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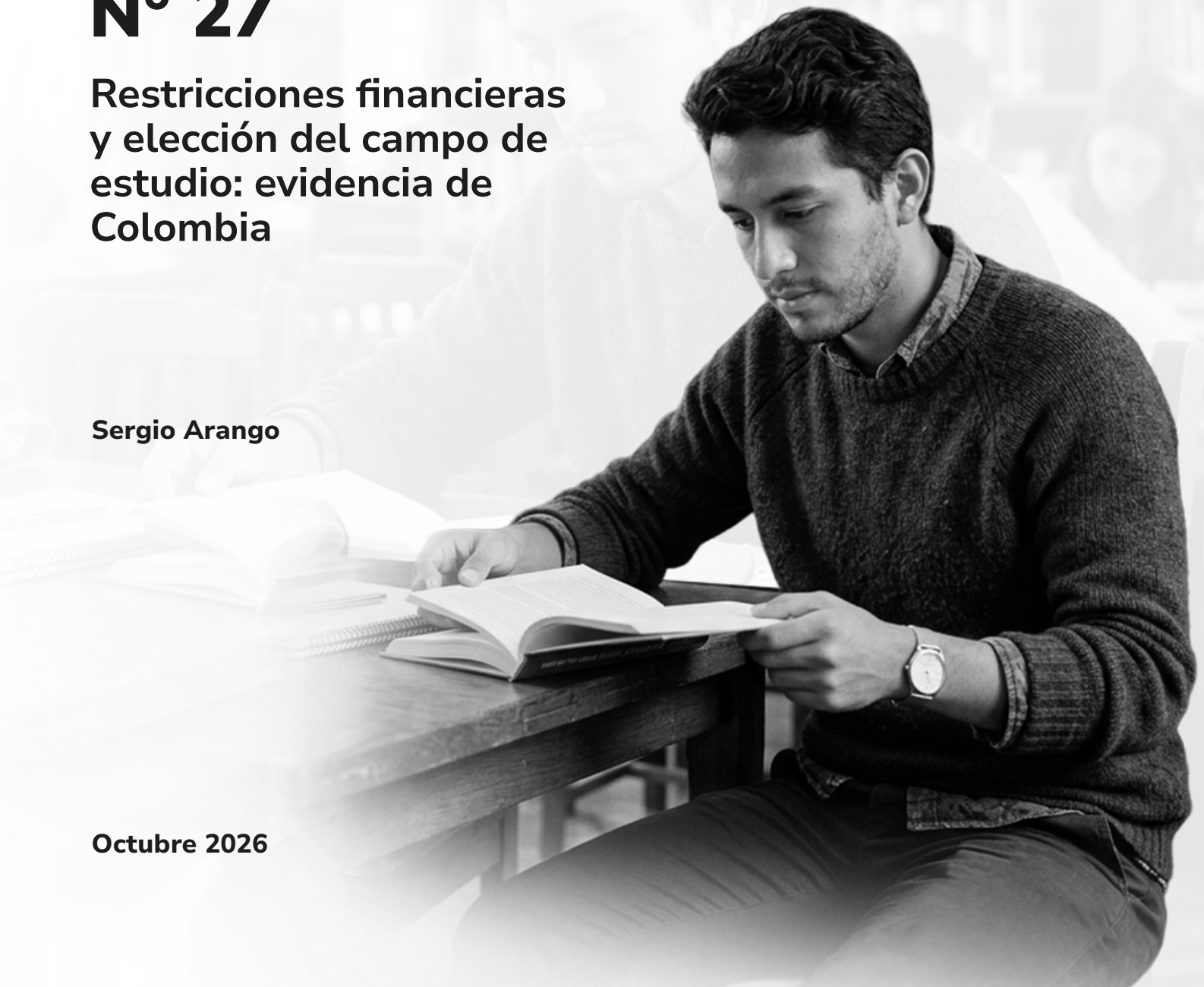
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**Restricciones financieras
y elección del campo de
estudio: evidencia de
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Restricciones financieras y elección del campo de estudio: evidencia para Colombia*

Sergio Arango[†]

Resumen

Este documento estudia cómo las ayudas financieras afectan la elección del campo de estudio de los estudiantes y la asignación del talento entre programas de educación superior. Las restricciones financieras pueden distorsionar no solo el acceso a la educación superior, sino también la asignación de los estudiantes entre campos y tipos de programa con retornos económicos diferentes. Examinamos esta pregunta a partir de dos programas nacionales de becas en Colombia, *Ser Pilo Paga* (2014–2017) y *Generación E Excelencia* (2018–2019), que otorgaron créditos condonables para cubrir la totalidad de la matrícula en universidades acreditadas a estudiantes de alto desempeño y bajos ingresos. Aprovechando los umbrales nítidos de elegibilidad académica (*Saber 11*) y socioeconómica (SISBEN) de los programas en un diseño de regresión discontinua, encontramos una reasignación en dos márgenes distintos, condicional a la matrícula. Dentro de cada campo, la elegibilidad desplaza a los estudiantes de programas técnicos y tecnológicos hacia programas profesionales universitarios, con mayor claridad en ingeniería, donde la matrícula en programas técnicos y tecnológicos cae entre 78 y 100 por ciento con respecto a la línea de base. Entre campos, la elegibilidad reduce de manera consistente la matrícula en ciencias de la educación entre 35 y 52 por ciento con respecto a la línea de base, mientras aumenta la matrícula en programas profesionales de ciencias sociales y humanas y de bellas artes. Estos cambios se orientan hacia combinaciones institución-programa con mejores perspectivas en el mercado laboral: los salarios mensuales esperados aumentan entre 10 y 14 por ciento un año después del grado, con efectos significativos sobre los salarios a cinco años y las tasas de empleo formal. Los resultados indican que las restricciones financieras distorsionan la asignación de los estudiantes entre campos y tipos de programa, y que relajarlas induce una reasignación hacia programas asociados con mayores retornos esperados, lo que tiene implicaciones para la eficiencia en la asignación del capital humano en sistemas de educación superior caracterizados por una especialización temprana.

Palabras clave: ayudas financieras, elección del campo de estudio, educación superior, regresión discontinua, asignación del capital humano, Ser Pilo Paga, Generación E, Colombia.

Códigos JEL: I22, I24, I28, J24

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Financial Constraints and Field-of-Study Choices: Evidence from Colombia

Sergio Arango

Abstract

This paper studies how financial aid affects students' field-of-study choices and the allocation of talent across college majors. Financial constraints may distort not only access to higher education but also the allocation of students across fields and program tracks with different economic returns. I examine this question using two Colombian nationwide scholarship programs — *Ser Pilo Paga* (2014–2017) and *Generación E Excelencia* (2018–2019) — which offered forgivable loans covering full tuition at accredited universities for high-achieving, low-income students. Exploiting the programs' sharp academic (*Saber 11*) and socioeconomic (SISBEN) eligibility thresholds in a regression discontinuity design I find reallocation along two distinct margins conditional on enrollment. Within fields, eligibility shifts students from vocational to professional programs, most clearly in engineering where vocational enrollment falls by 78–100 percent relative to the baseline. Across fields, eligibility consistently reduces education sciences enrollment by 35–52 percent relative to the baseline, while increasing enrollment in social and human sciences and fine arts professional programs. These shifts are toward college–major combinations with stronger labor market prospects: expected monthly salaries increase by 10–14 percent at one year after graduation, with significant effects on five-year salaries and formal sector employment rates. The results indicate that financial constraints distort the allocation of students across fields and program tracks, and that relaxing them induces reallocation toward programs associated with higher expected returns — with implications for the efficiency of human capital allocation in higher education systems characterized by early specialization.

Keywords: financial aid, field-of-study choice, higher education, regression discontinuity, human capital allocation, Ser Pilo Paga, Generación E, Colombia

JEL Codes: I22, I24, I28, J24



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1 Introduction

The specific type of human capital individuals acquire is among the most consequential investment decisions they make. For most young people, this investment materializes through the choice of field of study in higher education — the primary mechanism through which students develop the specialized knowledge and skills that determine their comparative advantage in the labor market. Returns differ substantially across fields ([Kirkebøen et al., 2016](#); [Hastings et al., 2013](#); [Arcidiacono, 2004](#)) — often by more than the average earnings premium associated with college attendance itself — and these differences persist over the life cycle. At the aggregate level, the distribution of graduates across fields determines the skill composition of the labor force and, through it, total factor productivity and long-run economic growth. The efficiency of this allocation therefore carries consequences that extend well beyond individual career outcomes.

Field-of-study choices, however, may not reflect unconstrained preferences, ability, or expected returns alone ([Altonji, 1993](#); [Arcidiacono, 2004](#); [Saks and Shore, 2005](#); [Wiswall and Zafar, 2014](#)). Financial constraints — which bind more tightly for students from low-income families — may systematically distort choices regardless of ability ([Carneiro and Heckman, 2002](#)). In the United States, for instance, [Hampole \(2024\)](#) finds that students from low-income neighborhoods and students whose parents have low credit scores choose majors with higher initial earnings but lower lifetime earnings, consistent with liquidity constraints forcing a short-horizon trade-off. In developing and middle-income economies, these distortions are amplified further. Credit markets are thinner, student loan systems less developed, and higher education structures typically require students to commit to a specific field at the point of enrollment — before preferences are fully formed, and financing options are fully exhausted. In these settings, financial constraints may prevent talented students not only from accessing higher education altogether, but from selecting the fields and program types that best match their ability and long-run labor market prospects.

Studying this question empirically is challenging for two main reasons. First, observed correlations between socioeconomic background and major choice confound the effect of fi-



nancial constraints with differences in ability, preferences, risk attitudes, and expected returns (Altonji, 1993; Arcidiacono, 2004; Saks and Shore, 2005; Wiswall and Zafar, 2014). Separating these channels requires exogenous variation in the ability to finance higher education — variation that is rarely available outside of specific institutional contexts. Second, even when such variation exists, the enrollment and field-of-study decisions are jointly determined in most higher education systems worldwide, where students must commit to a specific institution–field combination at the point of application rather than accessing college first and declaring a major later. Relaxing financial constraints may therefore simultaneously affect both whether a student enrolls and which field they choose, making it difficult to disentangle the intensive margin — reallocation across fields among students who would have enrolled regardless — from the extensive margin — entry of students who would not otherwise have accessed higher education. In these settings, the counterfactual field choices of constrained students are unobserved along both dimensions simultaneously.

Two strands of literature speak directly to this question, though neither fully bridges the gap between them. The first documents the determinants of college major choice, examining how ability, earnings uncertainty, and earnings expectations shape the fields students select (Altonji, 1993; Arcidiacono, 2004; Saks and Shore, 2005; Wiswall and Zafar, 2014; Zafar, 2013; Arcidiacono et al., 2012). More recently, Leighton and Speer (2024) show that students with more educated parents choose majors associated with higher lifetime earnings, and Hampole (2024) documents that students from low-income neighborhoods systematically choose majors with higher initial but lower lifetime earnings — a pattern consistent with financial constraints forcing a short-horizon trade-off. The second strand examines the causal effects of financial aid on educational outcomes, exploiting exogenous variation in aid eligibility to show that need-based scholarships substantially increase college enrollment and degree attainment (Dynarski and Scott-Clayton, 2013; Bettinger et al., 2019; Denning et al., 2019; Scott-Clayton and Zafar, 2019; Black et al., 2023; Londoño-Vélez et al., 2020, 2025). This literature provides credible causal estimates but has focused almost exclusively on whether students access higher education at all, leaving largely unanswered the question of how financial aid shapes the specific fields and programs students choose conditional on enrollment.



Despite these contributions, two important limitations remain. First, most studies of major choice are correlational, documenting associations between socioeconomic background and field selection without isolating the causal role of financial constraints from the many other dimensions along which low- and high-income students differ. The exception is [Hampole \(2024\)](#), who exploits the staggered implementation of no-loan policies at United States universities between 2001 and 2021 to estimate the causal impact of student loan availability on major choice — a credible identification strategy, though one that identifies the effect of loan removal rather than of financial aid provision. Second, the existing evidence comes almost entirely from the United States, which limits its external validity along two dimensions. In terms of economic context, credit markets are thinner, student loan systems less developed, and liquidity constraints more likely to bind in developing and middle-income economies, suggesting that the effects of financial constraints on field choice may be larger where alternative financing mechanisms are less available. In terms of institutional structure, the United States follows a liberal arts model in which students access college before declaring a major and can switch fields at relatively low cost — a feature that limits the persistence of any initial distortion. In systems where students must commit to a specific institution–field combination at the point of application, as in Colombia and most of Latin America, continental Europe, and East Asia, an initially constrained choice has no low-cost correction mechanism, and its consequences compound over an entire career.

This paper overcomes these challenges by exploiting the sharp eligibility rules of two nationwide merit- and need-based financial aid programs in Colombia — *Ser Pilo Paga* (2014–2017) and its successor *Generación E Excelencia* (2018–2019) — which offered forgivable loans covering full tuition at accredited high-quality universities for high-achieving, low-income students. Colombia’s higher education system is particularly well-suited to study this question: admissions are decentralized, students must commit to a specific institution–field combination at the point of enrollment, and tuition costs vary substantially across fields and program types — a setting where financial constraints are plausibly binding at the moment of field and track choice, and where the consequences of constrained choices are amplified by the rigidity of early specialization. Eligibility for the programs was determined jointly by performance on the *Saber 11* national exit exam and by a socioeconomic poverty



index (SISBEN), generating two complementary regression discontinuity designs that compare students just above and just below each eligibility threshold, conditioning on the other dimension. I implement these designs separately for each cohort from 2014 to 2019, using administrative microdata linking high school exam scores to postsecondary enrollment records and labor market outcomes for more than 500,000 high school seniors per year.

The results document large and statistically significant effects on higher education enrollment for the early cohorts, with eligibility raising enrollment probabilities by 21–25 percentage points across the 2014–2017 cohorts, consistent with prior evidence ([Londoño-Vélez et al., 2020, 2025](#)). These extensive-margin effects attenuate sharply as the academic threshold tightened from the 91st to the 98th percentile of the national score distribution, reaching zero by 2018. Turning to field-of-study and program track choices conditional on enrollment, the results reveal reallocation along two distinct margins. Within fields, eligibility shifts students from vocational to professional programs, most clearly in engineering where vocational enrollment falls by 78–100 percent relative to the baseline across the 2014–2017 cohorts, accompanied by increases in professional engineering enrollment of 15–24 percent above the baseline. Across fields, eligibility consistently reduces education sciences enrollment by 35–52 percent relative to the baseline across all six cohorts, while increasing enrollment in social and human sciences and fine arts professional programs. In economics and administration, vocational enrollment declines sharply without a corresponding professional increase, pointing to cross-field reallocation.

