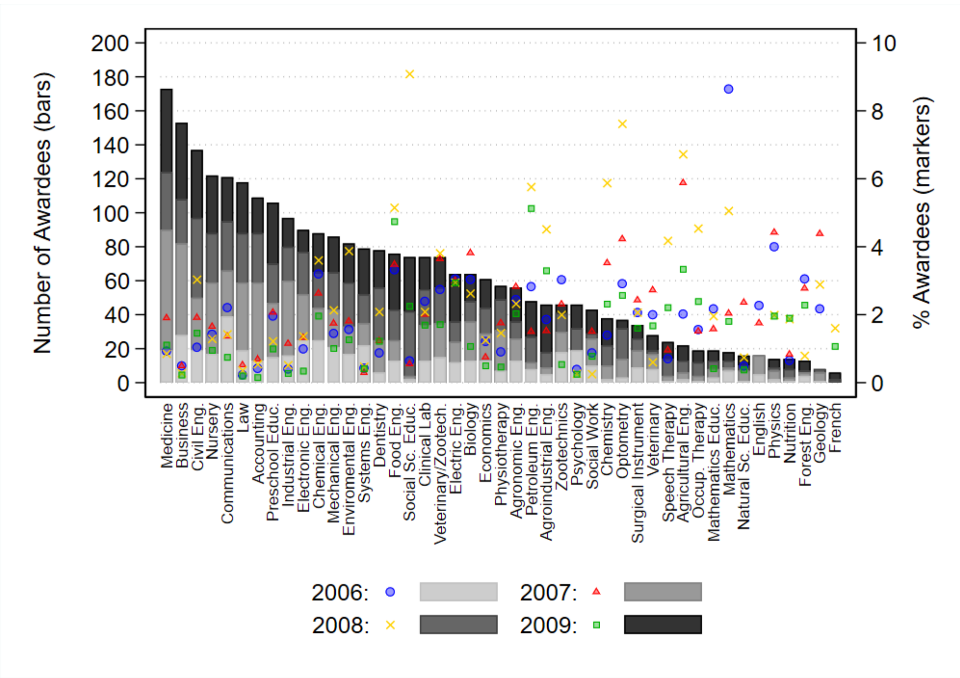
Description.– The National Distinction Award was added to a long tradition of national awards based on standardized tests in Colombia. In 1976, the Ministry of Education instituted distinctions for the students with the highest test scores in the elementary and high school standardized tests. Since 1994,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

The Saber Pro national academic award was instituted in 2003, along with the introduction of the exam, to recognize top scorers from each field. Recipients of the national distinction award benefit from it by receiving priority when applying to scholarships or education loans offered by the government, as well as from public recognition and media coverage at an event annually held by the Colombian Ministry of Education.

Award certificates are assigned to the best ten overall test scores in each one of the *field-specific* components. Based on this rule the national award might go to more than ten students. This will happen if more than one student gets the same score among the top ten.

Awards by field of study.– The number of awardees varies across field-specific exams and years, with more students in popular fields (i.e., with a large number of enrollees) receiving more awards. Appendix Figure A.3 and Appendix Table A.3 show that the number of awardees varies across field-specific exams and years.[43] They also show that more popular fields might assign more than ten national awards. Despite the assignment rule, of the total of 174 field-years combinations in our data, 63 field-years have fewer than 10 awardees, 30 field-years have fewer than 5 awardees, and 18 field-years have 2 awardees or fewer. We show in the robustness section that our results do not change when we drop these small fields or when we balance the number of observations to the right and left of the threshold for award assignment.

Appendix Figure A.3: Distinction Recipients by Field of Study and Exam Year



Notes. This figure plots the number of recipients of the national distinction award (in bars) and the percentage they represent within each field-specific exam (in markers). Bars stack the number of recipients of the national award across time.

[43]We include the 45 field-specific exams that are under consideration in this analysis. Details about them are presented in Appendix B.

Appendix Table A.3: Description of Students Around Threshold by Field-Specific Exam

Exam Field	Area	Test Takers	Awardees	MSE-Bandwidth	
				Awardees	Non-Awardees
		(1)	(2)	(3)	(4)
Agricultural Eng.	Agricultural Sc.	540	22	13	36
Agroindustrial Eng.	Agricultural Sc.	1,578	46	30	67
Agronomic Eng.	Agricultural Sc.	2,402	56	42	97
Veterinary	Agricultural Sc.	1,593	28	22	51
Veterinary/Zootech.	Agricultural Sc.	2,692	74	50	110
Zootechnics	Agricultural Sc.	2,582	46	28	78
Accounting	Business & Econ	28,178	109	80	209
Business	Business & Econ	44,818	153	120	284
Economics	Business & Econ	7,762	61	37	94
Civil Eng.	Engineering	7,716	137	97	232
Electric Eng.	Engineering	2,149	64	47	80
Electronic Eng.	Engineering	10,085	90	58	129
Enviromental Eng.	Engineering	4,447	82	51	75
Food Eng.	Engineering	1,780	76	50	65
Forest Eng.	Engineering	590	13	8	8
Industrial Eng.	Engineering	17,722	97	71	175
Mechanical Eng.	Engineering	5,802	86	53	105
Petroleum Eng.	Engineering	1,218	48	28	82
Systems Eng.	Engineering	19,643	79	37	91
Clinical Lab	Health	3,709	74	48	123
Dentistry	Health	5,503	78	50	130
Medicine	Health	14,127	173	133	342
Nursery	Health	9,507	122	95	275
Nutrition	Health	973	14	11	36
Occup. Therapy	Health	730	19	14	28
Optometry	Health	793	37	23	22
Physiotherapy	Health	5,063	57	46	131
Speech Therapy	Health	1,145	24	19	52
Surgical Instrument	Health	1,681	34	28	75
Biology	Math and Sc.	2,975	64	38	88
Chemical Eng.	Math and Sc.	3,253	88	64	117
Chemistry	Math and Sc.	1,263	38	25	58
Geology	Math and Sc.	229	8	4	4
Mathematics	Math and Sc.	534	18	9	16
Mathematics Educ.	Math and Sc.	2,135	19	13	33
Physics	Math and Sc.	517	14	9	9
Communications	Social Sc.	9,209	121	100	374
English	Social Sc.	846	16	11	20
French	Social Sc.	496	6	5	7
Law	Social Sc.	38,278	118	91	254
Natural Sc. Educ.	Social Sc.	2,418	16	12	48
Preschool Educ.	Social Sc.	7,779	106	87	264
Psychology	Social Sc.	15,093	46	38	144
Social Sc. Educ.	Social Sc.	2,510	74	59	205
Social Work	Social Sc.	5,138	43	34	119

Notes. This table provides a description of our sample of analysis by field-specific exams and their corresponding area of study. Column (1) displays the number of students taking the same field exam. Column (2) shows the number of recipients of the national distinction award within each field. Columns (3) and (4) display students with scores arbitrarily close to the national award's cutoff. We set a distance of 0.449 standard deviations from the cutoff to compute the number of awardees (students with scores above the cutoff) and non-awardees (students with scores below the cutoff). This distance is equal to the MSE-optimal bandwidth used to estimate our main results in Table 1.

Who are the awardees?– Appendix Table A.4 describes some characteristics of test takers, awardees, and the colleges where they were enrolled.[44] Among the top five most selective colleges, two are private; while among the top 20, 10 are private. Award recipients are more likely to be enrolled in public and top-ranked schools. This does not invalidate our research design. As shown in Figure 2 and Appendix Figure C.2, the probability of attending a top 5 college, a private college, or the measure of college reputation, are all continuous measures around the threshold that determines who receives the national distinction award.

Appendix Table A.4: Description of Estimation Sample by College Ranking

	Top 5	Top 6-20	Above 20	Total
	(1)	(2)	(3)	(4)
Number of:				
Public Universities	3	7	54	64
Private Universities	2	8	140	150
Field Exams	40	42	44	45
Number of Test Takers per Year:				
2006	6,161	8,196	40,463	54,820
2007	7,736	9,105	47,592	64,433
2008	7,562	8,046	47,178	62,786
2009	11,959	16,739	88,464	117,162
Number of Awardees:				
Public University	919	429	359	1,707
Private University	435	246	406	1,087

Notes. This table provides counts of our sample of analysis by college ranking. Colleges are divided into three categories: top tier (schools in the top 5), middle tier (schools ranked 6th to 20th), and bottom tier (schools below the top 20). Columns (1) to (3) provide the counts for public and private colleges, field exams, test takers, and recipients of the national award within each category. Column (4) presents the overall totals.

The award as a signal.– Because the award is given based on a national mandatory standardized college exit exam, receiving the national distinction award signals to employers that a job seeker is a top performer in their specific fields of study (relative to the universe of graduates in the country from that field of study).

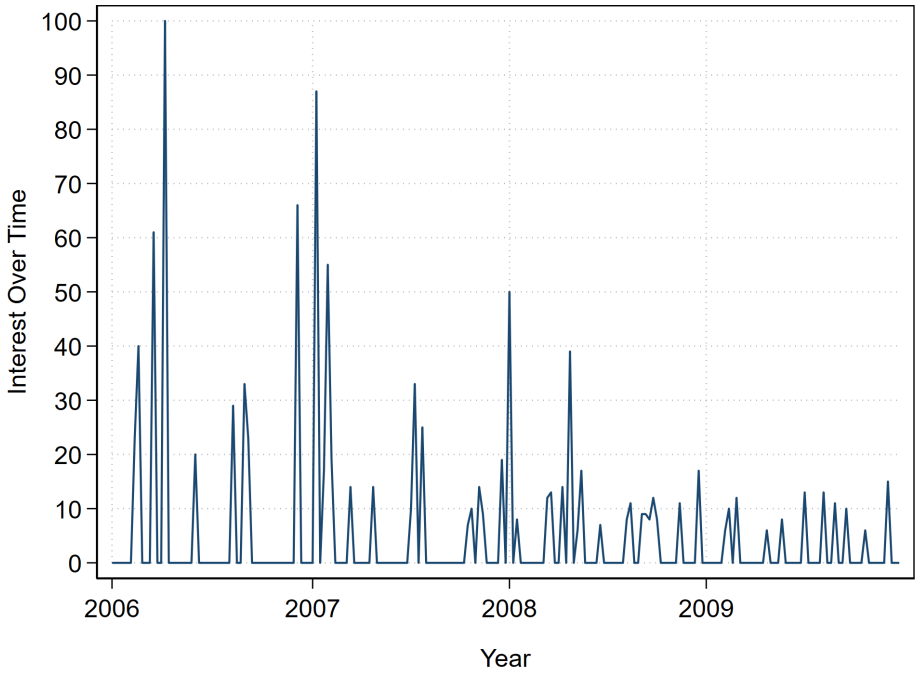
We used public information to search online for the profiles of 59 random students who won the award in 2009. As of June 2022, all of them were still listed as awardees on their universities' websites. We found the LinkedIn profiles of 36 students; *thirteen years after winning the distinction*, 25 percent 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.

Colombia is also a unique setting to study signals because firms in the country are widely aware of some of them. The national distinction award, in particular, is

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

strongly publicized. We performed a Google trends search about the national distinction award and plot the results in Appendix Figure A.4.[45] We observe several spikes within the year indicating the dates when the national distinction award is given. This information is public and available to employers.

Appendix Figure A.4: Google Trends Interest for National Distinction Award



Notes. This figure illustrates the level of interest in the national distinction award, as measured by Google search activity. The graph shows weekly interest from January 2006 to December 2009.

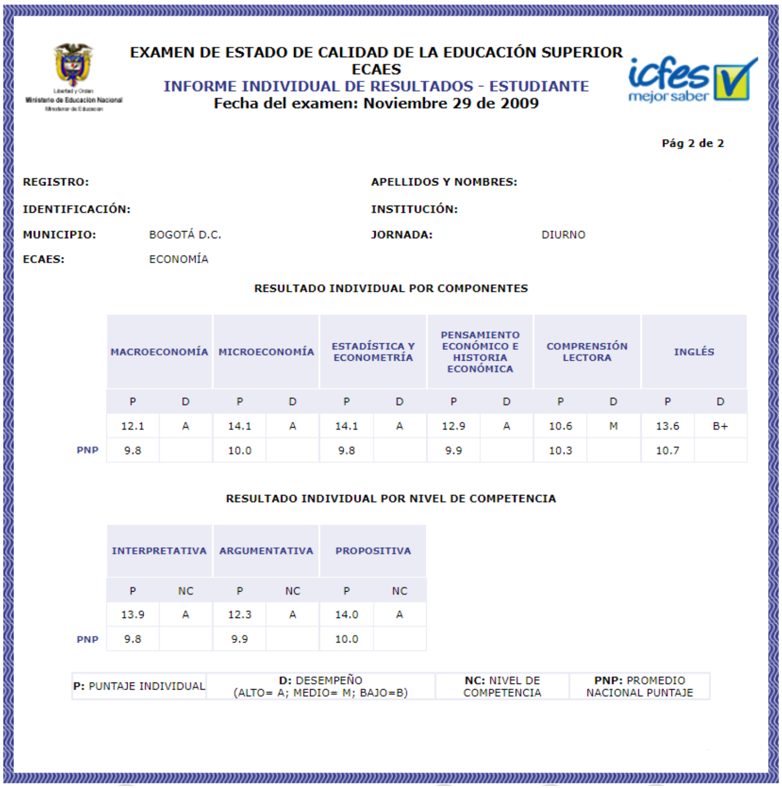
No award, no signal.– It is more difficult for students who did not receive the award to use the Saber Pro score as a signal of their field-specific abilities for three reasons. First, test scores for the core component and the specific component are numbers that are not informative per se. The range of test scores varies from year to year and by field of specialization. (In our sample scores range from zero to 158.) Second, 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 Figure A.5 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 categorizes subject scores into three groups: i) low, ii) medium, and iii) high. Even though the national average for each

[45]We performed the search as "Mejores Ecaes" and restricted the search to Colombia between 2006 and 2009.

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.

Appendix Figure A.5: 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

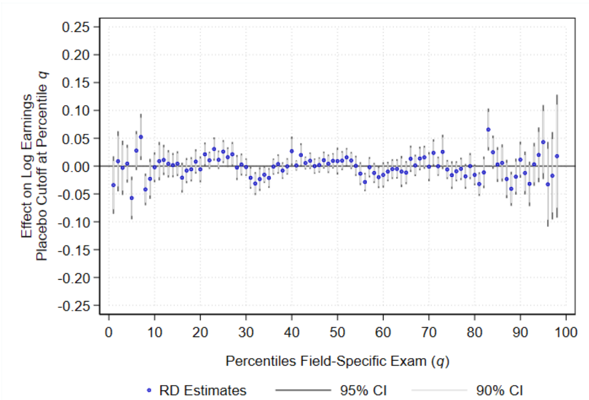
Notes. This figure displays a sample report card of a student who took the economics field exam in 2009. The report presents test scores in four field-specific tests: macroeconomics, microeconomics, statistics and econometrics, and economic thinking and history. Scores in reading comprehension and English proficiency, which are part of the *core* component of the college exit exam, are also displayed in the report. Test scores are classified into three performance groups: high (A), medium (M), and low (B). The student's performance is shown alongside the numerical score for each assessed subject. The report does not include overall scores or order statistics for the field-specific component of the exam.

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 on LinkedIn. None mention their scores in either the high school exit exam (Saber 11) or the college exit exam (Saber Pro).

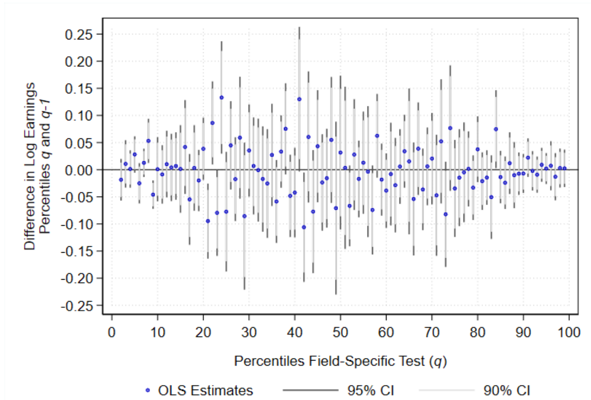
Placebo tests across the test distribution.– The national distinction award is given to, roughly, the top one percent of test takers. We do not expect to observe the difference in earnings in lower percentiles. We conduct a placebo test by varying the regression discontinuity cutoffs to each percentile of the distribution. Appendix Figure A.6a shows the results. As expected, consistent with the fact that job seekers who did not receive the award cannot send a signal about their field-specific abilities, the estimated effects of the award on earnings are small and not statistically significant almost everywhere else in the test score distribution. Similarly, Appendix Figure A.6b presents OLS estimates of the earnings difference among non-awardees in percentiles q and $q-1$ of the field-specific test score (i.e., the running variable). There are no systematic differences anywhere in the percentiles of the distribution.

Appendix Figure A.6: Placebo Tests and Differences in Earnings Between Contiguous Percentiles

(a) Placebo Test



(b) Earnings Differences



Notes. Panel (a) presents regression discontinuity estimates of the effect on early-career earnings using placebo cutoffs based on borderline scores between percentiles of the running variable. Panel (b) presents ordinary least squares estimates of the difference in early-career earnings between students in consecutive percentiles of the running variable. To estimate the difference we restrict the sample to students in percentiles q and $q-1$, and regress earnings on an indicator variable equal to one if the student is in percentile q. The outcome variable in both panels is the log of early-career earnings, defined as the first observed earnings after graduating college. The running variable is the distance of scores (measured in standard deviations) from the cutoff for the national distinction award. Regression discontinuity estimates use linear local regressions, an Epanechnikov kernel, and MSE-optimal bandwidths. All estimates control for area-year fixed effects, test scores, and covariates. Test scores include scores from the high school exit exam and scores from the core component tests (Reading and English Proficiency) of the college exit exam. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. 90 and 95 percent confidence intervals, based on robust standard errors clustered at the area-year level, are displayed around coefficients.

B Data

Construction.– We start with a universe of 323,683 students who took the college exit exam between 2006 and 2009. 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. Out of these 55 field exams, however, seven exams were designed for students in vocational schools. We additionally lack information on three field-specific exams (architecture, physical education, and education majors), where the overall score used to assign the award is missing. This same issue occurs for a sample of students registered to take specific exams 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). We drop these observations, which implies that we remain with a total of 45 field-specific exams under analysis. This is equivalent to 299,201 students, corresponding to 92.4 percent of the sample.

We combine this universe with other data sources in three steps. First, we downloaded public information about students who received the national academic award (2,924 individuals) 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 merged the awardees in the universe of test-takers from 2006 to 2009. We perfectly matched the entire list of awardees.

Second, we merged the universe of study with the administrative records of the universe of students enrolled in higher education. We matched 272,185 (91 percent) individuals. This merge provided us with test score measures in the high school exit exam, as well as information on the college and program of enrollment.

Third, we merge the universe of analysis –merged with the college records– with the social security records. These records correspond to all workers who graduated after 2001 from any higher education degree and worked formally from 2007 to 2015.[46] Around 75 percent of Colombian workers with a higher education degree work formally (Fedesarrollo, 2013). From this match, we merge 73 percent (198,742 individuals) which is very close to the 75 percent share of higher education graduates who work formally during this period.

Appendix Table B.1 provides detailed information on how we construct our estimating sample. From the universe of 323,683, we drop students in fields and cohorts that lack test score information. This results in 299,201 students. We then drop those students who were not matched to the college or social security records. The remaining 198,742 constitute our estimating sample.

[46] Formality is defined as a worker who contributes to either health or pensions.

Appendix Table B.1: Description of the Estimation Sample

	Fields	Test Takers	Awardees
	(1)	(2)	(3)
Universe Under Analysis	48	323,683	2,924
Fields with Missing Running Variable			
Some Cohorts	4	7,022	37
All Cohorts	3	17,460	93
Sample of Analysis	45	299,201	2,794
College Graduates	45	272,185 (90.9%)	2,714 (97.1%)
Graduates with Earnings	45	198,742 (73.0%)	2,146 (79.0%)

Notes. This table describes the process we use to obtain our estimation sample. The universe of analysis corresponds to all four- and five-year college students without a previous college diploma who took the college exit exam between 2006 and 2009 ($N = 323,683$). 48 field-specific exams were available during this period for bachelor's degree students enrolled in their senior year. Scores from the field-specific component of the exam are not available for 17,460 students in three fields (Architecture, Physical Education, and Spanish Education). Scores for students taking the English Education exam in 2008 and 2009 ($N = 2,133$), the French Education exam in 2006 and 2007 ($N = 313$), the Geology exam in 2009 ($N = 189$), and the Psychology exam in 2007 ($N = 4,387$) are unavailable. Our sample of analysis consists of 299,201 test-takers in 45 fields with available scores from the field-specific component of the college exit exam. A total of 2,794 students were granted the national distinction award for their outstanding performance in their field exams. 91 percent of the test takers in the sample graduated from college between 2007 and 2016 ($N = 272,185$). Formal sector earnings are observed for college graduates between 2008 and 2016. We observe earnings for 73 percent of the test takers who graduate from college ($N = 198,742$).