These reallocations are toward college–major combinations with stronger expected labor market outcomes. Expected monthly salaries associated with the chosen college–major combination increase by 10–14 percent at one year after graduation across the 2014–2017 cohorts, with significant effects on five-year salaries and formal sector employment rates. Since these outcomes reflect averages at the college–major level rather than individual earnings, they are best interpreted as evidence that eligibility shifted students toward programs whose graduates systematically earn more — not as evidence of individual wage gains. The consistency of the salary effects across the one- and five-year horizons suggests that this reallocation is toward programs with persistently stronger labor market returns, rather than programs that



offer a temporary earnings advantage at entry.

The interpretation of these field-of-study responses requires care because the large extensive-margin effects imply that the enrolled sample includes both always-takers — students who would have enrolled regardless of eligibility — and compliers — students newly induced into higher education by the scholarship. The observed patterns of field and track choice therefore reflect a combination of intensive-margin adjustments among always-takers and the initial field-of-study decisions of newly induced entrants. To shed light on the contribution of each margin, I complement the main results with two exercises: Lee bounds on the intensive-margin effects (Lee, 2009), and RD estimates re-estimated on a subsample of predicted always-takers identified using a gradient boosted tree model trained on the 2013 pre-program cohort. Both exercises suggest that the documented reallocation is not driven solely by the choices of newly induced entrants, and that always-takers also adjusted their field and track choices in response to eligibility.

This paper contributes directly to three bodies of literature. First, it contributes to the literature on determinants of college major choice (Altonji, 1993; Arcidiacono, 2004; Saks and Shore, 2005; Zafar, 2013; Wiswall and Zafar, 2014; Leighton and Speer, 2024; Hampole, 2024) by providing quasi-experimental evidence on how merit-and-need-based financial aid affects field-of-study choices, identifying financial constraints as an independent determinant of specialization that operates separately from ability and preferences. Second, it contributes to the literature on financial aid and upward mobility (Dynarski and Scott-Clayton, 2013; Bettinger et al., 2019; Denning et al., 2019; Nguyen, 2019; Scott-Clayton and Zafar, 2019; Black et al., 2023; Londoño-Vélez et al., 2020, 2025) by showing that financial aid allows students not only to access higher education but to enroll in higher-return fields and program tracks, documenting a channel through which scholarships generate long-run earnings gains beyond the returns to college attendance alone. Third, it extends the literature on college decisions of high-achieving low-income students (Hoxby and Avery, 2012; Hoxby and Turner, 2013; Dynarski et al., 2021) to a middle-income country setting where, beyond behavioral and informational barriers, binding financial and credit constraints continue to play a first-order role in determining which programs students can access.



More broadly, the findings inform debates about human capital misallocation and the design of education finance policy. The evidence that financial constraints push students toward lower-cost, lower-return programs — and that relaxing them induces reallocation toward programs with better labor market prospects — suggests that the welfare consequences of credit constraints in education extend beyond the extensive margin of college access. In higher education systems characterized by early specialization, decentralized admissions, and variation in program costs, demand-side subsidies may generate efficiency gains not only by expanding access but by improving the match between student ability and program choice. These considerations are particularly relevant in middle-income countries where supply-side capacity constraints limit the scope for institutional expansion, and where targeted financial aid may offer a cost-effective mechanism for improving the allocation of human capital.

The remainder of the paper is organized as follows. Section 2 provides background on the scholarship programs and the Colombian higher education system, and describes the data. Section 3 outlines the empirical strategy. Section 4 presents the main results. Section 5 concludes.

2 Context and Data

2.1 The Colombian Higher Education System

Colombia's higher education system is characterized by early specialization, decentralized admissions, and significant variation in tuition costs and institutional quality. Unlike the liberal arts model prevalent in the United States, students in Colombia must apply directly to *college-major* pairs, often at a young age and under conditions of uncertainty. This institutional structure restricts flexibility in switching fields and amplifies the consequences of early choices.

Higher education in Colombia enrolled between 2.2 and 2.4 million undergraduate students over the 2014–2019 period, corresponding to gross enrollment rates of between 50 and 54 percent of the population aged 17 to 21. Enrollment is split between two broad program



types that differ substantially in their orientation and duration. Professional university programs (*nivel universitario*), lasting four to five years, account for approximately two thirds of total undergraduate enrollment, reaching 1.37 million students in 2014 and growing to 1.55 million by 2019. Vocational programs, comprising short-cycle technical (*técnica profesional*, one to two years) and technological (*tecnológica*, two to three years) credentials, account for the remaining third, with combined enrollment of approximately 711,000 students in 2014. The distinction between the two tracks is not merely one of duration: professional programs provide comprehensive disciplinary training and lead to a university degree, while vocational programs are designed around specific occupational competencies and oriented toward direct entry into the labor market. Enrollment is divided approximately equally between the public and private sectors, with official institutions accounting for 51 percent of total enrollment.

All programs, regardless of track, are classified by the Ministry of Education into eight *áreas del conocimiento* (knowledge areas) — Agronomy, Veterinary and Related; Fine Arts; Education Sciences; Health Sciences; Social and Human Sciences; Economics, Administration and Accounting; Engineering, Architecture and Urbanism; and Mathematics and Natural Sciences — each of which maps to a subset of the 55 *Núcleos Básicos del Conocimiento* (NBC) that together constitute the full disciplinary classification of the Colombian higher education system. For example, Agronomy, Veterinary and Related maps to three NBC subcategories, while Engineering, Architecture and Urbanism maps to sixteen. This classification applies uniformly across professional and vocational tracks: within a given NBC, a professional program and a vocational program may exist side by side, offering credentials of different levels and durations within the same disciplinary domain. The key distinction is that while professional programs provide broad disciplinary formation leading to a university degree, vocational programs within the same NBC are oriented toward specific occupational competencies directly linked to labor market tasks. For instance, within the NBC for Economics, a student may choose between a five-year university degree in Economics and a one-year vocational credential such as Technical Certificate in Commercial Processes (*Técnica Profesional en Procesos Comerciales*), a program designed to train students for specific clerical and commercial occupations rather than for broad professional practice. Appendix Tables [A.1](#) and [A.2](#) summarize the eight knowledge areas with their NBC subcategories and provide

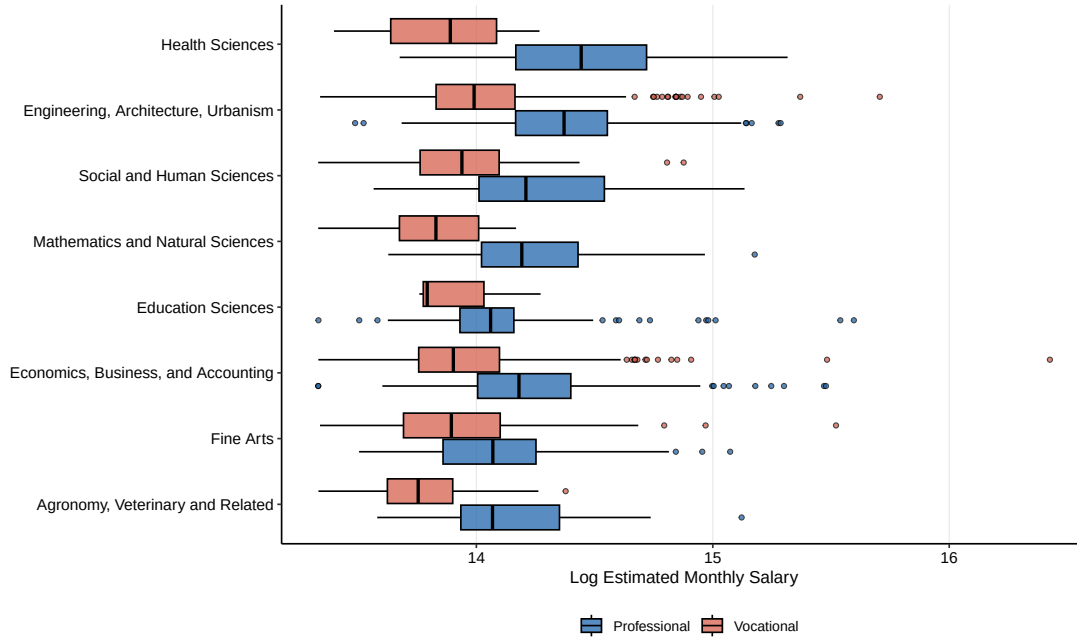


illustrative examples of professional–vocational pairs within the same NBC.

Admissions are decentralized and highly reliant on performance in the national standardized high school exit exam *Saber 11* (OECD, 2012). This exam, administered by the Colombian Institute for the Evaluation of Education (ICFES), is taken by most high school seniors as a requirement for graduation under Colombian law, regardless of their intention to pursue tertiary education. It assesses competencies in critical reading, mathematics, social studies, natural sciences, and English, and plays a central role in admissions decisions across higher education institutions. Unlike the SAT in the United States, which is optional and used in conjunction with holistic criteria, *Saber 11* often serves as the sole admissions criterion in many public and private universities. There is no centralized application platform or calendar: each institution defines its own admissions processes, deadlines, and score thresholds, creating a complex landscape for applicants who must monitor and apply to multiple institutions independently.

Figure 1 documents the heterogeneity in expected earnings across field and program type combinations. Expected earnings vary substantially not only across fields but also within fields across tracks: professional programs are associated with systematically higher salaries than vocational programs in the same field at one year after graduation, with the gap particularly pronounced in health sciences, engineering, architecture and urbanism, and economics, administration and accounting. These differences are not transitory: Figure A.1 in the appendix shows that the salary advantage of professional over vocational programs within the same field persists and in several cases widens at five years after graduation. Engineering and Math and Natural Sciences exhibit the largest gaps at the five-year horizon. Together, these patterns indicate that both the field of study and the track chosen at enrollment carry lasting consequences for expected labor market outcomes — consequences that are not reducible to either dimension alone and that persist well beyond the point of graduation.

FIGURE 1: Expected Log Monthly Salary by Field and Program Type (1 Year After Graduation)

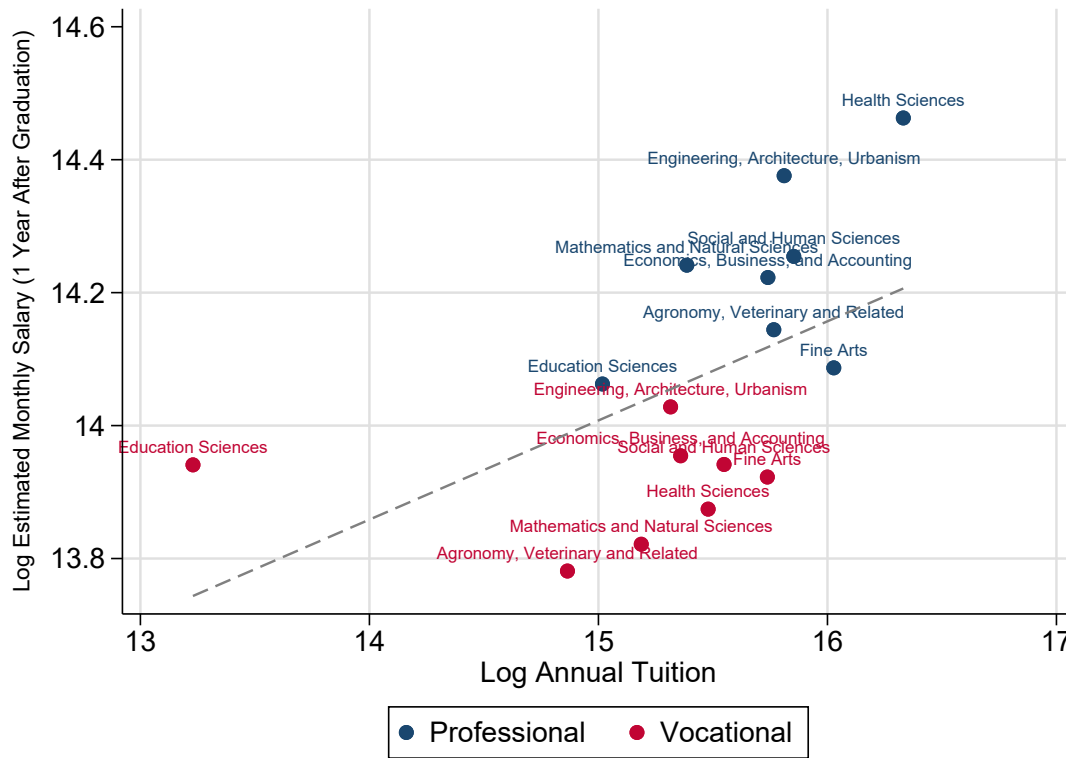


Notes: Each observation represents the average log monthly salary across all college–major combinations within a given field and program type. Salary data are from the Observatorio Laboral para la Educación (OLE) and reflect average earnings among graduates at one year after graduation. See Figure A.1 in the appendix for the corresponding figure at five years after graduation.

The cost structure of higher education further complicates both access and program choice. Public universities offer tuition that is either free of charge or subsidized and scaled according to family income, with some students paying as little as 10 percent of the monthly minimum wage. However, these institutions tend to be highly selective and frequently over-subscribed, limiting access for many low-income students despite their favorable cost structure. Tuition at private universities can exceed 13 times the monthly minimum wage and varies substantially by field of study and institution (Bonilla-Mejía et al., 2019). This variation in costs is not random: Figure 2 shows a clear positive association between log annual tuition and expected log monthly salary at one year after graduation across field–track combinations, with professional programs clustering at higher tuition and higher expected earnings relative to vocational programs, and this pattern holding within fields as well as across them. Programs associated with better labor market prospects therefore require larger upfront financial investments, so that low-income students who face binding liquidity constraints at the time of enrollment may be systematically pushed toward lower-cost, lower-return pro-

grams — not because of preferences or ability, but because of the financial barriers that higher-return options impose.

FIGURE 2: Expected Log Monthly Salary versus Log Annual Tuition by Field and Program Type



Notes: Each observation represents the average log monthly salary and average log annual tuition across all college–major combinations within a given field and program type. Salary data are from the Observatorio Laboral para la Educación (OLE) and reflect average earnings among graduates at one year after graduation. Tuition data are from SNIES (Sistema Nacional de Información de la Educación Superior). Professional programs are represented by solid markers and vocational programs by hollow markers.