Appendix Table B.2: Summary Statistics of College Exit Exam Test-Takers, 2006-2009

	Main Sample (N = 198,742)		Industry Sample (N = 187,331)		Firms Sample (N = 188,566)	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
	(1)	(2)	(3)	(4)	(5)	(6)
Individual Characteristics :						
National Award	0.01	0.10	0.01	0.10	0.01	0.10
Female	0.58	0.49	0.58	0.49	0.58	0.49
Age at Exam Date	25.60	5.15	25.59	5.12	25.56	5.10
Socioeconomic Stratum	3.06	1.13	3.06	1.13	3.06	1.12
Mother's Educ: HS	0.38	0.49	0.38	0.49	0.38	0.49
Mother's Educ: College	0.30	0.46	0.30	0.46	0.30	0.46
Mother's Educ: Graduate	0.08	0.27	0.08	0.27	0.08	0.27
College Characteristics :						
Private College	0.61	0.49	0.60	0.49	0.61	0.49
Top 5 College	0.13	0.34	0.14	0.34	0.13	0.34
Top 6–20	0.15	0.36	0.16	0.36	0.15	0.36
Area of Study :						
Agricultural Sciences	0.03	0.17	0.03	0.17	0.03	0.17
Health	0.15	0.35	0.14	0.35	0.15	0.35
Social Sciences	0.25	0.44	0.26	0.44	0.26	0.44
Business and Economics	0.27	0.44	0.27	0.44	0.26	0.44
Engineering	0.26	0.44	0.26	0.44	0.27	0.44
Math and Natural Sc.	0.04	0.19	0.04	0.20	0.04	0.19

Notes. This table provides summary statistics (mean and standard deviation) describing our estimation sample. The main sample of analysis consists of test takers for whom we observe earnings data ($N = 198,742$). The table also presents summary statistics for the subsample of students with available 4-digit industry codes ($N = 187,331$) and the subsample of students with information about employers ($N = 188,566$). Socioeconomic stratum is a variable with six categories determined by the characteristics of a household's living conditions. Households classified by the Colombian government in stratum 1 correspond to the poorest families.

Description.– We provide descriptive statistics about the estimation sample in Appendix Table B.2. Around one percent of the sample received the award (this is consistent with the fact that those in the 99th percentile receive the award), 58 percent are women, and the average age of the exam is around 26 years old. We also provide information about the college and programs of the students.

The social security records lack firm identifiers for the year 2008. Therefore, we are unable to gather information about firms and industries for a subgroup of the estimating sample. We provide summary statistics for those sub-samples that lack information on industries and firms in columns (3) to (6) of Appendix Table B.2. These two sub-samples are used in some of our main results displayed in Section 6.

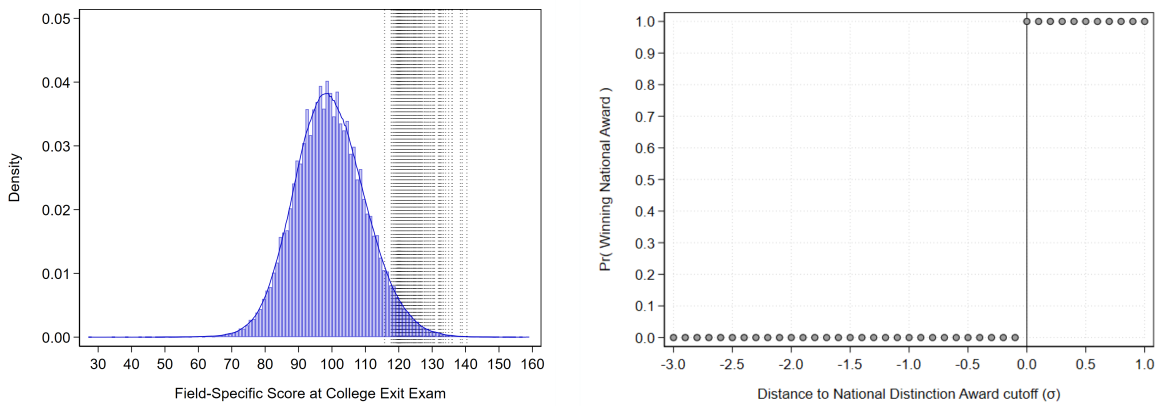
C Assessing the Validity of the Research Design

In this appendix, we present complementary evidence regarding the identifying assumptions of our regression discontinuity strategy.

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

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

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

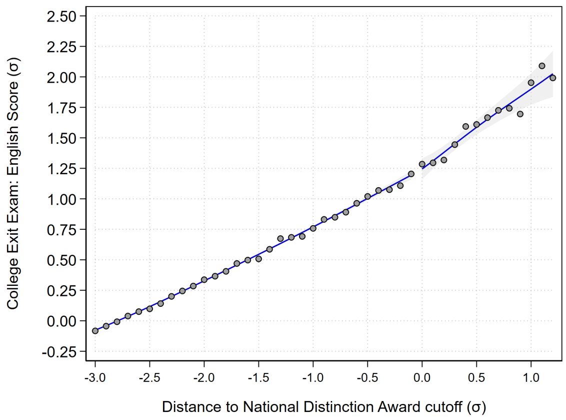


Notes. Panel (a) plots the distribution of scores in the field-specific component of the college exit exam. Students taking the exam (in 45 fields) from 2006 to 2009 are pooled to estimate the density. Vertical lines represent the cutoffs set by the exam authorities to confer the national distinction award in each field. Panel (b) plots the probability of receiving the national distinction award as a function of the running variable. Dots correspond to local averages within equidistant bins of the running variable. The running variable is the distance of scores (measured in standard deviations) from the cutoff for the national distinction award.

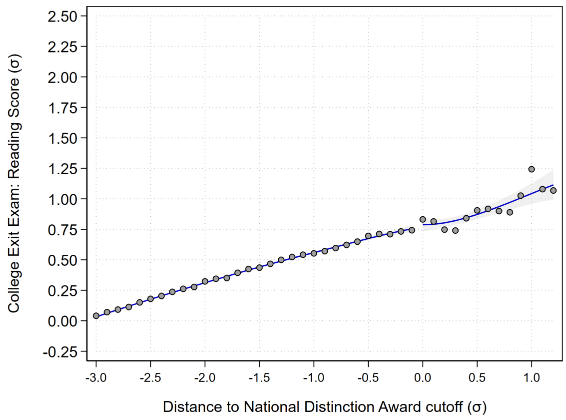
Balance. Appendix Figures C.2 and C.3 complement the evidence presented in Figure 2 regarding the comparability between award recipients and non-recipients around the cutoff. The empirical literature using sharp RD designs describes this assumption as continuity in pre-treatment covariates. Graphical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

Appendix Figure C.2: Continuity in Pretreatment Covariates

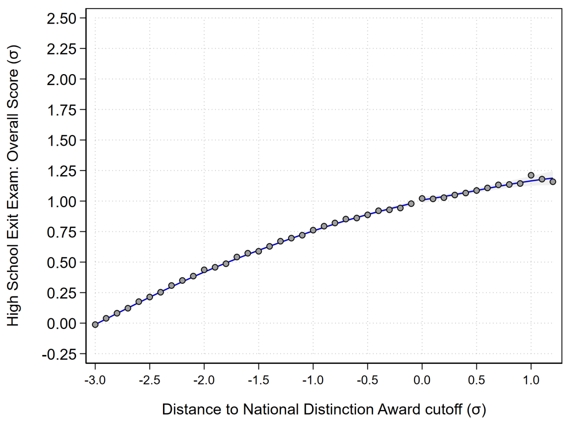
(a) English Score (sd)



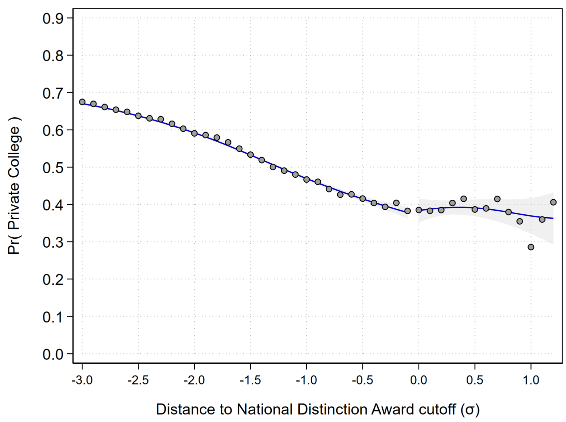
(b) Reading Score (sd)



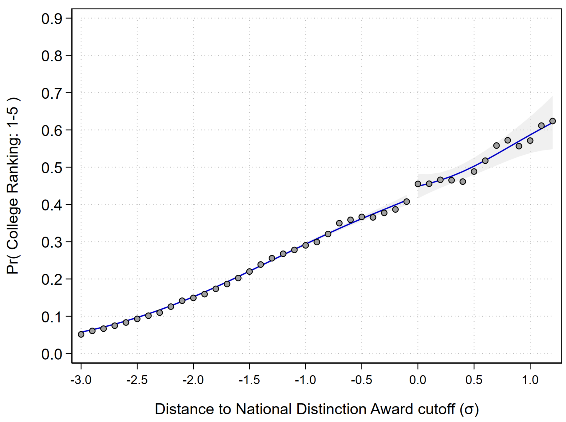
(c) High School Exit Exam (sd)