2.2 The Ser Pilo Paga and Generación E Programs

To address persistent inequality in access to high-quality tertiary education, the Colombian government launched the *Ser Pilo Paga* (SPP) program in 2014. The program aimed to expand access for high-achieving, low-income students by providing full financial aid to attend any accredited “high-quality” university in the country, whether public or private. SPP was one of the most ambitious and well-publicized education reforms in Colombia in the past decade, reaching more than 40,000 students between 2014 and 2017.



Eligibility for SPP was determined by a combination of academic performance, socioeconomic status, and university admission. First, students were required to score above a threshold on the *Saber 11* national exit exam. This threshold varied across cohorts, increasing from 310 points for the 2014 cohort — corresponding to the 91.1st percentile of the national score distribution — to 318 points (91.8th percentile) for the 2015 cohort, 342 points (95.7th percentile) for the 2016 cohort, and 348 points (96.8th percentile) for the 2017 cohort. Second, students had to fall below a poverty threshold in SISBEN, Colombia’s proxy means-testing system used to target social programs; these SISBEN eligibility cutoffs remained unchanged during the period of analysis. Finally, students were required to gain admission to a university with High-Quality Accreditation, a certification granted by the Ministry of Education. Loans awarded through SPP were fully forgiven upon graduation, effectively transforming the program into a merit- and need-based scholarship. Between 2014 and 2017, approximately 10,000 scholarships were awarded each year, reaching a substantial share of high-achieving students from low-income households.

Following the election of President Iván Duque in 2018, SPP was replaced by *Generación E* (Generation E), launched in October 2018 and operational from 2019 onwards. The new program preserved the core structure of SPP — providing forgivable loans covering full tuition at accredited institutions for high-achieving, low-income students — while introducing two distinct components. The *Excelencia* (Excellence) component closely mirrors SPP, targeting students who achieve high scores on the *Saber 11* exam and meet the SISBEN socioeconomic criterion, offering forgivable loans at both public and private accredited institutions. The *Equidad* (Equity) component, by contrast, focuses on broader access by covering tuition costs at public institutions for students from low-income households, without imposing an academic performance threshold. For the purposes of this paper, the relevant component is *Excelencia*, which preserves the eligibility rules that allow for the regression discontinuity identification strategy employed here.

Under *Generación E Excelencia*, the *Saber 11* academic eligibility threshold was set at 359 points for the 2018 cohort — corresponding to the 98.2nd percentile of the national score distribution — and reduced to 350 points (97.5th percentile) for the 2019 cohort. As under



SPP, the SISBEN socioeconomic thresholds remained unchanged. The progressive increase in the academic cutoff across the full duration of the two programs — from the 91.1st percentile in 2014 to the 98.2nd percentile in 2018 — reflects a systematic tightening of eligibility criteria that concentrated the scholarship population increasingly among high-achieving students who would likely have accessed higher education regardless of financial support.

Figure 3 illustrates the distribution of *Saber 11* scores together with the eligibility cutoffs for each cohort from 2014 to 2019. The academic eligibility threshold shifts progressively to the right over time, reflecting the changes in program criteria described above, and the share of students qualifying under the academic criterion declines correspondingly as the cutoff increases across cohorts. Figure 4 displays the distribution of SISBEN III scores and the corresponding poverty thresholds used to determine socioeconomic eligibility. In contrast to the *Saber 11* cutoff, these thresholds remain fixed over time but vary by geographic classification. Students residing in the 14 largest metropolitan areas and in other urban municipalities must have SISBEN scores below 57.21 and 56.32 respectively, while students in rural areas qualify with scores below 40.75. These thresholds reflect the program's targeting of economically disadvantaged students while accounting for differences in the distribution of poverty across geographic areas.

FIGURE 3: Distribution of Saber 11 as running variable and eligibility thresholds

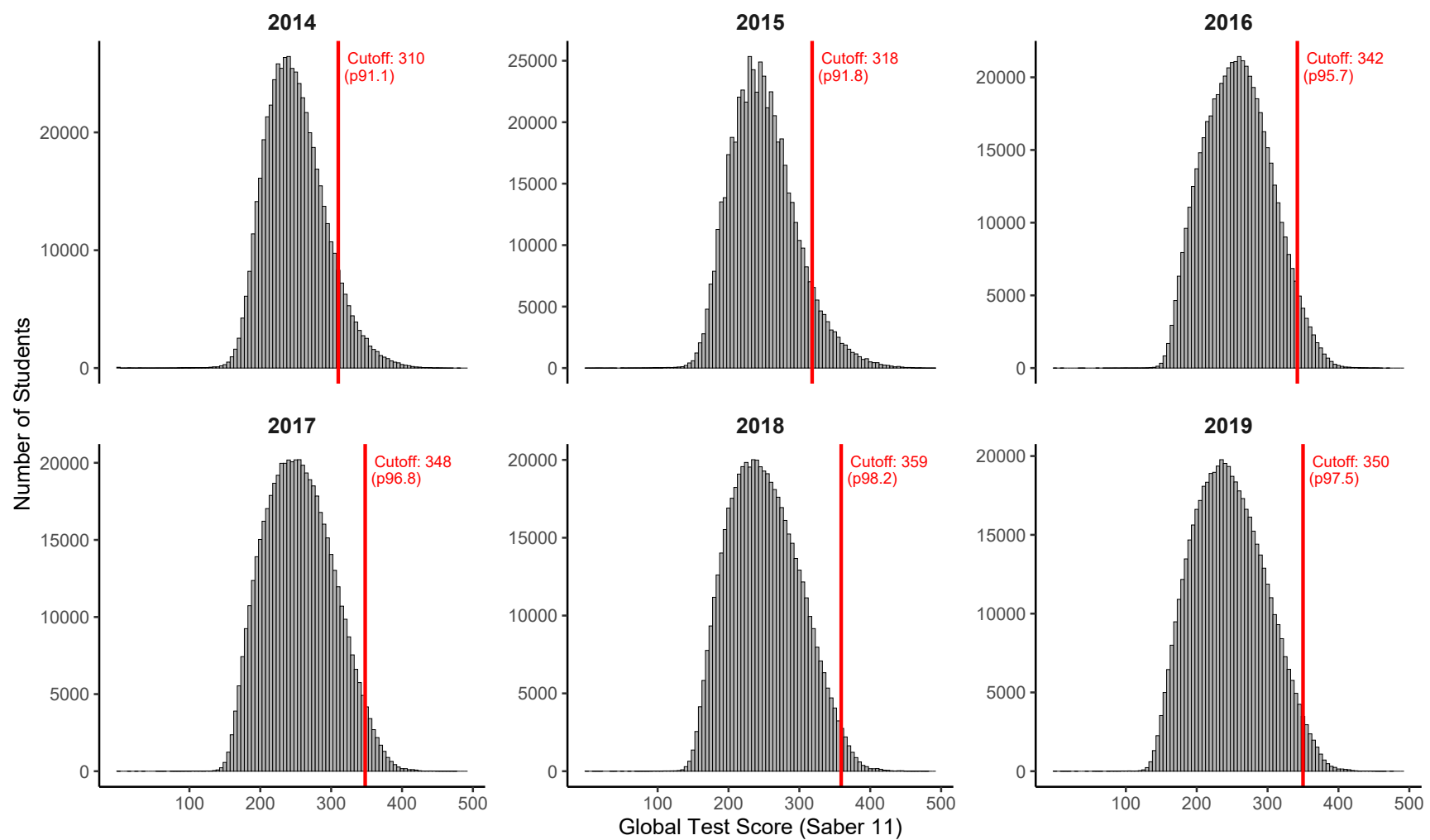
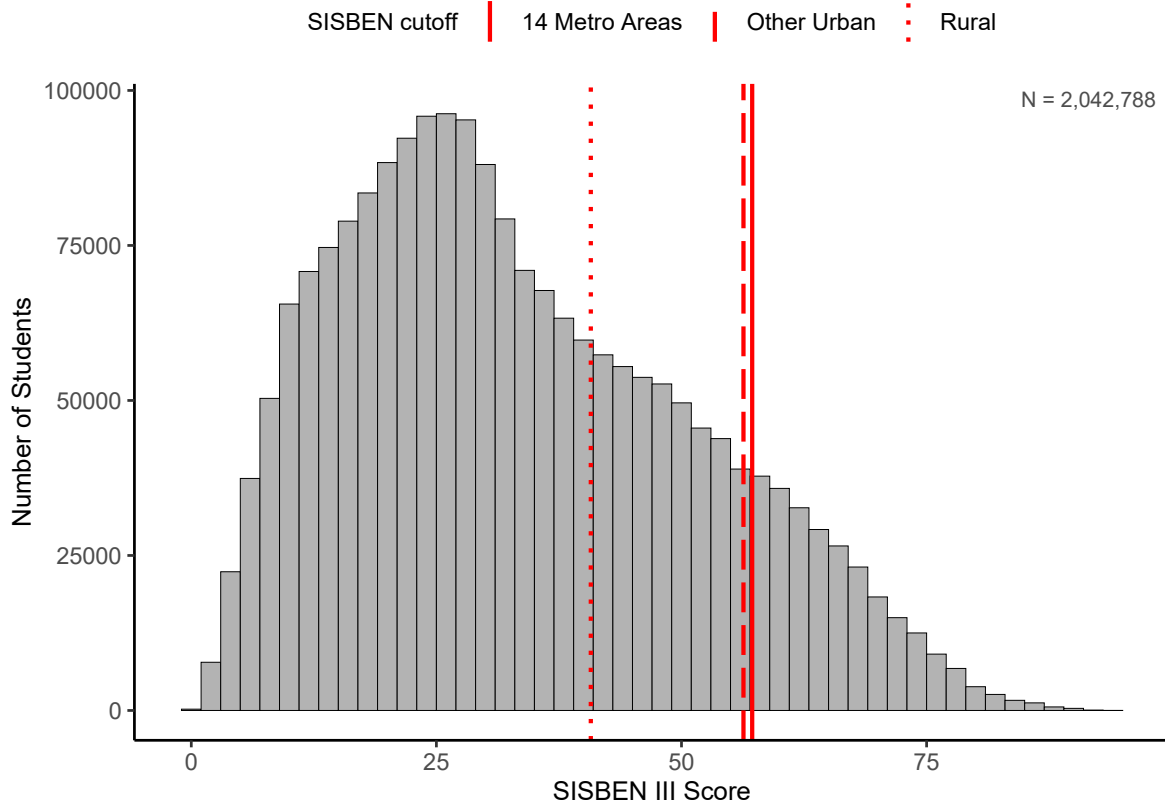


FIGURE 4: Distribution of SISBEN as running variable and eligibility thresholds



2.3 Data

The starting point is the universe of high school seniors who took the national standardized high school exit exam, *Saber 11*, between 2014 and 2019. These data are obtained from the Instituto Colombiano para la Evaluación de la Educación (ICFES), the national agency responsible for administering standardized tests in Colombia. The dataset includes detailed information on test scores, demographic characteristics (e.g., gender, parental education, household size, and socioeconomic stratum), and geographic location. Each cohort includes more than 500,000 students nationwide.

To identify students who were eligible for the scholarship programs based on socioeconomic status, the *Saber 11* records are merged with data from SISBEN, the Colombian government's proxy means-testing system used to target social programs. This merge was carried out by ICFES as part of a research partnership, ensuring accurate identification of



the eligible population using official thresholds across all six cohorts.

The administrative microdata combining *Saber 11* scores and SISBEN records are then linked to postsecondary enrollment records from SNIES (Sistema Nacional de Información de la Educación Superior), maintained by the Ministry of Education, covering the first semesters of 2015 through 2020. SNIES provides semester-level information on whether students enrolled in higher education, and if so, the institution, degree program, field of study, and program type. This linkage allows the construction of the primary outcomes of interest: students' first enrollment decision in a specific college–major pair, the field of study chosen, and the track of the program — professional or vocational — in which they enrolled.

Finally, the enrollment data are complemented with college–major level labor market outcomes from the Observatorio Laboral para la Educación (OLE), which tracks graduates of each college–major combination in the formal labor market. For each college–major pair, the OLE data provide average formal sector labor force participation rates and average monthly salaries at one and five years after graduation. These outcomes are merged to the enrollment records at the college–major level, so that each enrolled student is assigned the average labor market outcomes observed among graduates of their chosen program. These variables are used to assess whether scholarship eligibility induced students to select into college–major combinations with better expected labor market prospects.

Table 1 presents summary statistics for the population of high school seniors who took the *Saber 11* exam between 2014 and 2019. Each cohort includes more than 500,000 students nationwide, with the gender composition remaining stable throughout — approximately 55 percent female in the 2014–2017 cohorts and 54 percent in 2018 and 2019. The average *Saber 11* score fluctuates modestly across cohorts, ranging from 246 in 2019 to 258 in 2016, with substantial within-cohort variation reflected in standard deviations of approximately 43 to 51 points. Students come from predominantly low socioeconomic backgrounds: between 32 and 46 percent belong to stratum 1 — the lowest category — and between 34 and 38 percent belong to stratum 2, together accounting for more than 70 percent of the student population in every cohort. Mean SISBEN III scores range from approximately 32 to 37 and decline

TABLE 1: Summary Statistics: High School Senior Cohorts 2014–2019

	2014	2015	2016	2017	2018	2019
Female student (1 = female)	0.55 (0.50)	0.55 (0.50)	0.55 (0.50)	0.55 (0.50)	0.54 (0.50)	0.54 (0.50)
Global test score (Saber 11)	249.98 (42.99)	249.84 (46.92)	258.24 (47.37)	255.23 (48.48)	250.78 (50.09)	246.19 (51.39)
Socioeconomic stratum (%)						
Stratum 1	42.5	44.5	45.6	34.6	34.2	32.3
Stratum 2	34.8	34.5	34.2	37.4	37.9	38.1
Stratum 3	17.6	16.5	15.8	20.7	20.9	22.0
Stratum 4	3.5	3.3	3.1	4.8	4.7	5.2
Stratum 5	1.0	0.9	0.9	1.6	1.5	1.6
Stratum 6	0.4	0.4	0.4	0.8	0.7	0.8
SISBEN III score	36.52 (18.21)	34.43 (18.24)	33.11 (18.00)	32.23 (17.78)	31.93 (17.49)	32.75 (17.45)
Eligible via ICFES criteria (1 = yes)	0.09 (0.29)	0.08 (0.28)	0.05 (0.21)	0.03 (0.18)	0.02 (0.13)	0.03 (0.16)
Eligible via SISBEN criteria (1 = yes)	0.47 (0.50)	0.51 (0.50)	0.54 (0.50)	0.54 (0.50)	0.56 (0.50)	0.58 (0.49)
Eligible via SPP criteria (1 = yes)	0.03 (0.16)	0.03 (0.17)	0.02 (0.13)	0.01 (0.12)	0.01 (0.08)	0.01 (0.09)
Enrolled in higher education (1 = yes)	0.19 (0.39)	0.20 (0.40)	0.22 (0.41)	0.20 (0.40)	0.20 (0.40)	0.21 (0.41)
Observations	549,638	546,657	548,205	546,261	549,934	546,212



modestly over the sample period.