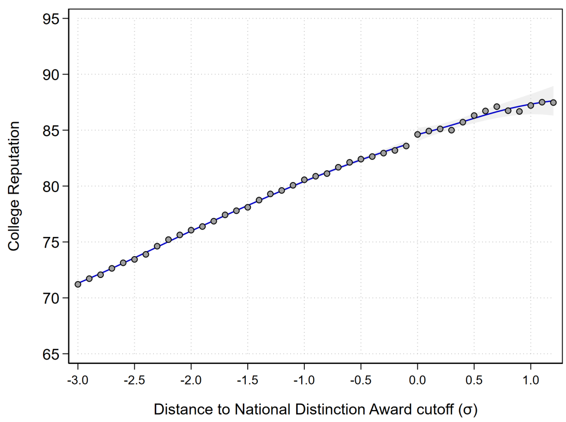
(d) Enrolled at a Private University



(e) Enrolled at a Top 5 University

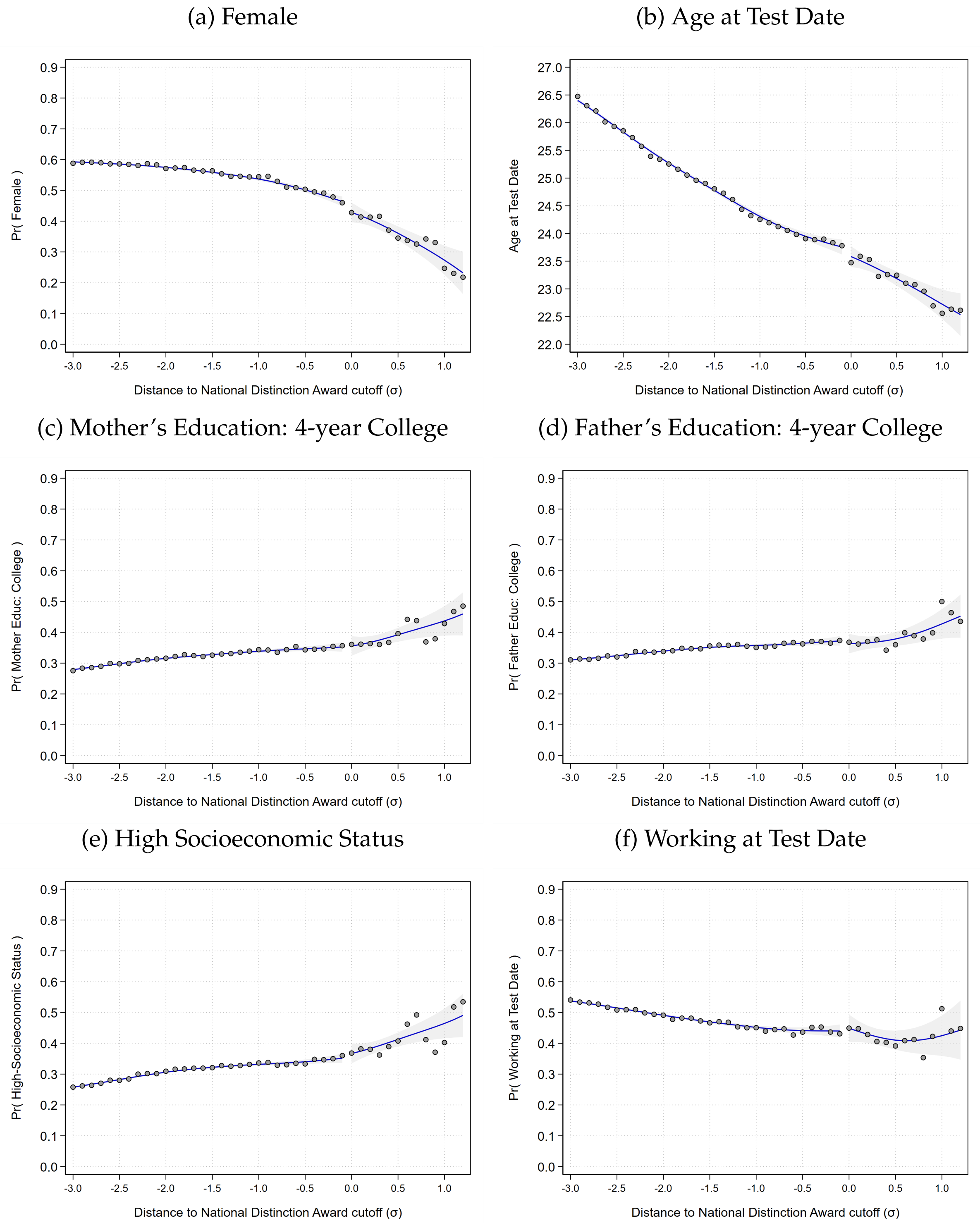


(f) College Reputation



Notes. This figure presents evidence of no discontinuity in "pre-treatment" covariates. Each panel plots a covariate as a function of the distance (in standard deviations) to the cutoff for the national distinction award. Across panels, plotted dots represent local averages within equidistant bins of the running variable. A width of 0.2 is used to compute local averages. Solid lines represent linear local regressions using a bandwidth equal to 0.449 and an Epanechnikov kernel. 95 percent confidence intervals are displayed around the local regressions on both sides of the cutoff. Panels (a) and (b) display scores from the core component of the college exit exam, which are not used by exam authorities to confer the national distinction award. Panel (c) plots the scores from the high school exit exam (known, as *Saber 11*). Test scores are standardized to have a mean zero and a standard deviation of one within cohorts of the exam. Panels (d) and (e) plot indicator variables equal to one if the student is enrolled at a private college and a college ranked among the top 5, respectively. Panel (f) shows a measure of college reputation, defined as the average pre-college test scores of graduates (see MacLeod et al. (2017)).

Appendix Figure C.3: Continuity in Pretreatment Covariates

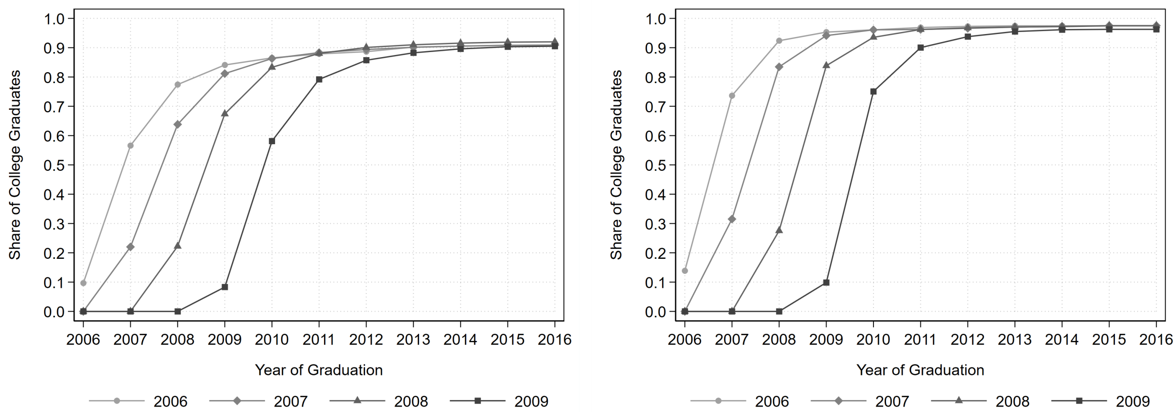


Notes. This figure presents evidence of no discontinuity in "pre-treatment" covariates. Each panel plots a covariate as a function of the distance (in standard deviations) to the cutoff for the national distinction award. Across panels, plotted dots represent local averages within equidistant bins of the running variable. A width of 0.2 is used to compute local averages. Solid lines represent linear local regressions using a bandwidth equal to 0.449 and an Epanechnikov kernel. 95 percent confidence intervals are displayed around the local regressions on both sides of the cutoff. Panel (a) displays an indicator equal to one if the student is a female. Panel (b) plots the students' age at the date of the exam. Panel (c) and (d) use, respectively, indicators equal to one if the student's mother and father have college education. Panel (e) plots an indicator equal to one if the student's socioeconomic stratum is four or higher. Households are classified into six strata based on the family's living conditions. Panel (f) plots an indicator equal to one if the student reports being employed, regardless of whether it's with or without a salary, due to a college requirement, or to cover personal expenses.

Sample selection. Our results might be subject to sample selection coming from different sources. First, our sample can be selected if there are merging issues between the universe of analysis and the social security records. Recall that the sub-sample of social security records used herein corresponds to those individuals who graduated with a college degree after 2001 and worked formally between 2007 and 2015. Therefore, sample selection can arise if there are differences around the threshold for (1) the probability of college graduation or (2) the probability of observing earnings. We provide evidence against this in Figure 3 in the main text. Nonetheless, we provide additional evidence in Appendix Figure C.4 where we plot the timing and share of graduates during the four years we analyze. Graduation rates among test takers are around 90 percent and do not vary systematically compared to awardees. Most students, independent if they received or not the award, graduate in the second or third year after they take the exam.

Appendix Figure C.4: Graduation Rates among Saber Pro Test Takers

(a) All Test Takers (b) Distinction Awardees



Notes. Panel (a) displays the share of students who graduate across time from each of the cohorts that took the college exit exam between 2006 and 2009. Panel (b) shows the graduation rate of students who were awarded the national distinction award between 2006 and 2009.

A second potential source of sample selection can arise if individuals above the threshold are observed at different points in their careers. Our main outcome of interest is the first observed earnings after college graduation, implying that the timing of observing earnings matters. We directly test for this by building a measure of months from the exam date or the graduation date to the first observed earnings and run our regression discontinuity design to estimate the difference between students just above and just below the threshold.[47] Appendix Table C.1 shows that this is not the case and

[47]The administrative records of the universe of college students include an indicator variable for whether the student graduates, as well as the exact date when the degree is granted. On the other hand, the social security records include the month earnings were observed between 2008 and 2016. Using this information along with the date when the student took the college exit exam, we compute the number of months (from the exam date and the student's graduation date) until earnings are observed for the first time.

the timing of the first observed earnings does not vary around the threshold.

Appendix Table C.1: Months from College Exit Exam and Graduation Date to First Observed Earnings

	Dependent Variable : Log of Months to Observed Earnings					
	Months From Exam Date			Months From Graduation Date		
	(1)	(2)	(3)	(4)	(5)	(6)
National Award	–0.016	–0.014	–0.014	–0.032	–0.030	–0.034
	[0.026]	[0.026]	[0.025]	[0.026]	[0.026]	[0.026]
Observations	198,742	198,742	198,742	198,742	198,742	198,742
Bandwidth	0.386	0.400	0.383	0.394	0.396	0.379
Control obs.	3038	3275	3017	3194	3204	2984
Treatment obs.	1403	1423	1399	1413	1419	1391
Mean Control	3.617	3.613	3.616	3.259	3.260	3.256
Area x Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Test Scores		Yes	Yes		Yes	Yes
Covariates			Yes			Yes

Notes. This table presents regression discontinuity estimates of the effect of the national distinction award on the time when labor market earnings are observed from the exam date (columns 1 to 3) and from the student's graduation date (columns 4 to 6). In columns (1) to (3), the outcome variable is the log of months from the date of the exam until the date when we first observe earnings for a student. In columns (4) to (6), the outcome variable is the log of months from the student's graduation date until the date when we first observe earnings for a student. The running variable is the distance of scores (measured in standard deviations) from the cutoff for the national distinction award. 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. Scores from the core component tests are not used by the exam authorities to confer the national distinction award. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. All estimates use linear local regressions, an Epanechnikov kernel, and MSE-optimal bandwidths. Robust standard errors are clustered at the area-year level and displayed in squared brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