Eligibility for the scholarship programs varies substantially across cohorts, primarily driven by changes in the academic threshold. The share of students meeting the *Saber 11* academic criterion declines from 9 percent in 2014 to 2 percent in 2018, as the *Saber 11* cutoff rose from 310 to 359 points, before recovering marginally to 3 percent in 2019 following the reduction of the cutoff to 350 points. The share of students satisfying both eligibility conditions jointly — and thus qualifying for the scholarship — declines from 3 percent in 2014 and 2015 to 1 percent in 2017 through 2019, consistent with the progressive tightening of the academic criterion. Finally, between 19 and 22 percent of students enroll in higher education in the semester immediately following the *Saber 11* examination, with no clear trend across the sample period.

Table 2 reports the distribution of fields of study among students who enroll in higher education in the semester immediately following high school graduation for the 2014–2019 cohorts. Engineering, architecture, and urbanism is the largest field throughout, accounting for 36 percent of enrollments in 2014 and 2015 before declining modestly to 33–35 percent in later cohorts. Economics, business, and accounting is the second largest category, with enrollment shares ranging from 23 percent in 2014 and 2015 to 27 percent in 2019. Social and human sciences account for approximately 19–21 percent of enrollments across cohorts.

Other fields attract smaller and broadly stable fractions of students. Health sciences account for 6–7 percent of enrollments, education sciences for 5–6 percent, and fine arts and agronomy and veterinary programs each for approximately 3–4 percent. Mathematics and natural sciences represent the smallest category, with a share of 2 percent in the early cohorts rising modestly to 3 percent by 2017. Overall, the distribution of field choices remains broadly stable across cohorts, suggesting that aggregate preferences for fields of study do not change substantially over the sample period in the overall population.

Tables A.3 and A.4 in the appendix report the distribution of enrolled students across field and program type combinations. As mentioned in a previous section, Colombian higher



education institutions offer two broad types of programs that differ substantially in their orientation and duration. Professional programs, lasting four to five years, provide comprehensive disciplinary training and lead to a university degree (*título universitario*), preparing graduates for careers that require specialized theoretical and analytical competencies. Vocational programs, lasting one to two years, are designed around specific occupational competencies and lead to technical (*técnico profesional*) or technological (*tecnólogo*) credentials, as defined by the Ministry of Education. The distinction between the two tracks is therefore not merely one of duration but of educational purpose: professional programs emphasize broad disciplinary formation, while vocational programs are oriented toward the direct acquisition of labor market skills in a specific occupation.

TABLE 2: Distribution of Higher Education Field Choices: High School Cohorts 2014–2019

	2014	2015	2016	2017	2018	2019
Social and Human Sciences	0.20 (0.40)	0.21 (0.41)	0.19 (0.39)	0.20 (0.40)	0.20 (0.40)	0.19 (0.39)
Mathematics and Natural Sciences	0.02 (0.15)	0.02 (0.15)	0.02 (0.16)	0.03 (0.16)	0.03 (0.17)	0.03 (0.17)
Health Sciences	0.06 (0.24)	0.06 (0.24)	0.06 (0.24)	0.07 (0.25)	0.07 (0.25)	0.06 (0.25)
Engineering, Architecture, Urbanism	0.36 (0.48)	0.36 (0.48)	0.35 (0.48)	0.33 (0.47)	0.34 (0.47)	0.33 (0.47)
Education Sciences	0.06 (0.24)	0.06 (0.23)	0.05 (0.23)	0.05 (0.21)	0.06 (0.23)	0.06 (0.23)
Economics, Business, and Accounting	0.23 (0.42)	0.23 (0.42)	0.26 (0.44)	0.26 (0.44)	0.24 (0.43)	0.27 (0.44)
Fine Arts	0.04 (0.19)	0.03 (0.18)	0.03 (0.18)	0.03 (0.18)	0.04 (0.19)	0.04 (0.19)
Agronomy, Veterinary and Related	0.03 (0.16)	0.03 (0.16)	0.03 (0.17)	0.03 (0.17)	0.03 (0.16)	0.03 (0.17)
Observations	103,397	108,860	120,660	108,745	112,711	117,430

Tables A.3 and A.4 report the distribution of enrolled students across field and program type combinations. Engineering, architecture, and urbanism is the largest field overall, accounting for 33–36 percent of all enrolled students (Table 2), with approximately two thirds of those students enrolled in professional programs and the remaining third in vocational programs. Economics, administration, and accounting follows a similar pattern: the field ac-



counts for 23–27 percent of total enrollments, split roughly equally between professional and vocational tracks, with vocational programs accounting for 10–15 percent of all enrolled students across cohorts. These two fields together absorb the majority of vocational enrollment, reflecting the occupational orientation of vocational credentials in business administration, accounting, and technology-related programs, which map naturally onto specific clerical, commercial, and technical occupations for which short-cycle credentials are well recognized by employers.

The remaining fields are enrolled almost exclusively through the professional track. Social and human sciences accounts for 19–21 percent of total enrollments, virtually all in professional programs, given the near-complete absence of vocational offerings in this field. Education sciences and health sciences each represent approximately 5–6 percent of total enrollments, again concentrated in professional programs, with vocational counterparts at or near zero. The same pattern holds for fine arts, mathematics and natural sciences, and agronomy and veterinary programs, each accounting for 1–4 percent of total enrollments with negligible vocational participation.

3 Empirical Strategy

To estimate the impact of financial aid eligibility on students' field-of-study choices, I exploit the sharp assignment rules of the *Ser Pilo Paga* (SPP) and *Generación E Excelencia* programs and implement a pair of one-dimensional regression discontinuity (RD) designs. These designs take advantage of two distinct but simultaneously required eligibility conditions: an academic condition based on performance on the *Saber 11* national exit exam, and a socioeconomic condition based on the SISBEN poverty index. The socioeconomic SISBEN thresholds remained fixed throughout the sample period. The academic *Saber 11* threshold, by contrast, was adjusted each year by program administrators across both programs, as described above. In each cohort, I exploit the cohort-specific threshold as a sharp discontinuity, so that the identification strategy is applied separately within each year using the threshold that was actually in force for that cohort.



Eligibility for the scholarship programs was determined by a two-part rule: students needed to score above a cohort-specific threshold on the academic *Saber 11* exam and fall below a poverty threshold defined by the socioeconomic SISBEN index. I exploit this rule by estimating two separate sharp RD designs. In the first design, I use *Saber 11* scores as the running variable, restricting the sample to students who satisfy the socioeconomic SISBEN criterion. This design identifies the causal effect of crossing the academic *Saber 11* threshold among socioeconomically eligible students. In the second design, I use the SISBEN index as the running variable, restricting the sample to students who satisfy the academic *Saber 11* threshold. This design identifies the causal effect of crossing the socioeconomic SISBEN threshold among academically qualified students. Each design compares students just above and just below the relevant eligibility threshold, holding the other eligibility dimension fixed, and is estimated separately for each cohort. The reported estimates are robust bias-corrected intent-to-treat (ITT) effects. The primary outcomes of interest are binary indicators for higher education enrollment, field-of-study choice, and program type — professional or vocational — in which students first matriculate, as well as the average formal sector labor force participation rate and average log monthly salary associated with the college-major combination chosen by each student.

The credibility of the RD designs rests on the assumption that students cannot precisely manipulate their position relative to either threshold. The academic *Saber 11* threshold is determined by a national standardized exam administered under controlled conditions, making precise manipulation unlikely. The socioeconomic SISBEN threshold is based on a proxy means-testing score constructed from household characteristics, which students have limited ability to manipulate in the short run. Appendix A.2 presents graphical and formal evidence supporting both identifying assumptions, including continuity tests for the density of both running variables at their respective eligibility thresholds using the `rddensity` procedure of Cattaneo et al. (2020). These diagnostics are consistent with the design validity evidence reported in Londoño-Vélez et al. (2020) and Londoño-Vélez et al. (2025), who implement the same RD designs using the cohorts of the *Ser Pilo Paga* and Gen E program and find no evidence of systematic manipulation around either threshold.



An important consideration for the interpretation of the field-of-study results concerns the composition of students at the eligibility margin. Because scholarship eligibility substantially increases higher education enrollment, the estimated effects on field-of-study choices conditional on enrollment reflect a combination of two distinct behavioral responses: adjustments in the field-of-study choices of students who would have enrolled regardless of financial aid — the always-takers — and the initial field-of-study decisions of students who were induced into higher education by the scholarship — the compliers. The conditional estimates presented in this paper should therefore be interpreted as causal effects that combine both margins, rather than as estimates of either margin in isolation.

To shed light on the contribution of each margin, Appendix [A.3](#) presents two exercises aimed at isolating the effects on the always-taker population. First, I apply the Lee bounds approach of [Lee \(2009\)](#) to construct sharp bounds on the intensive-margin effects that are robust to the selection problem introduced by conditioning on enrollment, without requiring assumptions about the identity of always-takers. Second, I directly approximate the always-taker population using a neural network trained on the 2013 pre-program cohort — for whom no scholarship was available and enrollment therefore reflects unconstrained choices — to predict the probability of higher education enrollment as a function of observable student characteristics. Students in the 2014–2019 cohorts whose predicted enrollment probability exceeds the 2013 baseline enrollment rate are classified as predicted always-takers, and the RD estimates are re-estimated on this subsample using both the academic *Saber 11* threshold and the socioeconomic SISBEN threshold as running variables.

4 Results

Extensive-Margin Effects on Higher Education Enrollment

Figure [5](#) presents the estimated effects of scholarship eligibility on the probability of enrolling in higher education in the semester immediately following the *Saber 11* examination, using both the *Saber 11* academic threshold and the SISBEN socioeconomic threshold as running variables. The figure reveals that effects are large and precisely estimated for the early co-

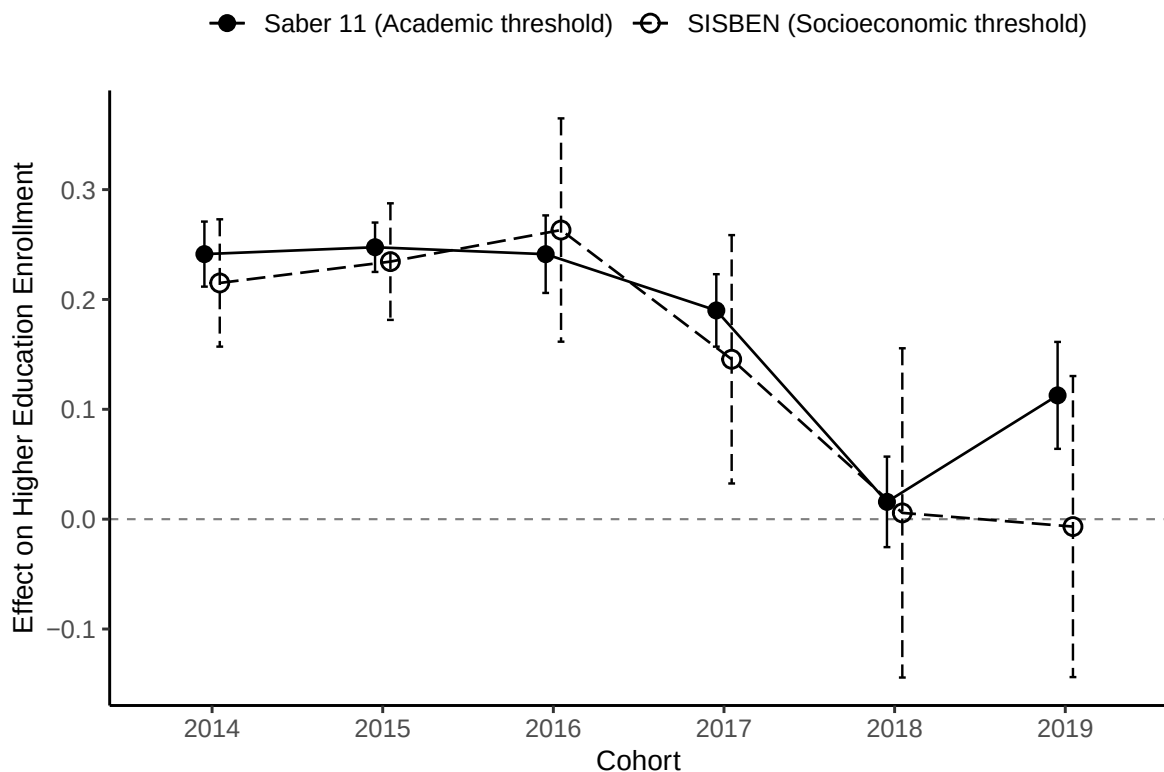


horts of the program, decline progressively as eligibility criteria tighten, and are statistically indistinguishable from zero by 2018. Table 3 reports the underlying point estimates, control group means, and effective sample sizes for each cohort.

The results document large and statistically significant enrollment effects for the early cohorts of the program. Under the Saber 11 threshold, eligibility raises the probability of enrolling in higher education by 24.1 percentage points for the 2014 cohort, 24.8 percentage points for the 2015 cohort, and 24.1 percentage points for the 2016 cohort. These estimates are economically substantial. Given control group means of 0.342, 0.423, and 0.516 for those cohorts respectively, the implied enrollment increases relative to the baseline rate are approximately 70, 59, and 47 percent. The SISBEN-based estimates are broadly consistent, yielding effects of 21.5, 23.4, and 26.3 percentage points for the same cohorts, again large relative to control group means ranging between 0.422 and 0.523.

The pattern changes markedly in later cohorts, as shown in Figure 5 and confirmed by the estimates in Table 3. For the 2017 cohort, effects remain positive and statistically significant at 19.0 and 14.6 percentage points under the Saber 11 and SISBEN thresholds respectively, though attenuated relative to earlier years. By 2018, estimated effects are statistically indistinguishable from zero under both identification strategies.

FIGURE 5: Effects on the extensive margin



This attenuation reflects the progressive tightening of the academic eligibility criterion over the program's duration. The Saber 11 score threshold rose from 310 points in 2014 to 318 in 2015, 342 in 2016, 348 in 2017, and 359 in 2018, corresponding to percentile ranks of approximately 91.1, 91.8, 95.7, 96.8, and 98.2 of the national score distribution. As the cutoff moved further into the right tail of the distribution, eligibility became increasingly concentrated among students with sufficiently strong academic preparation to have accessed higher education independently of the scholarship. The 2019 cohort exhibits a partial recovery, with an effect of 11.3 percentage points under the Saber 11 threshold, consistent with a modest relaxation of the cutoff to 350 points corresponding to the 97.5th percentile which expanded eligibility toward a population with a somewhat larger complier share. The SISBEN-based estimate for 2019 is not statistically distinguishable from zero.

These estimates are broadly consistent with previous evidence on the impacts of the Ser Pilo Paga (SPP) program on higher education access. In particular, [Londoño-Vélez et al.](#)

(2020) and Londoño-Vélez et al. (2025) document large enrollment responses among eligible students. The estimates reported here closely align with those findings across cohorts and identification strategies.

The presence of such large extensive-margin responses has important implications for the interpretation of the results that follow. The analysis in the next section focuses on field-of-study choices conditional on enrollment. However, because the program significantly increased access to higher education, the observed patterns of field choice reflect both intensive-margin adjustments among students who would have enrolled regardless of financial aid and decisions made by newly induced entrants to higher education. In other words, the estimated effects on field choice capture a combination of students switching fields and new enrollees making their field-of-study decision.

TABLE 3: RD ITT Effects on Higher Education Enrollment (Extensive Margin)

	2014	2015	2016	2017	2018	2019
<i>Panel A: Saber 11 (Academic threshold) as running variable</i>						
Higher Education Enrollment	0.241 (0.015)	0.248 (0.011)	0.241 (0.018)	0.190 (0.017)	0.016 (0.021)	0.113 (0.025)
Control group mean	0.342	0.423	0.516	0.496	0.631	0.580
Observations (left of threshold)	17,746	38,678	11,814	18,360	12,840	7,401
Observations (right of threshold)	9,150	12,578	6,599	6,392	3,142	3,557
<i>Panel B: SISBEN (Socioeconomic threshold) as running variable</i>						
Higher Education Enrollment	0.215 (0.030)	0.234 (0.027)	0.263 (0.052)	0.146 (0.058)	0.006 (0.076)	-0.007 (0.070)
Control group mean	0.422	0.492	0.523	0.567	0.684	0.625
Observations (left of threshold)	3,588	4,038	970	841	451	533
Observations (right of threshold)	3,581	4,463	1,189	1,082	577	578

Notes: Robust bias-corrected (RBC) point estimates from `rdrobust`. Robust standard errors in parentheses. Control group mean is the estimated outcome at the threshold on the control side. N left and N right are observations within the optimal bandwidth on each side.

Intensive-Margin Effects on Field of Study Choice

Figure 6 presents the estimated effects of scholarship eligibility on enrollment across field and track combinations, conditional on higher education enrollment, using the Saber 11 academic threshold as the running variable. The figure reveals a pattern of reallocation along two dis-



tinct margins: within certain fields, eligibility induces a shift from vocational to professional tracks, and across fields, it redirects students away from education and toward other professional programs. Table 4 reports the underlying point estimates, control group means, and effective sample sizes for each field, track, and cohort.

The within-field track switching is most clearly documented in engineering, architecture, and urbanism. Eligibility reduces vocational track enrollment across the 2014–2017 cohorts, with effects ranging from 3.4 to 8.6 percentage points and representing reductions of between 78 and 100 percent relative to control group means that decline from 0.107 in 2014 to 0.034 in 2017. Professional engineering enrollment increases over the same horizon, with statistically significant effects in 2014, 2015, and 2019 ranging from 6.9 to 8.6 percentage points — between 15 and 24 percent above control group means of approximately 0.35 to 0.45. Notably, in 2017 the reduction in vocational engineering enrollment of 3.4 percentage points is of comparable magnitude to the increase in professional engineering enrollment, suggestive of a near-complete transition from vocational to professional programs within this field for students at the eligibility margin. A similar but more limited pattern is observed in fine arts, where professional track enrollment increases by between 1.3 and 2.9 percentage points across the 2014–2016 cohorts — representing increases of between 72 and 290 percent relative to control group means that range from 0.010 to 0.019 — while vocational fine arts enrollment declines significantly in 2014, though this effect does not persist in subsequent cohorts.

The evidence for cross-field reallocation is strongest in education sciences, where eligibility reduces professional track enrollment by between 1.7 and 4.6 percentage points across all six cohorts, with the largest effect observed in 2014 and effects remaining statistically significant and negative through 2019, corresponding to declines of between 35 and 52 percent relative to control group means that range from 0.049 to 0.089. The absence of any detectable effect on vocational education enrollment is not surprising: vocational programs in education sciences are virtually nonexistent in the Colombian higher education system, with very few institutions offering credentials at that level and correspondingly negligible baseline enrollment near the threshold. The reduction in education enrollment therefore cannot re-



flect within-field track switching and instead suggests that eligible students are reallocating toward other fields. This interpretation is consistent with the positive effects on professional enrollment documented in social and human sciences — 6.1 and 6.7 percentage points in 2014 and 2017, corresponding to increases of 41 and 44 percent above control group means of 0.149 and 0.152 — and in fine arts and engineering over the same period. As in education sciences, vocational programs in social and human sciences represent a negligible share of the higher education offering in Colombia, so the positive effects on professional enrollment in this field reflect an inflow from other fields rather than within-field track switching.

The pattern in economics, administration, and accounting — a broad field that encompasses programs in economics, business administration, accounting, and related disciplines — is consistent with both mechanisms operating simultaneously. Eligibility reduces vocational track enrollment in this field by between 2.4 and 3.9 percentage points across the 2014–2017 cohorts, representing reductions of between 71 and 95 percent relative to control group means that range from 0.026 to 0.049. Estimated effects on professional economics, administration, and accounting enrollment are not statistically distinguishable from zero across any of the six cohorts, however, indicating that the outflow from vocational tracks in this field does not translate into a detectable increase in professional enrollment within the same field. This asymmetry suggests that students leaving vocational economics and administration tracks are reallocating toward other fields rather than upgrading within the same field, a pattern consistent with the positive effects documented in engineering and social sciences professional programs over the same cohorts.

FIGURE 6: Saber 11 as running variable

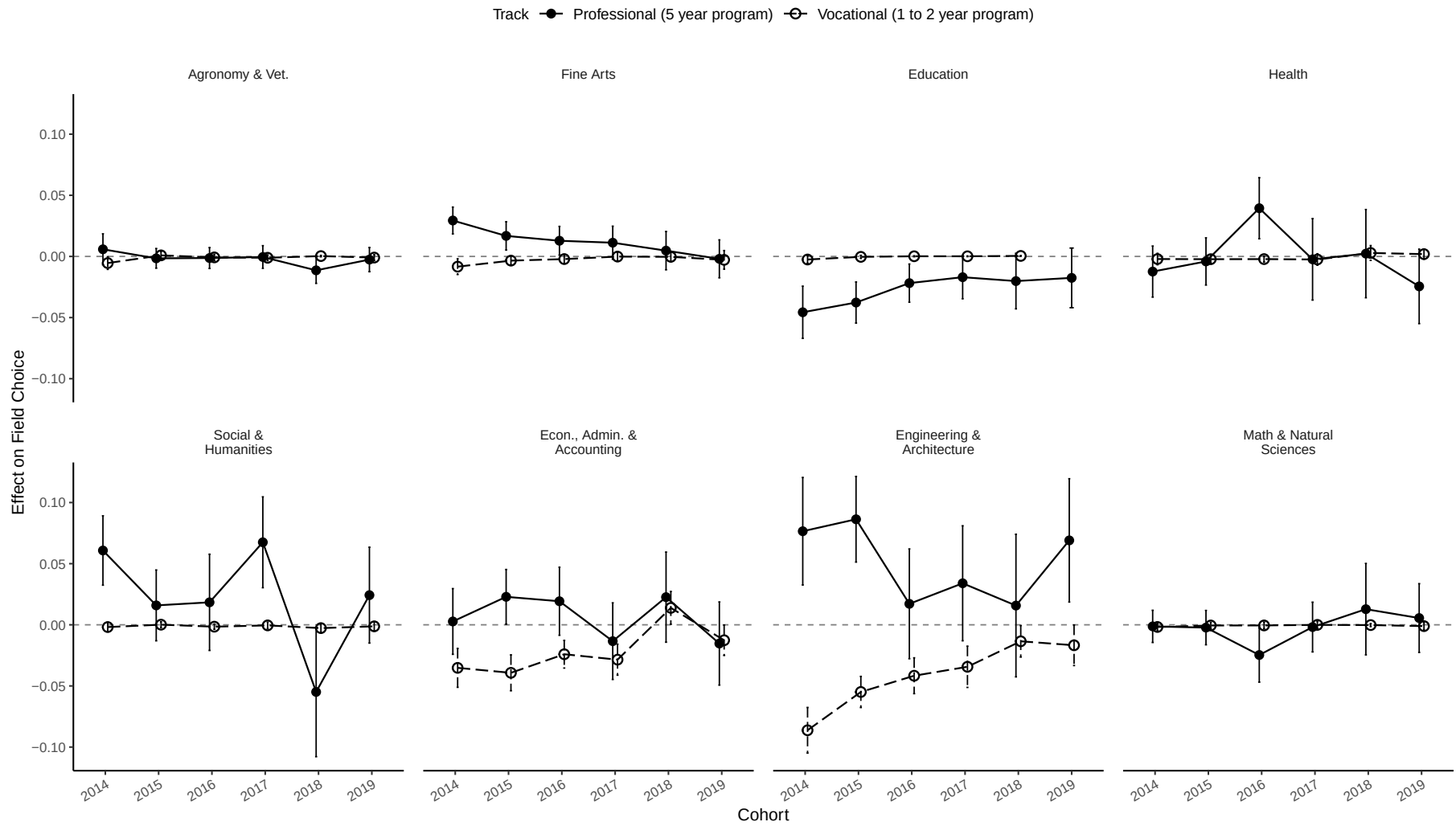


TABLE 4: Intensive-Margin Effects on Field $\times$ Program Type: Saber 11 as Running Variable

	<i>Professional (5 yr)</i>						<i>Vocational (1–2 yr)</i>					
	2014	2015	2016	2017	2018	2019	2014	2015	2016	2017	2018	2019
<i>Notes:</i>												
Agronomy, Veterinary and Related												
Effect	0.006 (0.006)	-0.002 (0.004)	-0.001 (0.004)	-0.000 (0.005)	-0.011 (0.005)	-0.003 (0.005)	-0.005 (0.003)	0.001 (0.002)	-0.001 (0.001)	-0.001 (0.001)	0.000 (0.000)	-0.001 (0.001)
Control mean	0.017	0.018	0.011	0.012	0.010	0.006	0.006	0.000	0.001	0.001	-0.000	0.001
N (left)	6,464	16,619	8,028	8,608	3,204	4,022	7,109	5,907	9,654	5,879	5,714	7,972
N (right)	6,250	9,739	6,059	4,783	1,730	2,565	6,525	6,123	6,494	4,272	2,106	3,255
Fine Arts												
Effect	0.029 (0.006)	0.017 (0.006)	0.013 (0.006)	0.011 (0.007)	0.005 (0.008)	-0.002 (0.008)	-0.008 (0.003)	-0.003 (0.002)	-0.002 (0.002)	-0.000 (0.002)	-0.000 (0.002)	-0.003 (0.004)
Control mean	0.010	0.019	0.018	0.017	0.015	0.020	0.010	0.004	0.004	0.001	0.001	0.005
N (left)	8,721	10,889	10,488	7,310	7,223	5,709	7,527	9,749	8,791	10,393	8,829	4,526
N (right)	7,044	8,417	6,674	4,556	2,202	2,989	6,647	8,031	6,285	4,949	2,275	2,718
Education Sciences												
Effect	-0.046 (0.011)	-0.038 (0.009)	-0.022 (0.008)	-0.017 (0.009)	-0.020 (0.012)	-0.018 (0.012)	-0.003 (0.002)	-0.000 (0.001)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	
Control mean	0.089	0.077	0.051	0.049	0.057	0.052	0.002	0.000	-0.000	-0.000	-0.000	
N (left)	7,744	10,889	9,210	7,310	7,821	4,526	9,134	7,629	5,399	5,623	55,519	
N (right)	6,723	8,417	6,391	4,556	2,238	2,718	7,150	7,079	5,091	4,165	2,506	

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	<i>Professional (5 yr)</i>						<i>Vocational (1–2 yr)</i>					
	2014	2015	2016	2017	2018	2019	2014	2015	2016	2017	2018	2019
Health Sciences												
Effect	-0.012 (0.011)	-0.004 (0.010)	0.039 (0.013)	-0.002 (0.017)	0.002 (0.018)	-0.024 (0.016)	-0.002 (0.002)	-0.002 (0.002)	-0.002 (0.001)	-0.002 (0.002)	0.003 (0.003)	0.002 (0.002)
Control mean	0.053	0.058	0.060	0.088	0.090	0.077	0.004	0.002	0.002	0.003	0.001	-0.000
N (left)	5,112	6,640	5,399	3,880	5,105	4,332	8,721	9,501	12,652	7,540	7,472	4,022
N (right)	5,578	6,515	5,091	3,536	2,058	2,657	7,044	7,872	7,071	4,625	2,222	2,565
Social and Human Sciences												
Effect	0.061 (0.014)	0.016 (0.015)	0.018 (0.020)	0.067 (0.019)	-0.055 (0.027)	0.024 (0.020)	-0.002 (0.002)	0.000 (0.001)	-0.002 (0.001)	-0.000 (0.001)	-0.003 (0.002)	-0.001 (0.002)
Control mean	0.149	0.192	0.188	0.152	0.185	0.156	0.003	0.001	0.001	0.001	0.002	0.002
N (left)	9,408	10,889	5,399	6,661	2,942	6,891	10,975	10,889	16,956	6,930	6,268	6,300
N (right)	7,214	8,417	5,091	4,414	1,699	3,147	7,531	8,417	7,431	4,496	2,152	3,076
Economics, Administration and Accounting												
Effect	0.003 (0.014)	0.023 (0.011)	0.019 (0.014)	-0.013 (0.016)	0.023 (0.019)	-0.015 (0.017)	-0.035 (0.008)	-0.039 (0.007)	-0.024 (0.006)	-0.029 (0.006)	0.014 (0.007)	-0.013 (0.006)
Control mean	0.144	0.133	0.113	0.133	0.095	0.107	0.049	0.041	0.026	0.026	0.001	0.018
N (left)	9,854	14,187	7,242	7,310	5,953	5,709	7,527	5,528	9,654	5,039	3,845	5,373
N (right)	7,310	9,205	5,793	4,556	2,130	2,989	6,647	5,999	6,494	3,987	1,881	2,912
Engineering, Architecture and Urbanism												