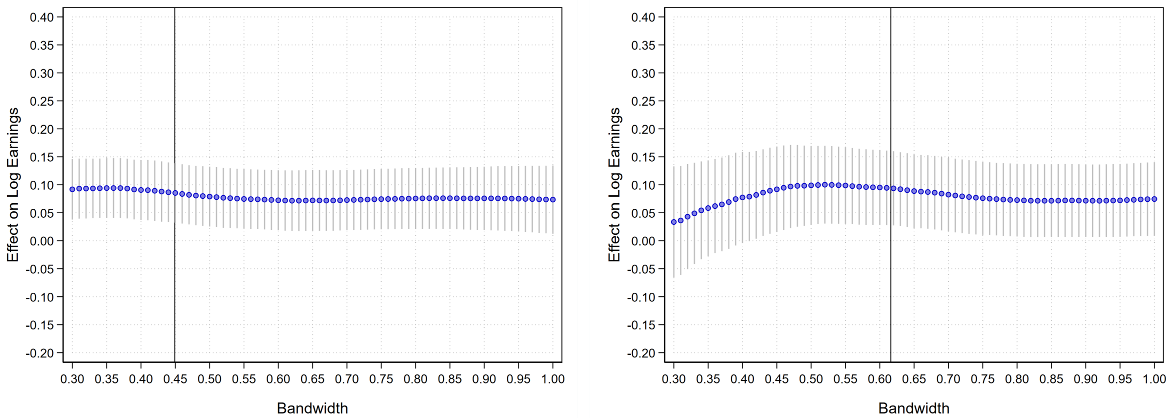
D Additional Robustness Checks for the Main Result

D.1 Robustness to Tuning Parameters

Bandwidth and Degree of Local Polynomial Fit.– Following Imbens and Lemieux (2008), we also estimate the effect on initial earnings using local polynomial regressions of different orders and considering multiple bandwidths. Appendix Figure D.1 shows that our estimates are robust to a wide range of bandwidths and to the degree of the local polynomial regression. As in any empirical work using a sharp regression discontinuity design, bandwidths closer to zero will reduce the bias – since treated and control group individuals are more similar closer to the cutoff – but will also reduce the precision of the estimates. Such a pattern is observed in the following figure.

Appendix Figure D.1: RD Estimates as Function of the Bandwidth

(a) Linear Polynomial (b) Quadratic Polynomial



Notes. This figure shows that our estimates of the effect of the national distinction award on earnings are robust to different bandwidths and the order of the local polynomial regressions. The outcome variable is the log of early-career earnings, defined as the first observed earnings after graduating college. Plotted dots in Panels (a) and (b) represent regression discontinuity estimates using, respectively, linear and quadratic local regressions. All estimates use an Epanechnikov kernel and control for test scores and covariates. Test scores include scores from the high school exit exam and scores from the core component tests (Reading and English Proficiency) of the college exit exam. Scores from the core component tests are not used by the exam authorities to confer the national distinction award. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. Vertical solid lines in both panels represent MSE-optimal bandwidths as a benchmark. 90 and 95 percent confidence intervals, based on robust standard errors clustered at the area-year level, are displayed around coefficients.

D.2 Robustness to Alternative Definitions of Early Career Earnings

The estimated effects of being awarded the national distinction are robust to alternative measures of an individual's early-career earnings. We consider three different measures: *i)* first observed earnings after graduation; *ii)* earnings observed one year after college graduation; and *iii)* earnings observed between ages 23 and 28. Appendix Table D.1 presents regression discontinuity estimates using each of these outcomes. Estimates are similar across alternative measures and range between 7 and 11 percent.

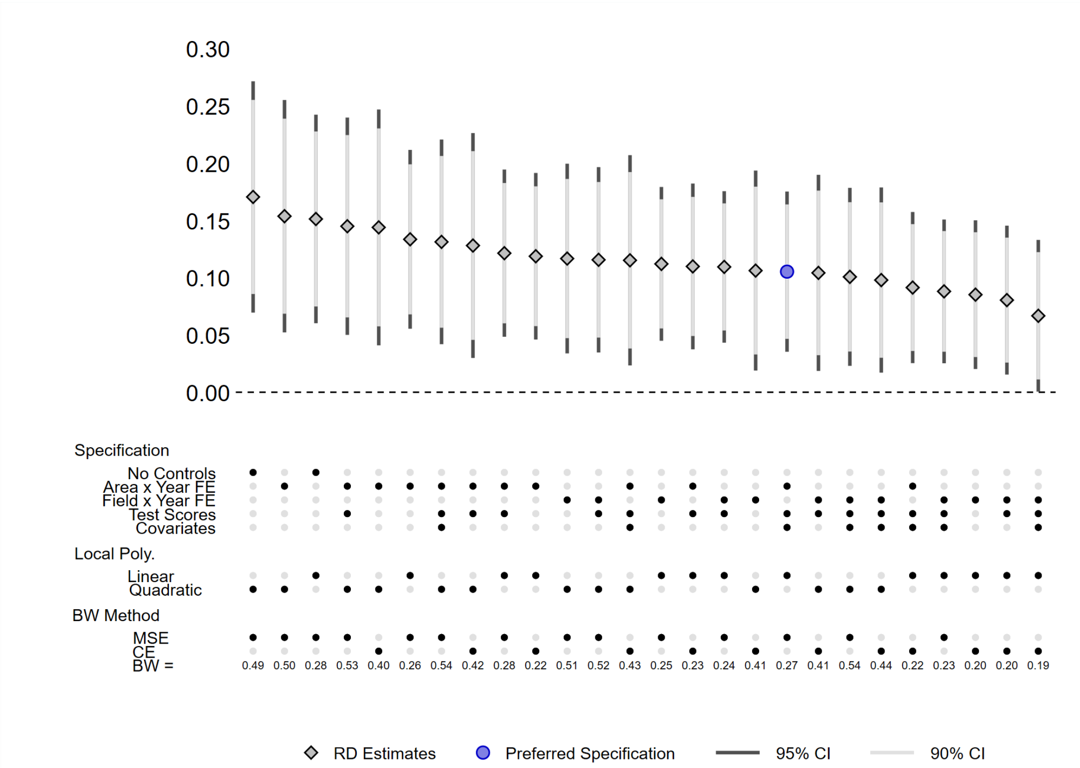
Appendix Table D.1: Effect of the National Award on Different Measures of Early-Career Earnings

	Dependent Variable :					
Panel A :	Log First Observed Earnings					
	(1)	(2)	(3)	(4)	(5)	(6)
National Award	0.098***	0.089***	0.086***	0.072***	0.070***	0.073***
	[0.030]	[0.026]	[0.027]	[0.025]	[0.024]	[0.026]
Observations	198,742	198,742	198,742	198,742	198,742	198,742
Bandwidth	0.431	0.455	0.449	0.456	0.460	0.430
Control obs.	3618	3920	3807	3921	3985	3615
Treatment obs.	1499	1548	1538	1548	1556	1499
Panel B :	Log Earnings One Year After Graduation					
	(1)	(2)	(3)	(4)	(5)	(6)
National Award	0.093***	0.088***	0.084***	0.088***	0.088***	0.088***
	[0.031]	[0.029]	[0.031]	[0.027]	[0.028]	[0.030]
Observations	129,884	129,884	129,884	129,884	129,884	129,884
Bandwidth	0.476	0.485	0.468	0.465	0.461	0.461
Control obs.	2799	2886	2742	2732	2680	2680
Treatment obs.	1059	1069	1052	1049	1045	1045
Panel C :	Log Avg. Earnings Age 23 to 28					
	(1)	(2)	(3)	(4)	(5)	(6)
National Award	0.114***	0.108***	0.095***	0.099***	0.099***	0.090***
	[0.039]	[0.036]	[0.034]	[0.031]	[0.030]	[0.030]
Observations	130,497	130,497	130,497	130,497	130,497	130,497
Bandwidth	0.297	0.309	0.299	0.270	0.262	0.248
Control obs.	1724	1821	1740	1556	1530	1436
Treatment obs.	1034	1055	1043	992	978	944
Area x Year FE	Yes	Yes	Yes			
Field x Year FE				Yes	Yes	Yes
Test Scores		Yes	Yes		Yes	Yes
Covariates			Yes			Yes

Notes. This table presents regression discontinuity estimates of the effect of the national distinction award on different measures of early-career earnings. In Panel A, the outcome corresponds to the log of first observed earnings after graduating college. In Panel B, the outcome is the log of earnings observed one year after college graduation. In Panel C, the outcome is the average of observed earnings between ages 23 and 28. The running variable is the distance of scores (measured in standard deviations) from the cutoff for the national distinction award. 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. Scores from the core component tests are not used by the exam authorities to confer the national distinction award. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. All estimates use linear local regressions, an Epanechnikov kernel, and MSE-optimal bandwidths. Robust standard errors are clustered at the area-year level and displayed in squared brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

We provide robustness checks for the measure of earning between 23 and 28 in Appendix Figure D.2. These results follow the same pattern observed in Figure 5 and suggest that the earnings premium of winning the national distinction award is robust to alternative estimation methods and to alternative measures of early-career earnings.

Appendix Figure D.2: Robustness of the Effect of the National Award using Earnings between Ages 23 and 28



Notes. This figure shows that our estimates of the effect of the national distinction award on earnings are robust to changes in the tuning parameters of the research design and to different control variables. The outcome variable is the log of the average earnings after a student graduates college and between ages 23 and 28. Plotted dots represent regression discontinuity estimates using linear and quadratic local regressions and an Epanechnikov kernel. The MSE-optimal bandwidth used for each estimate is displayed at the bottom of the specification. The running variable is the distance of scores (measured in standard deviations) from the cutoff for the national distinction award. 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. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. 90 and 95 percent confidence intervals, based on robust standard errors clustered at the area-year level, are displayed around coefficients.