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	<i>Professional (5 yr)</i>						<i>Vocational (1–2 yr)</i>					
	2014	2015	2016	2017	2018	2019	2014	2015	2016	2017	2018	2019
Effect	0.077 (0.022)	0.086 (0.018)	0.017 (0.023)	0.034 (0.024)	0.016 (0.030)	0.069 (0.026)	-0.086 (0.010)	-0.055 (0.006)	-0.042 (0.007)	-0.034 (0.009)	-0.013 (0.007)	-0.017 (0.008)
Control mean	0.352	0.353	0.416	0.432	0.453	0.446	0.107	0.066	0.054	0.034	0.018	0.025
N (left)	5,456	10,889	5,738	6,930	6,268	7,288	10,975	14,606	8,791	4,701	7,472	4,832
N (right)	5,771	8,417	5,251	4,496	2,152	3,200	7,531	9,310	6,285	3,902	2,222	2,789
Mathematics and Natural Sciences												
Effect	-0.001 (0.007)	-0.002 (0.007)	-0.025 (0.011)	-0.002 (0.010)	0.013 (0.019)	0.006 (0.014)	-0.002 (0.002)	-0.001 (0.001)	-0.001 (0.001)	-0.000 (0.001)	-0.000 (0.001)	-0.001 (0.002)
Control mean	0.028	0.041	0.063	0.050	0.078	0.078	0.003	0.001	0.001	0.001	0.000	0.001
N (left)	8,110	10,455	5,399	6,661	3,845	7,288	10,975	8,632	8,791	9,269	9,447	4,832
N (right)	6,867	8,271	5,091	4,414	1,881	3,200	7,531	7,572	6,285	4,856	2,300	2,789

(continued on next page)



The results using the SISBEN socioeconomic threshold as the running variable, reported in Figure A.2 and Table A.5 in the appendix, are broadly consistent with the pattern documented above, though estimated with less precision given the smaller effective sample sizes near the SISBEN threshold. In engineering, architecture, and urbanism, eligibility reduces vocational track enrollment across the 2014–2017 cohorts, with effects ranging from 3.7 to 7.7 percentage points and representing reductions of between 70 and 100 percent relative to control group means that range from 0.041 to 0.076, closely mirroring the within-field track switching documented under the Saber 11 identification strategy. In social and human sciences, professional track enrollment increases by between 7.0 and 13.1 percentage points across the 2014–2017 and 2019 cohorts, corresponding to increases of between 41 and 93 percent above control group means that range from 0.079 to 0.165 — effects that are somewhat larger in magnitude than those estimated under the Saber 11 threshold and consistent across a broader set of cohorts. In economics, administration, and accounting, vocational track enrollment declines by 2.7 and 2.3 percentage points in 2014 and 2015 respectively, again without a corresponding increase in professional enrollment within the same field.

Estimated effects on all remaining fields, including education sciences, are not statistically distinguishable from zero across any cohort under this identification strategy, likely reflecting the reduced statistical power associated with the smaller samples near the SISBEN cutoff. Taken together, the SISBEN-based estimates reinforce the core margins of adjustment identified above: within-field track switching in engineering and a reallocation across fields away from vocational economics toward social sciences and engineering professional programs.

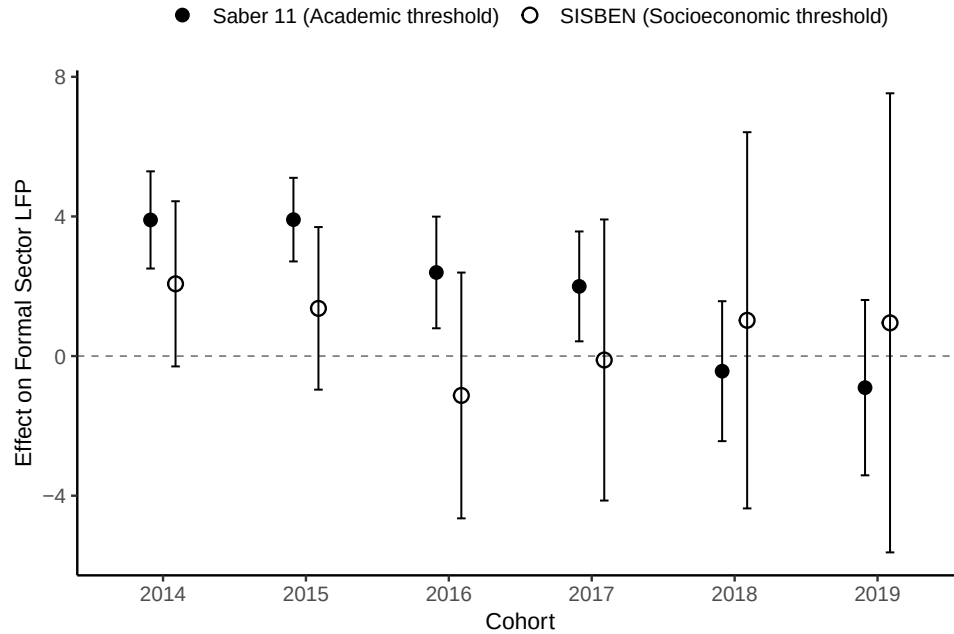
Effects on Expected Labor Market Outcomes of College–Major Choices

Figures 7 and 8 present the estimated effects of scholarship eligibility on the expected labor market outcomes associated with the college–major combination chosen by each student, conditional on higher education enrollment, using both the Saber 11 academic threshold and the SISBEN socioeconomic threshold as running variables. For each enrolled student, the outcomes reflect the average formal sector labor force participation rate and average log monthly salary observed among graduates of the same college–major combination, at one and five years after graduation. These estimates are therefore best interpreted as evidence

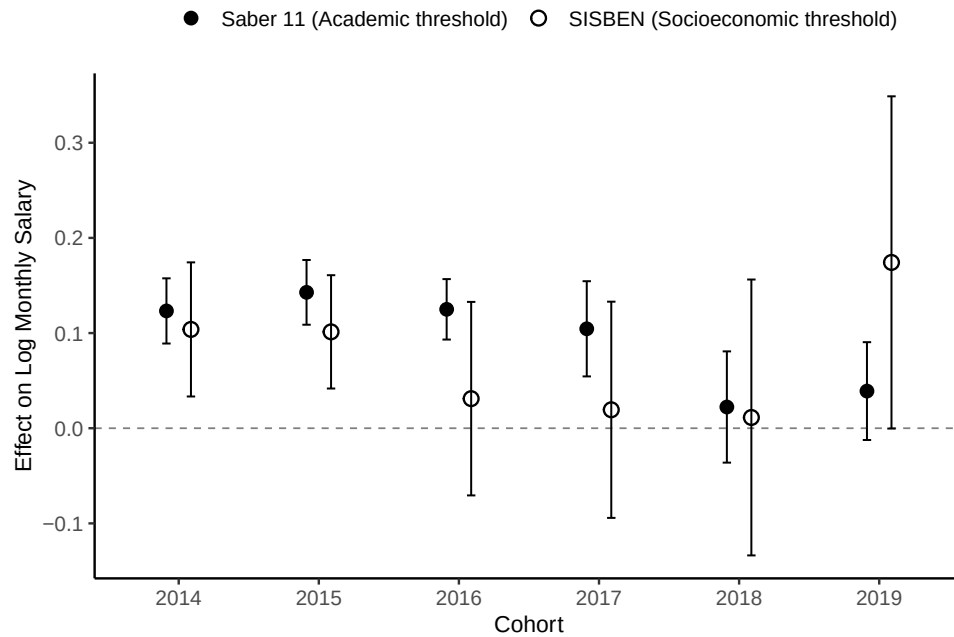


on whether eligibility induced students to select into college–major combinations with better expected labor market prospects, rather than as direct estimates of individual earnings effects. Tables 5 and A.6 report the underlying point estimates, control group means, and effective sample sizes for the Saber 11 and SISBEN identification strategies respectively, with the latter reported in the appendix. The figures reveal positive and precisely estimated effects for the early cohorts of the program, which attenuate and become statistically indistinguishable from zero for the 2018 and 2019 cohorts — a pattern consistent with the progressive tightening of the eligibility criterion documented in the extensive margin results.

FIGURE 7: Effects on Expected Labor Market Outcomes of College–Major Choices: Short-Run



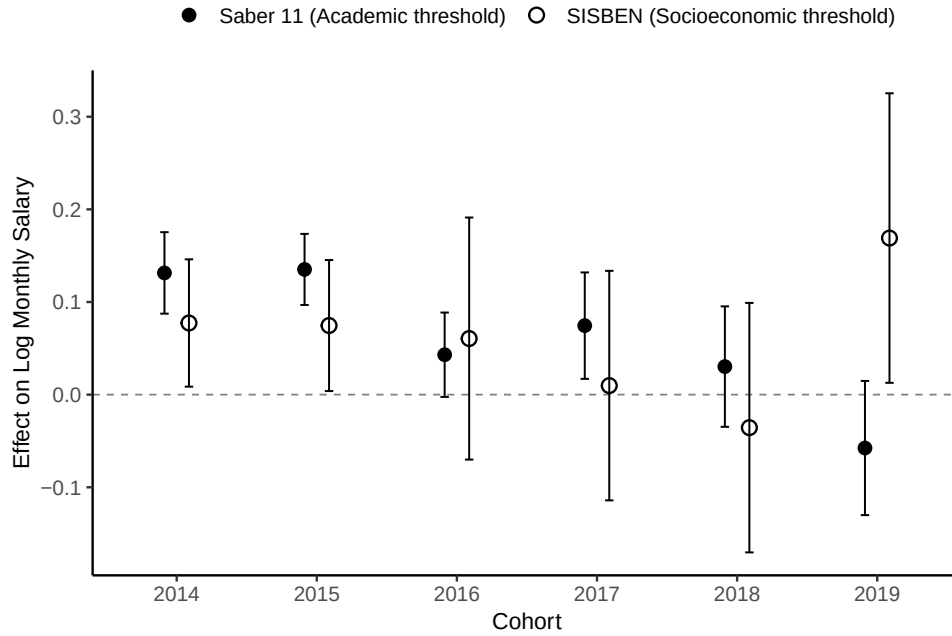
(A) Expected Formal Sector Labor Force Participation Rate (1 year after graduation).



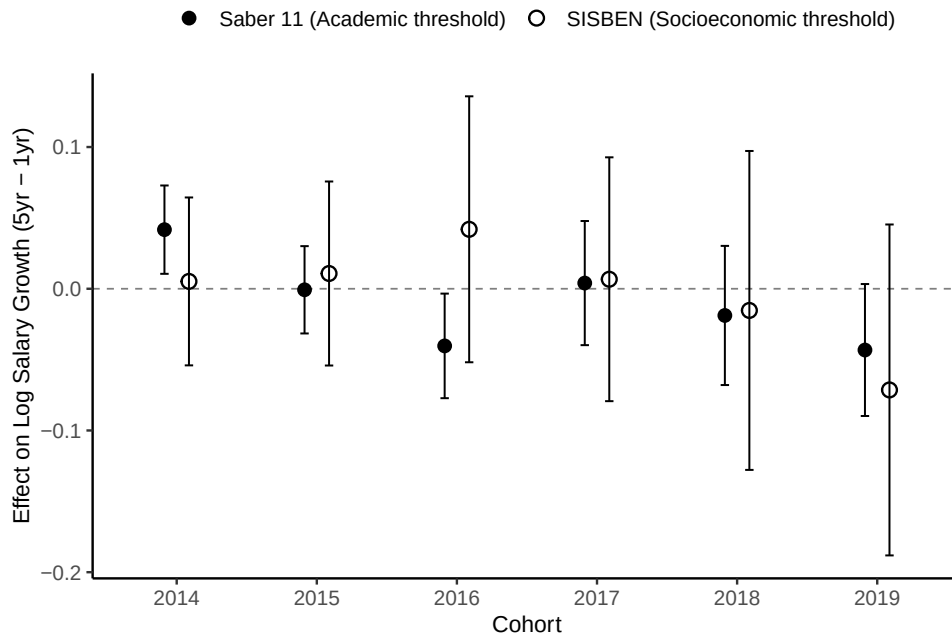
(B) Expected Log Monthly Salary (1 year after graduation).

Notes: Each outcome reflects the average labor market outcome among graduates of the same college–major combination. Estimates are conditional on higher education enrollment. Filled and open circles represent RBC point estimates using the Saber 11 and SISBEN thresholds respectively. Bars represent 95 percent robust confidence intervals.

FIGURE 8: Effects on Expected Labor Market Outcomes of College–Major Choices: Medium-Run



(A) Expected Log Monthly Salary (5 years after graduation).



(B) Expected Salary Growth (log salary at 5 years minus log salary at 1 year).

Notes: Each outcome reflects the average labor market outcome among graduates of the same college–major combination. Salary growth is defined as the difference in log monthly salary between the five- and one-year horizons. Estimates are conditional on higher education enrollment. Filled and open circles represent RBC point estimates using the Saber 11 and SISBEN thresholds respectively. Bars represent 95 percent robust confidence intervals.