D.3 Robustness to Dropping Small Fields and Each Field at a Time

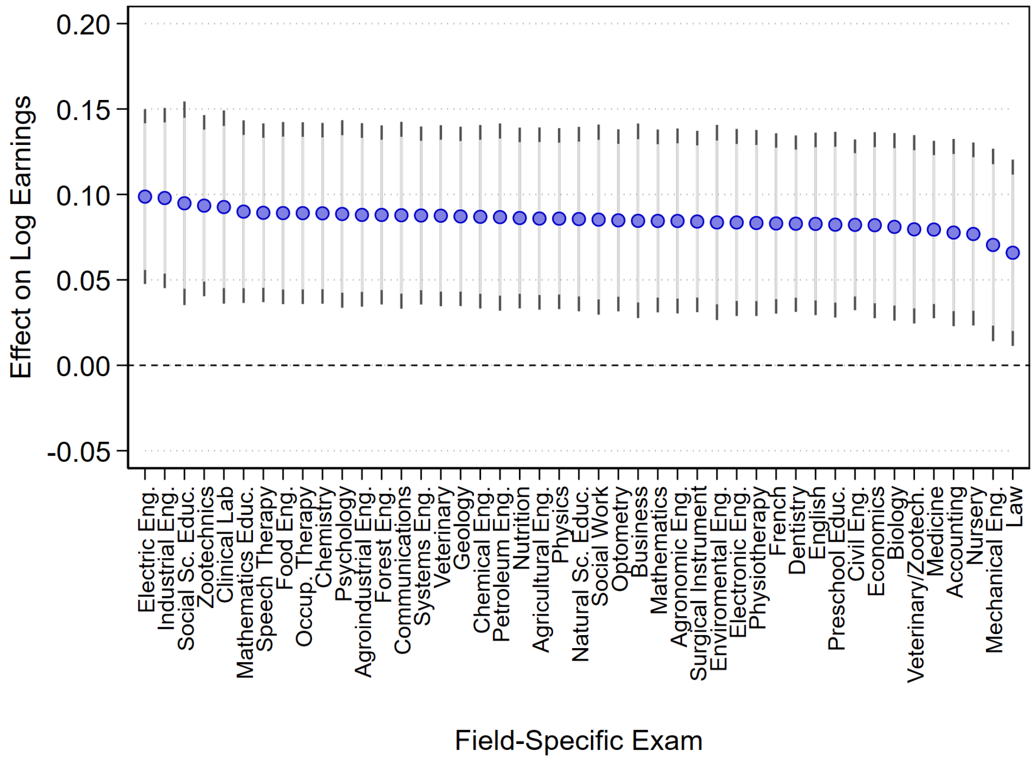
Our point estimates may be affected if there are not enough awardees within field-by-year cells. This occurs among fields with less than 1,000 test takers: Agricultural Engineering, English Education, Forest Engineering, French Education, Geology, Mathematics, Nutrition, Occupational Therapy, Optometry, and Physics. We present point estimates of our main results excluding these small fields in Appendix Table D.2. The effects remained mainly unchanged implying that our conclusions are not driven by small fields. We also estimate our main results by dropping each field-specific exam at a time. Appendix Figure D.3 shows the results of this exercise. These results further suggest that our main findings are not driven by a specific field.

Appendix Table D.2: Robustness of the Effect of the National Distinction on Early-Career Earnings

	Dependent Variable : Log Earnings					
	(1)	(2)	(3)	(4)	(5)	(6)
National Award	0.099***	0.091***	0.088***	0.070***	0.069***	0.069***
	[0.029]	[0.027]	[0.027]	[0.025]	[0.025]	[0.026]
Observations	194,405	194,405	194,405	194,405	194,405	194,405
Bandwidth	0.449	0.449	0.449	0.449	0.449	0.449
Control Obs.	3676	3676	3676	3676	3676	3676
Treatment Obs.	1470	1470	1470	1470	1470	1470
Area x Year FE	Yes	Yes	Yes			
Field x Year FE				Yes	Yes	Yes
Test Scores		Yes	Yes		Yes	Yes
Covariates			Yes			Yes

Notes. This table shows the estimated effect of the national distinction award on earnings is robust to dropping fields with a small sample size. Students from ten field exams are excluded: Agricultural Engineering, English Education, Forest Engineering, French Education, Geology, Mathematics, Nutrition, Occupational Therapy, Optometry, and Physics. Less than 1,000 students were assessed in such fields between 2006 and 2009. The outcome variable is the log of early-career earnings, defined as the first observed earnings after graduating college. The running variable is the distance of scores (measured in standard deviations) from the cutoff for the national distinction award. 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. Scores from the core component tests are not used by the exam authorities to confer the national distinction award. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. Estimates use linear local regressions and an Epanechnikov kernel. The common bandwidth across columns corresponds to the MSE-optimal bandwidth used to estimate our main results (see Table 1). Robust standard errors are clustered at the area-year level and displayed in squared brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Appendix Figure D.3: Robustness of the Effect of the National Distinction on Early-Career Earnings



Notes. This figure shows the estimated effect of the national distinction award on earnings is robust to dropping one field exam at a time. The horizontal axis displays the name of the field that is dropped from the sample of analysis. The outcome variable is the log of early-career earnings, defined as the first observed earnings after graduating college. Plotted dots represent regression discontinuity estimates using linear local regressions and an Epanechnikov kernel. The running variable is the distance of scores (measured in standard deviations) from the cutoff for the national distinction award. 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. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. All specifications use bandwidth of 0.449, which corresponds to the MSE-optimal bandwidth used to estimate our main results (see Table 1). 90 and 95 percent confidence intervals, based on robust standard errors clustered at the area-year level, are displayed around coefficients.

D.4 Ranking of Field-Specific Scores as Running Variable

We conduct an analysis changing the running variable and using instead the ranking in the test. This ranking is discrete, so we estimate the effect using ordinary least squares and restricting to observations above and below the threshold. We vary the bandwidth around the threshold and present the results in Appendix Table D.3. We observe very similar point estimates between 6 and 9 percent, although we lose some precision when the bandwidth is small because of a loss of sample size.

Appendix Table D.3: Effect of the National Distinction Award on Earnings Using the Ranking of Scores as Running Variable

	Dependent Variable : Log Earnings							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
National Award	0.060*	0.104**	0.064*	0.084**	0.066	0.092*	0.050	0.079**
	[0.033]	[0.048]	[0.034]	[0.031]	[0.041]	[0.045]	[0.030]	[0.031]
R-squared	0.101	0.130	0.127	0.117	0.401	0.274	0.252	0.233
Observations	902	2,829	4,944	7,424	902	2,829	4,944	7,424
Bandwidth	1	3	5	7	1	3	5	7
Control Obs.	473	1710	3378	5560	473	1710	3378	5560
Treatment Obs.	429	1119	1566	1864	429	1119	1566	1864
Area x Year FE	Yes	Yes	Yes	Yes				
Field x Year FE					Yes	Yes	Yes	Yes

Notes. This table presents ordinary least squares estimates of the effect of the national distinction award on early-career earnings. The outcome variable is the log of early-career earnings, defined as the first observed earnings after graduating college. The running variable is the normalized ranking of test scores in the field-specific component of the college exit exam. To compute the running variable we first rank test scores within field exams and then determine the position of the student (or students if they obtained the same score) with the lowest score who were awarded the national distinction. Then, we recenter the ranking so the new position of awardees is higher or equal to 1, and the new position of non-awardees is lower or equal to -1. Each column shows estimates of equation (1) restricting the sample to students whose position in the normalized ranking is arbitrarily close to 0. The "bandwidth" in each column refers to the number of positions away from 0. All specifications control for test scores and covariates. Test scores include scores from the high school exit exam and scores from the core component tests (Reading and English Proficiency) of the college exit exam. Scores from the core component tests are not used by the exam authorities to confer the national distinction award. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. Standard errors are clustered at the area-year level and displayed in squared brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

E Earnings Gaps In Different Scenarios

Are the heterogeneous effects of signaling specific skills enough to close the earnings gap between workers from advantaged and disadvantaged backgrounds? This is a broad question that unfortunately we are not able to to fully answer using the local average treatment effects derived from our regression discontinuity estimates. 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 gaps:

i. *Earnings 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 earnings of the advantaged and disadvantaged group, without the signal.

ii. *Earnings gap with one-sided signal :* We compare the earnings of the "disadvantaged" group marginally to the right (those who won the award but are close to the cutoff) with the earnings of 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.

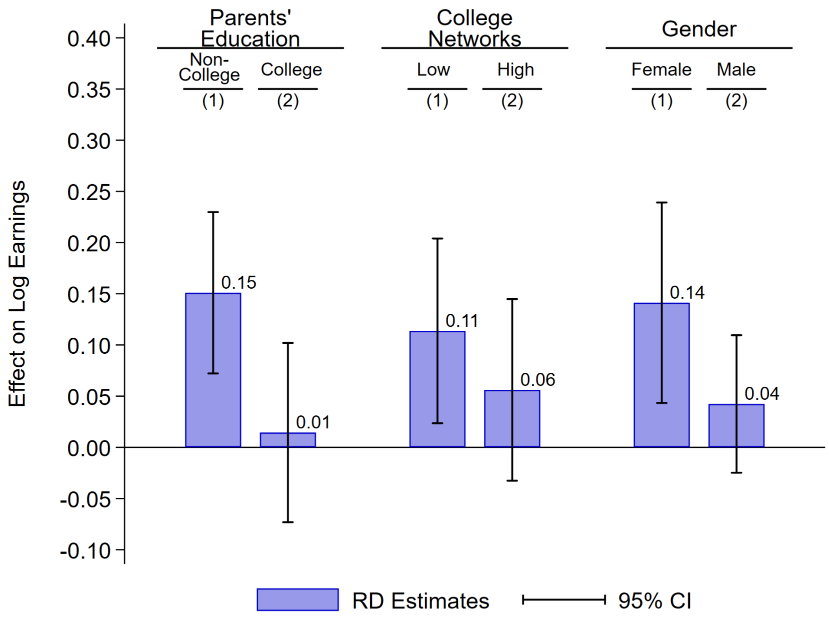
iii. *Earnings gap with signal:* We compare earnings of both groups slightly to the right of the cutoff (i.e., among award winners). This gap takes the following form: $Gap_S = (\log(\tilde{W}_a) + \beta_a) - (\log(\tilde{W}_d) + \beta_d)$, where β_a corresponds to the return of the signal to the advantaged group.

The introduction of the award can *per-se* increase earnings inequality if there is a big proportion of students from the advantaged group among the awardees. Our back-of-the-envelope calculations assume, first, that everyone is able to signal equally (e.g., by using skills certifications) and, second, that our local treatment effects can be extrapolated to the whole population of students. Under these strong assumptions, the earnings gap computed in step (3) could represent the case in which employers observe the full distribution of skills among job applicants.