Eligibility increases the expected formal sector labor force participation rate associated with the chosen college–major combination by between 2.0 and 3.9 percentage points across the 2014–2017 cohorts under the Saber 11 academic threshold, with all four estimates statistically significant. Given control group means of approximately 78 to 82 percent over this period, these effects represent increases of between 2.4 and 5.0 percent relative to the baseline, indicating that eligible students selected into college–major combinations with systematically higher formal employment rates. Effects for the 2018 and 2019 cohorts are not statistically distinguishable from zero, consistent with the near-complete absence of compliers in those cohorts. The expected monthly salary at one year after graduation increases by between 10.4 and 14.3 percent across the 2014–2017 cohorts under the Saber 11 academic threshold, with all four estimates statistically significant. The SISBEN socioeconomic threshold estimates are consistent in direction, with statistically significant increases of 10.4 and 10.1 percent in 2014 and 2015 respectively (Table A.6).

Figure 8 turns to the medium-run outcomes. At five years after graduation, significant positive effects on expected monthly salary under the Saber 11 academic threshold are estimated for the 2014 and 2015 cohorts at 13.1 and 13.5 percent respectively, and for the 2017 cohort at 7.4 percent, with the SISBEN socioeconomic threshold yielding consistent estimates of 7.7 and 7.5 percent in 2014 and 2015 respectively (Table A.6). Taken together, the one- and five-year salary estimates indicate that eligible students selected into college–major combinations that are associated with systematically higher salaries, suggesting a reallocation toward fields and programs with stronger labor market prospects. The expected salary growth between the one- and five-year horizons does not exhibit a consistent pattern across cohorts. Under the Saber 11 academic threshold, eligibility is associated with a statistically significant increase in expected salary growth of 4.2 percentage points in 2014 and a statistically significant reduction of 4.0 percentage points in 2016, relative to a control group mean of 39.3 percentage points. Estimates for the remaining cohorts, and for all cohorts under the SISBEN socioeconomic threshold (Table A.6), are not statistically distinguishable from zero. These results indicate that while eligibility consistently shifts students toward college–major combinations with higher expected earnings levels, it does not systematically alter the rate at which those earnings grow between the first and fifth year after graduation.

TABLE 5: RD ITT Effects on Labor Market Outcomes: Saber 11 (Academic Threshold) as Running Variable

	2014	2015	2016	2017	2018	2019
<i>Formal Sector Labor Force Participation (1 year)</i>						
Effect on Formal Sector LFP	3.900	3.909	2.395	1.996	-0.433	-0.904
	(0.710)	(0.611)	(0.816)	(0.803)	(1.023)	(1.281)
Control mean	78.261	79.706	81.253	81.576	82.020	81.491
N (left)	6,013	6,056	2,904	4,231	3,008	1,947
N (right)	3,406	3,759	2,184	2,063	1,131	1,144
<i>Log Monthly Salary (1 year after graduation)</i>						
Effect on Log Monthly Salary	0.123	0.143	0.125	0.104	0.022	0.039
	(0.017)	(0.017)	(0.016)	(0.026)	(0.030)	(0.026)
Control mean	14.156	14.192	14.248	14.317	14.386	14.334
N (left)	4,111	4,078	6,429	2,468	1,892	2,407
N (right)	2,970	3,090	3,011	1,604	953	1,257
<i>Log Monthly Salary (5 years after graduation)</i>						
Effect on Log Monthly Salary	0.131	0.135	0.043	0.074	0.030	-0.058
	(0.022)	(0.020)	(0.023)	(0.029)	(0.033)	(0.037)
Control mean	14.523	14.560	14.671	14.717	14.783	14.776
N (left)	2,888	3,379	2,743	2,314	2,119	1,397
N (right)	2,538	2,952	2,149	1,555	980	907
<i>Salary Growth (5 year minus 1 year)</i>						
Effect on Salary Growth	0.042	-0.001	-0.040	0.004	-0.019	-0.043
	(0.016)	(0.016)	(0.019)	(0.022)	(0.025)	(0.024)
Control mean	0.329	0.359	0.393	0.389	0.419	0.422
N (left)	2,821	2,602	2,659	2,989	2,921	1,667
N (right)	2,521	2,539	2,082	1,738	1,069	1,010



5 Conclusion

This paper studies how financial aid affects students' field-of-study choices and, more broadly, the allocation of talent across college majors. While much of the literature on higher education financing focuses on whether financial constraints affect college access, in many higher education systems students must choose a specific college–major combination at the time of enrollment. In such settings, financial constraints may distort not only access to higher education but also the allocation of students across fields with different skill requirements and labor market returns.

Using administrative microdata from Colombia and exploiting the eligibility rules of the *Ser Pilo Paga* and *Generación E Excelencia* programs, I estimate the causal impact of financial aid eligibility using two complementary regression discontinuity designs based on the academic *Saber 11* threshold and the socioeconomic SISBEN threshold. Consistent with previous evidence, the results show that eligibility substantially increased higher education enrollment for the early cohorts of the program, raising the probability of enrollment by between 21 and 25 percentage points across the 2014–2017 cohorts — effects that are large relative to control group means and that attenuate to zero by 2018 as the academic threshold tightened progressively toward the 98th percentile of the national score distribution. Beyond these extensive-margin effects, the results document meaningful reallocation across both fields of study and program tracks conditional on enrollment. Within engineering, architecture and urbanism, eligibility induces a shift from vocational to professional programs, with declines in vocational enrollment of between 78 and 100 percent relative to the baseline across the 2014–2017 cohorts, accompanied by increases in professional engineering enrollment of between 15 and 24 percent above the baseline. Across fields, eligibility consistently reduces enrollment in education sciences across all six cohorts — with declines of between 35 and 52 percent relative to the baseline — and increases enrollment in social and human sciences professional programs in 2014 and 2017. The pattern in economics, administration and accounting is consistent with both mechanisms: vocational enrollment declines sharply without a corresponding increase in professional enrollment within the same field, suggesting cross-field reallocation. Finally, eligibility shifts students toward college–major combinations



with higher expected labor market outcomes: at one year after graduation, expected monthly salaries increase by between 10.4 and 14.3 percent across the 2014–2017 cohorts under the *Saber 11* academic threshold, with significant effects on formal sector labor force participation and five-year salaries documented for the same cohorts.

These results highlight an important but often overlooked margin through which financial constraints may shape educational decisions. When students face binding financial constraints, they may not only delay or forego college enrollment, but also select into fields that are perceived to be less risky, less costly, or more compatible with limited financial resources. As a result, the distribution of students across majors may deviate from the allocation that would arise in the absence of such constraints. In this sense, financial frictions can generate a form of human capital misallocation, where talented students sort into fields that do not fully reflect their comparative advantage or the economic value of different skills in the labor market.

Demand-side financial aid policies may help reduce this type of misallocation by relaxing liquidity constraints and allowing students to choose among a broader set of educational options. By lowering the effective cost of attending high-quality institutions and programs, scholarships or income-contingent financing schemes can enable students to select majors based more closely on their preferences, abilities, and expected returns rather than on short-term financial considerations. In this way, financial aid may improve both equity and efficiency: it expands educational opportunities for disadvantaged students while also promoting a more efficient allocation of talent across fields with different productivity and earnings potential.

These considerations are particularly relevant in higher education systems characterized by early specialization and decentralized admissions, such as the Colombian system studied in this paper. In such environments, the choice of field is made early and switching across majors may be difficult once students enroll. As a result, distortions in initial field-of-study choices can have long-lasting consequences for both individual career trajectories and aggregate labor market outcomes. Policies that relax financial constraints at the point of entry



may therefore play an important role in shaping the composition of skills produced by the higher education system.

More broadly, the findings contribute to ongoing policy debates about the relative merits of supply-side and demand-side interventions in higher education. While many reforms focus on expanding the capacity of public institutions, targeted demand-side subsidies may offer a complementary mechanism for improving the allocation of human capital by allowing students to sort more efficiently across institutions and fields of study. Understanding these mechanisms is essential for evaluating the broader welfare implications of higher education financing policies.



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A Appendix

A.1 Additional Figures and Tables

TABLE A.1: Knowledge Areas and Basic Knowledge Clusters (*Áreas del Conocimiento* and *Núcleos Básicos del Conocimiento*)

Knowledge Area	NBC Subcategories
Agronomy, Veterinary and Related	Agronomy; Veterinary Medicine; Zootechnics
Fine Arts	Visual and Plastic Arts and Related; Performing Arts; Design; Advertising and Related; Other Fine Arts Programs
Education Sciences	Education
Health Sciences	Bacteriology; Nursing; Surgical Instrumentation; Medicine; Nutrition and Dietetics; Dentistry; Optometry; Public Health; Therapies; Other Health Sciences Programs
Social and Human Sciences	Anthropology and Liberal Arts; Library Science and Related; Political Science and International Relations; Social Communication, Journalism and Related; Sports, Physical Education and Recreation; Law and Related; Philosophy, Theology and Related; Military and Police Training; Geography; History; Modern Languages, Literature, Linguistics and Related; Psychology; Sociology, Social Work and Related
Economics, Administration, Accounting and Related	Administration; Public Accounting; Economics
Engineering, Architecture, Urbanism and Related	Architecture; Administrative Engineering and Related; Agricultural and Forestry Engineering and Related; Agroindustrial and Food Engineering and Related; Agronomic and Livestock Engineering and Related; Environmental and Sanitary Engineering and Related; Biomedical Engineering and Related; Civil Engineering and Related; Mining and Metallurgical Engineering and Related; Systems, Telematics and Related Engineering; Electrical Engineering and Related; Electronic and Telecommunications Engineering and Related; Industrial Engineering and Related; Mechanical Engineering and Related; Chemical Engineering and Related; Other Engineering Fields
Mathematics and Natural Sciences	Biology, Microbiology and Related; Physics, Geology and Other Natural Science Programs; Mathematics, Statistics and Related; Chemistry and Related

Notes: Classification as defined by the Ministerio de Educación Nacional (MEN) and reported in the Sistema Nacional de Información de la Educación Superior (SNIES). The full classification comprises 55 NBC subcategories across the eight knowledge areas. Both professional and vocational programs are classified within this same taxonomy, so that a given NBC may contain programs of different tracks and durations offering different types of credentials. Source: SNIES Glossary, Ministerio de Educación Nacional.

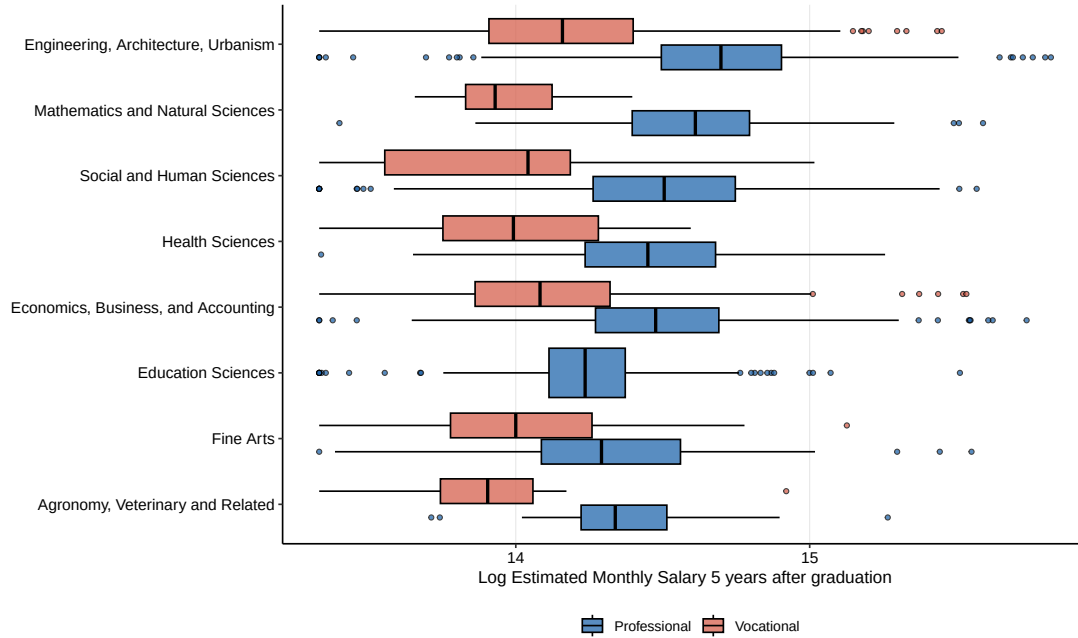


TABLE A.2: Professional and Vocational Programs within the Same Knowledge Area and NBC: Selected Examples

NBC	Professional Program	Vocational Program
Economics	Economics	Technical Certificate in Commercial Processes (<i>Técnica Profesional en Procesos Comerciales</i>); Technologist in Commercial and Financial Management (<i>Tecnología en Gestión Comercial y Financiera</i>)
Business & Administration	Business Administration	Technologist in Health Management (<i>Tecnología en Gestión de Salud</i>); Technologist in Agricultural Marketing (<i>Tecnología en Mercadeo Agropecuario</i>)
Engineering: Systems & Telematics	Systems & Computer Engineering	Technologist in Software Development (<i>Tecnología en Desarrollo de Software</i>); Technologist in Telematics (<i>Tecnología en Telemática</i>)
Industrial Engineering	Industrial Engineering	Technologist in Industrial Process Management (<i>Tecnología en Gestión de Procesos Industriales</i>); Technologist in Industrial Processes (<i>Tecnología en Procesos Industriales</i>)

Notes: Selected examples of professional (*nivel universitario*) and vocational (*técnica profesional* and *tecnológica*) programs offered within the same NBC subcategory. Programs within the same NBC share a common knowledge area and disciplinary classification regardless of track or duration. Professional programs lead to a university degree (*título universitario*), while vocational programs lead to a technical (*técnico profesional*) or technological (*tecnólogo*) credential. Source: SNIES, Ministerio de Educación Nacional.

FIGURE A.1: Expected Log Monthly Salary by Field and Program Type (5 Years After Graduation)



Notes: Each observation represents the average log monthly salary for each college–major combination within a given field and program type. Salary data are from the Observatorio Laboral para la Educación (OLE) and reflect average earnings among graduates at five years after graduation. See Figure 1 in the main text for the corresponding figure at one year after graduation.