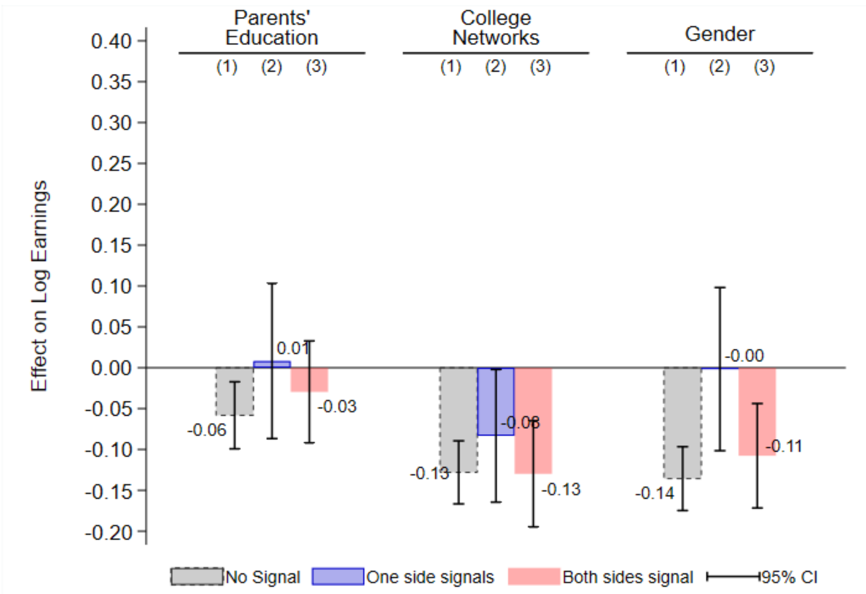
Panel B of Appendix Figure E.1 shows these back-of-the-envelope calculations. The gray bars represent earnings gaps *without* the signal, purple bars with *one-sided* signal, and pink bars *with* the signal. If only the disadvantaged group is able to signal their skills, then the earnings gaps drastically decrease. Being able to signal specific skills for both groups also reduces the magnitudes of the earnings gaps across all groups. The earning gap between students whose parents have and those who do not have

Appendix Figure E.1: Heterogeneous Effects of the Signal and Earnings Gaps

(a) Heterogeneous Effects



(b) Earnings Gaps in Different Scenarios



Notes. This figure presents estimates of the heterogeneous effects of the national distinction award on early-career earnings. The outcome variable is the log of early-career earnings, defined as the first observed earnings after graduating college. Bars in Panel (a) represent regression discontinuity estimates using linear local regressions, an Epanechnikov kernel, and MSE-optimal bandwidths. Estimates are computed within the subsample defined by the characteristic displayed at the top of each bar. Panel (b) displays estimates of the earnings gap around the cutoff for the national distinction award (or, the signal). For each characteristic described at the top of each bar, the gap is equivalent to the difference in earnings between groups (1) and (2) displayed in Panel (a). 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 sides signal" refer to OLS estimates among awardees whose scores are close to the cutoff. Estimates when "One side signals" refers to regression discontinuity estimates when the national distinction is awarded among individuals from group (1) in Panel (a), but not among individuals from group (2). All specifications control for area-year (of exam) fixed effects and test scores. Test scores include scores from the high school exit exam and scores from the core component tests (Reading and English Proficiency) of the college exit exam. 95 percent confidence intervals, based on robust standard errors clustered at the area-year level, are displayed around estimates.

college closes from six percent to three percent (the second is not statistically significant). Similarly, signaling reduces the gap between individuals with high and low levels of networks and with different genders.

Taken together, these results suggest that the signal can potentially level the playing field for workers coming from more disadvantaged backgrounds. The results should be interpreted with caution, however, as our treatment effect estimates are less informative about what happens on other parts of the test score distribution, especially in the lower-bottom.

F Results Fixing the Bandwidth

Estimates Using a Fixed Bandwidth.– The selected optimal bandwidth can affect the point estimates of a regression discontinuity design. In this section, we present the results displayed throughout Section 6 but using a fixed bandwidth equivalent to that in our main result in Table 1 (bandwidth = 0.449). The results displayed in the mechanisms section hold for the fixed sample defined in such a vicinity around the cutoff.

Appendix Table F.1: National Distinction Award and College Reputation

	Dependent Variable : Log Earnings					
		College Ranking :			Cross-sample Comparison : Top 5 Non-awardees vs.	
	Full Sample	Top 5	Top 6-20	Below 20	Top 6-20 Awardees	Below 20 Awardees
	(1)	(2)	(3)	(4)	(5)	(6)
National Award	0.086***	0.013	0.108*	0.153**	0.106*	–0.012
	[0.027]	[0.043]	[0.063]	[0.060]	[0.055]	[0.055]
Observations	198,742	26,577	30,278	141,887	26,074	26,094
Bandwidth	0.449	0.449	0.449	0.449	0.449	0.449
Control Obs.	3807	1553	960	1294	1553	1553
Treatment Obs.	1538	712	413	413	413	413
Mean Control	14.17	14.21	14.21	14.09	14.21	14.21

Notes. The outcome variable is the log of early-career earnings, defined as the first observed earnings after graduating college. Column (1) replicates the main results (Column 3 of Table 1). Regression discontinuity estimates within samples defined by college ranking are displayed in columns (2) to (6). Columns (2) to (4) show estimates for students in schools within the same tier of the college ranking. Colleges are divided into three categories: top tier (schools in the top 5), middle tier (schools ranked 6th to 20th), and bottom tier (schools below the top 20). Columns (5) and (6) display estimates for award recipients in middle- and bottom-tier colleges with respect to non-recipients in top-tier schools. Estimates across columns control for area-year (of exam) fixed effects, test scores, and covariates. Test scores include scores from the high school exit exam and scores from the core component tests (Reading and English Proficiency) of the college exit exam. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. Regression discontinuity estimates use linear local regressions and an Epanechnikov kernel. The common bandwidth across columns corresponds to the MSE-optimal bandwidth used to estimate our main results (see Table 1). Robust standard errors are clustered at the area-year level and displayed in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Appendix Table F.2: Effects on the Allocation of Skills

	Dependent Variable :					
	Field-Industry Match				Log Earnings	
	Full Sample	College Ranking :			Type of Skills :	
		Top 5	Top 6-20	Below 20	Specific	Transferable
	(1)	(2)	(3)	(4)	(5)	(6)
National Award	0.040	0.020	0.026	0.108*	0.088***	0.056
	[0.026]	[0.043]	[0.061]	[0.059]	[0.031]	[0.058]
Observations	187,331	25,664	29,314	132,353	122,779	75,963
Bandwidth	0.449	0.449	0.449	0.449	0.449	0.449
Control Obs.	3652	1498	923	1231	3067	740
Treatment Obs.	1460	680	395	385	1248	290
Mean Control	0.412	0.425	0.411	0.396	14.14	14.28

Notes. This table presents regression discontinuity estimates of the effect of the national distinction award on the likelihood of being employed in an industry related to the student's field of study (columns 1 to 4), and on early-career earnings by type of field (columns 5 and 6). The outcome variable in columns (1) to (4) is an indicator equal to one if a worker's industry matches the worker's field (college major). The outcome variable in columns (5) and (6) is the log of early-career earnings, defined as the first observed earnings after graduating college. Estimates across columns control for area-year (of exam) fixed effects, test scores, and covariates. Test scores include scores from the high school exit exam and scores from the core component tests (Reading and English Proficiency) of the college exit exam. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. All estimates use linear local regressions and an Epanechnikov kernel. The common bandwidth across columns corresponds to the MSE-optimal bandwidth used to estimate our main results (see Table 1). Robust standard errors are clustered at the area-year level and displayed in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Appendix Table F.3: Effects on the Match Probability with High-Productivity Firms

	Dependent Variable : Employer's Wage Premium			
	First Employer		Avg. Across Employers	
	Unconditional Ranking	AKM Ranking	Unconditional Ranking	AKM Ranking
	(1)	(2)	(3)	(4)
National Award	0.080**	0.120***	0.084**	0.092**
	[0.036]	[0.039]	[0.038]	[0.042]
Observations	188,566	188,609	188,566	188,609
Bandwidth	0.449	0.449	0.449	0.449
Control Obs.	3613	3613	3613	3613
Treatment Obs.	1463	1463	1463	1463
Mean Control	0.721	0.547	0.811	0.640

Notes. This table presents regression discontinuity estimates of the effect of the national distinction award on the likelihood of working at higher-productivity firms. Two time-invariant measures of firm productivity are considered: (i) *Unconditional ranking* : within-industry ranking based on the firm's average earnings, and (ii) *AKM ranking* : ranking based on the firm fixed effects from a regression that controls for individual fixed effects, year fixed effects, a graduate education indicator, and a degree two polynomial of age and potential experience (see Abowd, Kramarz and Margolis (1999) for details on the estimator). Both measures are rescaled to facilitate interpretation. First, rankings are expressed in percentile terms, and then they are standardized by subtracting the mean and dividing by the standard deviation. For additional details on the measures see Appendix G. Columns (1) and (2) present estimates of the effect on the productivity of the first observed employer. Columns (3) and (4) show estimates of the effect on the average productivity of all observed employers. Estimates across columns control for area-year (of exam) fixed effects, test scores, and covariates. Test scores include scores from the high school exit exam and scores from the core component tests (Reading and English Proficiency) of the college exit exam. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. All estimates use linear local regressions and an Epanechnikov kernel. The common bandwidth across columns corresponds to the MSE-optimal bandwidth used to estimate our main results (see Table 1). Robust standard errors are clustered at the area-year level and displayed in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Appendix Table F.4: Effects on Human Capital Accumulation

	Dependent Variable :				
	Months to College Grad. Date	Number of Subjects by Graduation			Graduate Education
		Total Registered	Registered After Exam:		
			Total	Passed	
	(1)	(2)	(3)	(4)	(5)
National Award	0.160	–0.533	–0.024	–0.013	0.034
	[0.527]	[0.851]	[0.279]	[0.266]	[0.031]
Observations	198,742	146,764	146,764	146,764	198,742
Bandwidth	0.449	0.449	0.449	0.449	0.449
Control Obs.	3807	3130	3130	3130	3807
Treatment Obs.	1538	1304	1304	1304	1538
Mean Control	11.44	59.72	6.553	6.208	0.254

Notes. This table presents regression discontinuity estimates of the effect of the national distinction award on different measures of human capital accumulation. The outcome variable in column (1) is the number of months from the date of the exam to the student's graduation date. In column (2), the outcome is the number of subjects in a student's academic history by the time she graduates. In columns (3) and (4), the outcomes correspond to the number of subjects a student registered for and successfully passed after taking the college exit exam. The outcome in columns (5) is an indicator equal to one if a student completes a graduate program within five years from the date of the exam. Estimates in all columns control for area-year (of exam) fixed effects, test scores, and covariates. Test scores include scores from the high school exit exam and scores from the core component tests (Reading and English Proficiency) of the college exit exam. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. All estimates use linear local regressions and an Epanechnikov kernel. The common bandwidth across columns corresponds to the MSE-optimal bandwidth used to estimate our main results (see Table 1). Robust standard errors are clustered at the area-year level and displayed in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

Appendix Table F.5: Effects on the Probability of Switching Jobs and Job Characteristics After Switching

	Dependent Variable :						
	Worker Switch Employers		Employer's Wage Premium Across Time, τ				
			First Employer			Δ Future Employers	
	Once	Twice	$\tau = 1$			$\tau = 2$	$\tau = 3$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Linear Polynomial							
National Award	–0.019	0.000	0.120***	0.082**	0.068	–0.042	–0.067
	[0.034]	[0.021]	[0.039]	[0.040]	[0.043]	[0.048]	[0.048]
Quadratic Polynomial							
National Award	–0.014	0.014	0.196***	0.183***	0.152**	–0.022	–0.039
	[0.050]	[0.037]	[0.058]	[0.064]	[0.075]	[0.069]	[0.074]
Observations	165,768	141,619	188,609	165,768	141,619	165,768	141,619
Bandwidth	0.449	0.449	0.449	0.449	0.449	0.449	0.449
Control Obs.	3193	2735	3613	3193	2735	3193	2735
Treatment Obs.	1283	1103	1463	1283	1103	1283	1103
Mean Control	0.358	0.131	0.547	0.568	0.596	0.0874	0.153

Notes. This table presents regression discontinuity estimates of the effect of the national distinction award on the probability of switching employers (columns 1 and 2) and on a measure of employer's productivity over time (columns 3 to 7). In columns (1) and (2), the outcome is an indicator equal to one if the worker switches employers once or twice after they graduate from college. The outcome in columns (3) to (5) corresponds to the productivity of the first observed employer. In columns (6) and (7), the outcome is the difference between the first employer's productivity and the second and third employer's. A sample of graduates for whom we observe two firms over time is used in columns (1), (4), and (6). A sample for which we observe three firms over time is used in columns (2), (5), and (7). The measure of productivity in this table corresponds to the *AKM ranking* of firms (see Table 5 for more details on this measure). Estimates across columns control for area-year (of exam) fixed effects, test scores, and covariates. Test scores include scores from the high school exit exam and scores from the core component tests (Reading and English Proficiency) of the college exit exam. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. Estimates use local regressions of different degrees and an Epanechnikov kernel. The common bandwidth across columns corresponds to the MSE-optimal bandwidth used to estimate our main results (see Table 1). Robust standard errors are clustered at the area-year level and displayed in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

G Field-Industry Match and Productivity Measures

G.1 Measure of Field-Industry Match

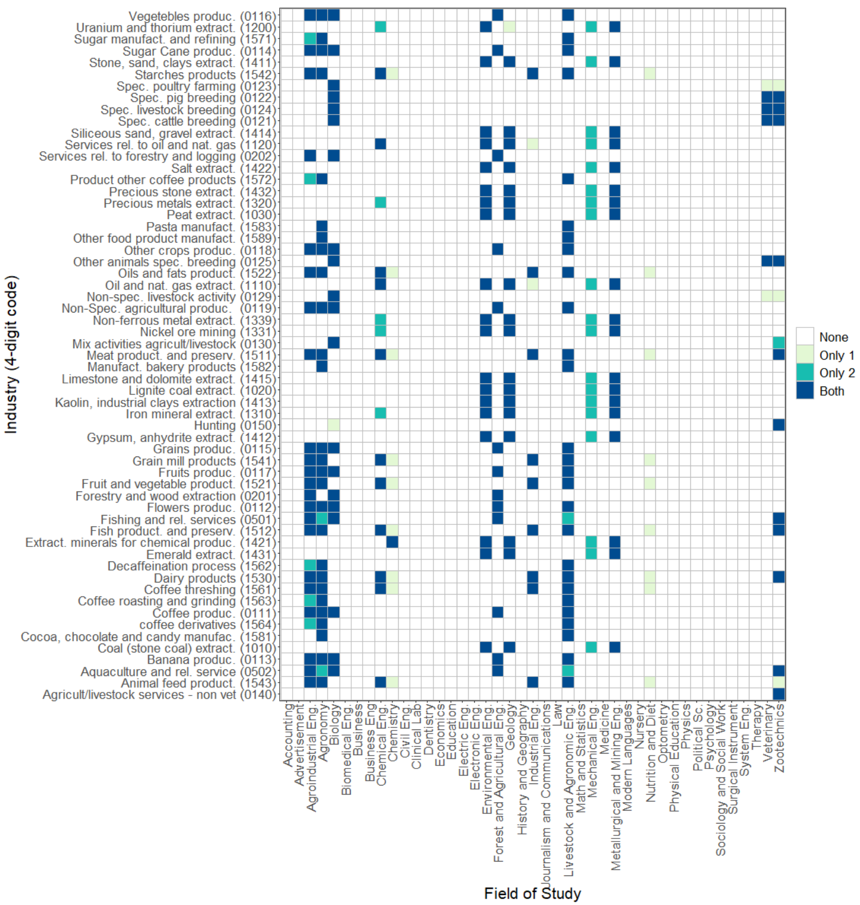
Table 3, in Section 6.3, provides evidence that college graduates who received the national distinction award are more likely to work in industries that better match their skills. We build a measure that captures the proper match between fields and industries by collecting information posted online by universities in Colombia regarding their "alumni profiles". Universities 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.

Appendix Figure G.1 describes the matches performed by both researchers over the fields of study and industries (at the four-digit level) contained in our data. They coincide in 70 percent of the industry-field pairs.

The results displayed in Table 3 use the match performed by research one as outcome. However, these results are consistent independent of the measure used. We display alternative measures of the outcome on Appendix Table G.1. Columns (1) and (2) display the point estimate using as outcome the measures performed by each researcher separately. Column (3) presents the estimate if we record as one only those industry-major pairs for which both researchers coincided and zero otherwise. Column (4) displays the estimated effect if we record as one any industry-major pair that at least one researcher deemed as a good match. Furthermore, Panel A focuses on the first industry of employment whereas Panel B includes any observed industry after graduation. All around, we observe consistent point estimates that pose evidence about the robustness of the effect of the signal on matching graduates to industries where their skills are better used.

Appendix Figure G.1: Direct Measure of Match Quality between Field of Study and Industry

(a) Industry Codes 0111 to 1589



(b) Industry Codes 7240 to 9900

Notes. This figure displays a sample of the exercise carried out by two independent researchers to determine whether the skills specific to a field of study match the skills required in the production process of different industries. Researchers relied on "alumni professional profiles" available online from universities in Colombia and on the description of industries (at the four-digit level) to classify the match in each cell of the field-industry matrix.

Appendix Table G.1: Effects on Allocation of Skills Using Different Measures

	Dependent Variable : Field-Industry Match			
Panel A :	First Industry of Employment			
	Researcher 1	Researcher 2	Union	Overlap
	(1)	(2)	(3)	(4)
National Award	0.049*	0.045*	0.058**	0.034
	[0.026]	[0.025]	[0.029]	[0.022]
Observations	187,331	187,331	187,331	187,331
Bandwidth	0.385	0.315	0.305	0.385
Control Obs.	2916	2239	2104	2916
Treatment Obs.	1333	1192	1157	1333
Mean Control	0.411	0.373	0.440	0.351
Panel B :	Any Industry of Employment After Graduation			
	Researcher 1	Researcher 2	Union	Overlap
	(1)	(2)	(3)	(4)
National Award	0.053*	0.074***	0.069**	0.056*
	[0.028]	[0.028]	[0.027]	[0.029]
Observations	187,331	187,331	187,331	187,331
Bandwidth	0.301	0.328	0.304	0.322
Control Obs.	2075	2379	2100	2332
Treatment Obs.	1155	1222	1157	1209
Mean Control	0.604	0.549	0.622	0.531

Notes. This table shows a robustness exercise regarding the effect on the likelihood that a student works in an industry that matches her field of study. Four measures based on indicator variables coded by two independent researchers are used as outcomes. First, two researchers determined if each 4-digit industry code matches the skills in which students get training in their fields of study. Using these two indicator variables we also define: i) the *Union*: an indicator equal to one if any of the two researchers matches a 4-industry code to a field, ii) the *Overlap*: an indicator equal to one only if both researchers agree that a 4-industry code matches a field. Panel A uses the first observed industry where the student works to determine if such industry matches her field of study. Panel B uses industry codes observed across years to determine if at any time the industry where the student has worked matches her field of study. Estimates across columns control for area-year (of exam) fixed effects, test scores, and covariates. Test scores include scores from the high school exit exam and scores from the core component tests (Reading and English Proficiency) of the college exit exam. Covariates include age at test date, gender, socioeconomic status indicators, number of semesters in college, and mother's education indicators. All estimates use linear local regressions, an Epanechnikov kernel, and MSE-optimal bandwidths. Robust standard errors are clustered at the area-year level and displayed in brackets. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

G.2 AKM-Firm Earnings Ranking

In sections 6.4 and 7, we use a measure of firm productivity that we compute based on the estimates of a model of log earnings that includes additive effects for workers and firms. The model, initially proposed by Abowd, Kramarz and Margolis (1999), can be described using the following equation:

$$\log w_{ijt} = \alpha_t + \alpha_i + \psi_j(i,t) + X_{it}'\beta + \varepsilon_{it}$$

where $\log w_{it}$ is the log earnings of individual i, working for firm j in time t. X_{it} is a vector of time-varying independent variables such as age or experience, α_t corresponds to year fixed effects, α_i to individual fixed effects, and $\psi_j(i,t)$ to firm fixed effects. ε_{it} is an idiosyncratic error term. Appendix Table G.2 displays the ordinary least squares estimates of the above model. We compute the earnings ranking of firms using the firm fixed effects estimated in column (4).

Appendix Table G.2: Earnings Regressions using Employer-Employee Data

	Dependent Variable : Log Earnings			
	(1)	(2)	(3)	(4)
Age	0.062***	0.062***	0.053***	
	[0.000]	[0.000]	[0.000]	
Age^2	–0.001***	–0.001***	–0.001***	–0.001***
	[0.000]	[0.000]	[0.000]	[0.000]
Experience	0.077***	0.078***	0.060***	
	[0.000]	[0.000]	[0.000]	
Experience^2	–0.003***	–0.003***	–0.002***	–0.002***
	[0.000]	[0.000]	[0.000]	[0.000]
Graduate Educ.	0.443***	0.442***	0.311***	0.081***
	[0.001]	[0.001]	[0.001]	[0.001]
R-squared	0.186	0.187	0.541	0.867
Observations	6,763,343	6,763,343	6,763,343	6,763,343
Num. Individuals	1,585,104	1,585,104	1,585,104	1,585,104
Num. Firms	56,070	56,070	56,070	56,070
Year FE		Yes	Yes	Yes
Firm FE			Yes	Yes
Individual FE				Yes

Notes. Ordinary least squares estimates using social security records of all college graduates between 2001 and 2015. The dependent variable is the log of formal sector earnings observed between 2009 and 2016. Workers' earnings are observed once per year and correspond to the last observed records between April and September. Experience is computed using the student's graduation date. Graduate education is a time-variant indicator equal to one if the worker has completed a graduate program by the end of each year, and zero otherwise. Standard errors clustered at the individual level. * p<0.10, ** p<0.05, *** p<0.01.