TABLE A.3: Distribution of Field Choices at Higher Education Entry: Professional Programs (4–5 year programs)

	2014	2015	2016	2017	2018	2019
Agronomy, Veterinary and Related	0.01 (0.12)	0.01 (0.12)	0.01 (0.12)	0.01 (0.11)	0.01 (0.12)	0.01 (0.12)
Fine Arts	0.02 (0.15)	0.02 (0.15)	0.02 (0.14)	0.02 (0.14)	0.02 (0.14)	0.02 (0.15)
Education Sciences	0.06 (0.24)	0.05 (0.23)	0.05 (0.22)	0.04 (0.21)	0.06 (0.23)	0.05 (0.23)
Health Sciences	0.05 (0.22)	0.05 (0.23)	0.05 (0.22)	0.05 (0.23)	0.06 (0.24)	0.06 (0.23)
Social and Human Sciences	0.19 (0.39)	0.20 (0.40)	0.18 (0.38)	0.18 (0.39)	0.18 (0.39)	0.17 (0.38)
Economics, Administration and Accounting	0.13 (0.33)	0.14 (0.34)	0.12 (0.33)	0.13 (0.33)	0.13 (0.33)	0.12 (0.32)
Engineering, Architecture and Urbanism	0.25 (0.43)	0.26 (0.44)	0.22 (0.41)	0.20 (0.40)	0.20 (0.40)	0.19 (0.39)
Mathematics and Natural Sciences	0.02 (0.14)	0.02 (0.14)	0.02 (0.14)	0.02 (0.15)	0.03 (0.16)	0.03 (0.16)
Observations	103,397	108,860	120,660	108,745	112,711	117,430

TABLE A.4: Distribution of Field Choices at Higher Education Entry: Vocational Programs (1–2 year programs)

	2014	2015	2016	2017	2018	2019
Agronomy, Veterinary and Related	0.01 (0.11)	0.01 (0.10)	0.02 (0.12)	0.02 (0.13)	0.01 (0.10)	0.01 (0.12)
Fine Arts	0.01 (0.12)	0.01 (0.10)	0.01 (0.12)	0.02 (0.12)	0.02 (0.12)	0.02 (0.12)
Education Sciences	0.00 (0.05)	0.00 (0.05)	0.00 (0.05)	0.00 (0.05)	0.00 (0.03)	0.00 (0.04)
Health Sciences	0.01 (0.09)	0.01 (0.09)	0.01 (0.10)	0.01 (0.11)	0.01 (0.09)	0.01 (0.08)
Social and Human Sciences	0.01 (0.10)	0.01 (0.10)	0.01 (0.11)	0.02 (0.12)	0.02 (0.13)	0.01 (0.12)
Economics, Administration and Accounting	0.10 (0.30)	0.10 (0.29)	0.14 (0.34)	0.14 (0.34)	0.12 (0.32)	0.15 (0.36)
Engineering, Architecture and Urbanism	0.11 (0.32)	0.10 (0.30)	0.13 (0.34)	0.13 (0.34)	0.14 (0.35)	0.13 (0.34)
Mathematics and Natural Sciences	0.00 (0.06)	0.00 (0.06)	0.00 (0.07)	0.00 (0.06)	0.00 (0.06)	0.00 (0.06)
Observations	103,397	108,860	120,660	108,745	112,711	117,430

FIGURE A.2: Sisben as running variable

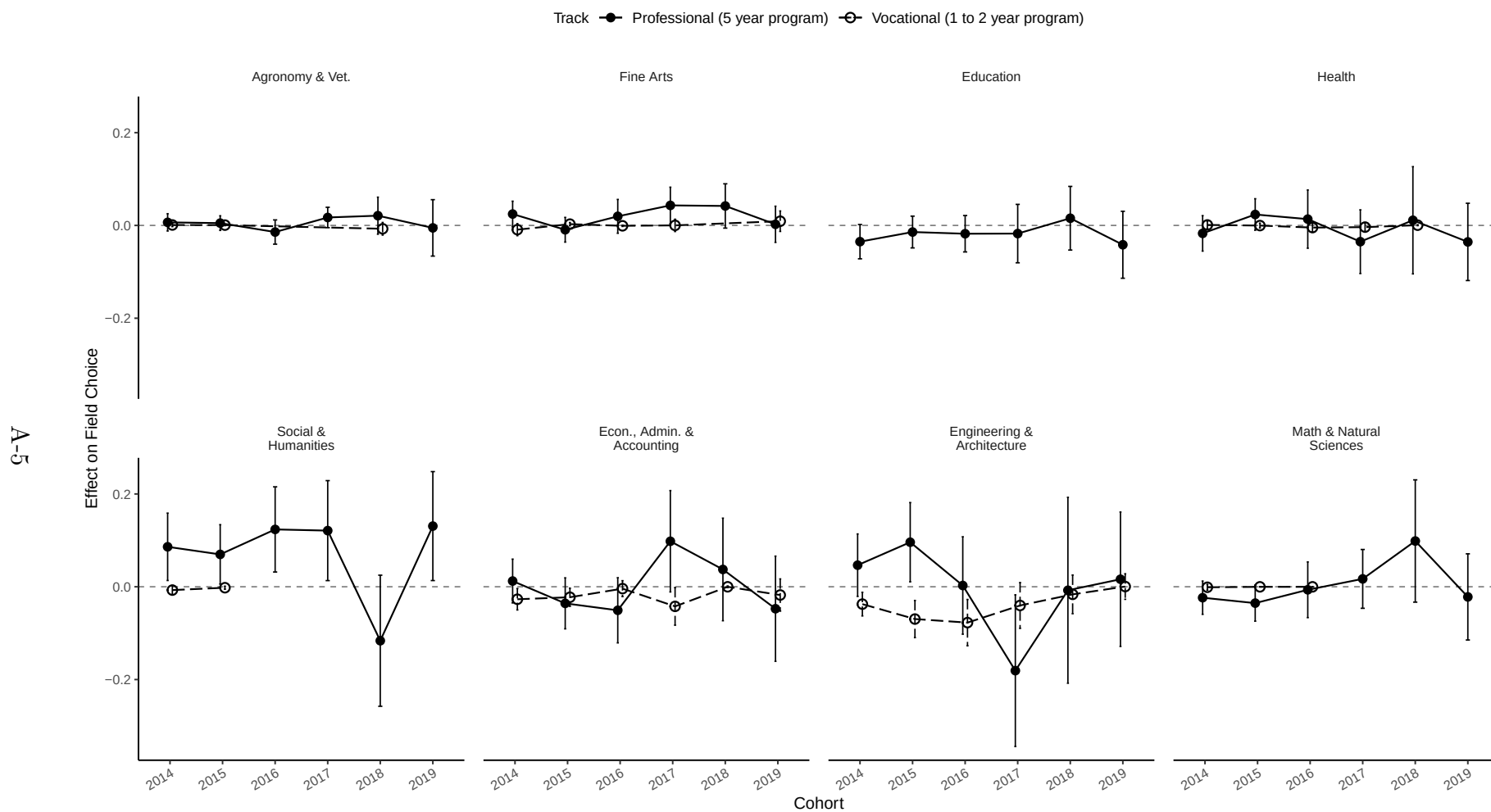


TABLE A.5: Intensive-Margin Effects on Field $\times$ Program Type: SISBEN as Running Variable

	<i>Professional (5 yr)</i>						<i>Vocational (1–2 yr)</i>					
	2014	2015	2016	2017	2018	2019	2014	2015	2016	2017	2018	2019
Agronomy, Veterinary and Related												
Effect	0.007 (0.010)	0.005 (0.008)	-0.014 (0.013)	0.017 (0.011)	0.021 (0.020)	-0.005 (0.031)	0.001 (0.002)	0.001 (0.001)			-0.007 (0.007)	
Control mean	0.015	0.005	0.021	-0.000	0.001	0.026	0.000	0.000			0.006	
N (left)	2,317	1,335	990	390	291	340	1,843	2,693			526	
N (right)	3,504	2,094	1,650	647	342	442	2,677	4,872			794	
Fine Arts												
Effect	0.025 (0.014)	-0.009 (0.014)	0.020 (0.019)	0.043 (0.020)	0.042 (0.024)	0.002 (0.020)	-0.009 (0.007)	0.003 (0.002)	-0.001 (0.001)	0.000 (0.007)		0.009 (0.011)
Control mean	0.018	0.031	0.018	-0.001	-0.003	0.015	0.012	-0.001	0.000	0.006		0.003
N (left)	1,635	1,534	761	398	386	318	1,696	1,028	375	505		372
N (right)	2,394	2,437	1,264	655	489	416	2,475	1,595	591	839		504
Education Sciences												
Effect	-0.035 (0.019)	-0.014 (0.017)	-0.018 (0.020)	-0.018 (0.032)	0.015 (0.035)	-0.042 (0.037)						
Control mean	0.060	0.042	0.042	0.047	0.022	0.043						
N (left)	1,424	1,267	1,004	444	320	315						
N (right)	2,060	2,002	1,655	716	392	410						
Health Sciences												

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	Professional (5 yr)						Vocational (1–2 yr)					
	2014	2015	2016	2017	2018	2019	2014	2015	2016	2017	2018	2019
Effect	-0.017 (0.019)	0.024 (0.017)	0.014 (0.032)	-0.035 (0.035)	0.011 (0.059)	-0.036 (0.042)	0.001 (0.004)	-0.000 (0.003)	-0.005 (0.005)	-0.004 (0.005)	0.001 (0.000)	
Control mean	0.071	0.041	0.058	0.089	0.067	0.079	0.002	0.002	0.004	0.003	0.000	
N (left)	1,650	1,629	744	619	337	424	2,386	2,535	1,088	717	181	
N (right)	2,413	2,608	1,216	1,064	420	576	3,661	4,354	1,811	1,265	211	
Social and Human Sciences												
Effect	0.086 (0.037)	0.070 (0.033)	0.124 (0.047)	0.121 (0.055)	-0.116 (0.072)	0.131 (0.060)	-0.007 (0.005)	-0.002 (0.002)				
Control mean	0.147	0.165	0.143	0.079	0.237	0.133	0.007	0.002				
N (left)	1,161	1,636	731	402	377	501	2,070	1,671				
N (right)	1,600	2,628	1,200	662	475	702	3,063	2,682				
Economics, Administration and Accounting												
Effect	0.012 (0.024)	-0.036 (0.028)	-0.051 (0.036)	0.098 (0.056)	0.037 (0.056)	-0.047 (0.058)	-0.027 (0.012)	-0.023 (0.010)	-0.004 (0.009)	-0.042 (0.021)	-0.000 (0.001)	-0.018 (0.018)
Control mean	0.098	0.149	0.113	0.068	0.055	0.138	0.029	0.025	0.006	0.035	0.000	0.016
N (left)	1,868	1,441	782	373	203	385	1,704	1,834	621	382	158	396
N (right)	2,746	2,257	1,282	596	234	523	2,487	2,890	1,010	637	178	537
Engineering, Architecture and Urbanism												
Effect	0.047	0.096	0.003	-0.181	-0.008	0.016	-0.037	-0.070	-0.077	-0.040	-0.016	0.000

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	<i>Professional (5 yr)</i>						<i>Vocational (1–2 yr)</i>					
	2014	2015	2016	2017	2018	2019	2014	2015	2016	2017	2018	2019
	(0.034)	(0.044)	(0.054)	(0.083)	(0.102)	(0.074)	(0.013)	(0.020)	(0.025)	(0.025)	(0.021)	(0.014)
Control mean	0.408	0.407	0.453	0.597	0.452	0.443	0.053	0.076	0.072	0.041	0.015	0.006
N (left)	2,255	1,361	981	371	304	472	2,166	1,171	734	488	368	350
N (right)	3,384	2,151	1,620	586	362	643	3,220	1,820	1,202	809	461	461
Mathematics and Natural Sciences												
Effect	-0.024	-0.035	-0.007	0.017	0.099	-0.022	-0.001	-0.000	-0.000			
	(0.018)	(0.020)	(0.031)	(0.032)	(0.067)	(0.047)	(0.003)	(0.000)	(0.000)			
Control mean	0.051	0.061	0.083	0.050	0.080	0.089	0.003	0.000	0.000			
N (left)	1,336	1,260	898	594	294	364	1,571	1,380	474			
N (right)	1,893	1,991	1,500	1,019	355	496	2,284	2,172	781			

Notes:

TABLE A.6: RD ITT Effects on Labor Market Outcomes: SISBEN (Socioeconomic Threshold) as Running Variable

	2014	2015	2016	2017	2018	2019
<i>Formal Sector Labor Force Participation (1 year)</i>						
Effect on Formal Sector LFP	2.070	1.367	-1.128	-0.112	1.025	0.952
	(1.207)	(1.188)	(1.796)	(2.054)	(2.749)	(3.355)
Control mean	81.896	83.081	83.965	84.822	82.240	82.713
N (left)	1,110	1,055	456	308	198	199
N (right)	1,325	1,350	618	410	249	265
<i>Log Monthly Salary (1 year after graduation)</i>						
Effect on Log Monthly Salary	0.104	0.101	0.031	0.019	0.011	0.174
	(0.036)	(0.030)	(0.052)	(0.058)	(0.074)	(0.089)
Control mean	14.265	14.294	14.337	14.437	14.387	14.303
N (left)	890	1,068	488	330	224	176
N (right)	1,093	1,356	667	434	273	218
<i>Log Monthly Salary (5 years after graduation)</i>						
Effect on Log Monthly Salary	0.077	0.075	0.061	0.010	-0.036	0.169
	(0.035)	(0.036)	(0.067)	(0.063)	(0.069)	(0.080)
Control mean	14.684	14.717	14.727	14.837	14.870	14.740
N (left)	960	1,000	308	317	223	139
N (right)	1,166	1,346	417	415	277	179
<i>Salary Growth (5 year minus 1 year)</i>						
Effect on Salary Growth	0.005	0.011	0.042	0.007	-0.015	-0.071
	(0.030)	(0.033)	(0.048)	(0.044)	(0.057)	(0.060)
Control mean	0.385	0.379	0.363	0.398	0.493	0.479
N (left)	808	753	258	333	225	189
N (right)	986	998	341	443	274	260

Notes:



A.2 Validity of the RD Design

This appendix presents graphical and statistical evidence supporting the validity of the regression discontinuity designs used in the paper. For each cohort from 2014 to 2019, I report continuity tests for the density of both running variables at their respective eligibility thresholds using the `rddensity` procedure of [Cattaneo et al. \(2020\)](#), as well as graphical evidence of sharp assignment at each threshold. The exercises cover the full sample period, spanning the *Ser Pilo Paga* program cohorts of 2014–2017 and the *Generación E Excelencia* cohorts of 2018–2019. Similar validation exercises for these programs have been previously documented in [Londoño-Vélez et al. \(2020\)](#) and [Londoño-Vélez et al. \(2025\)](#), and the diagnostics reported here are broadly consistent with those findings.

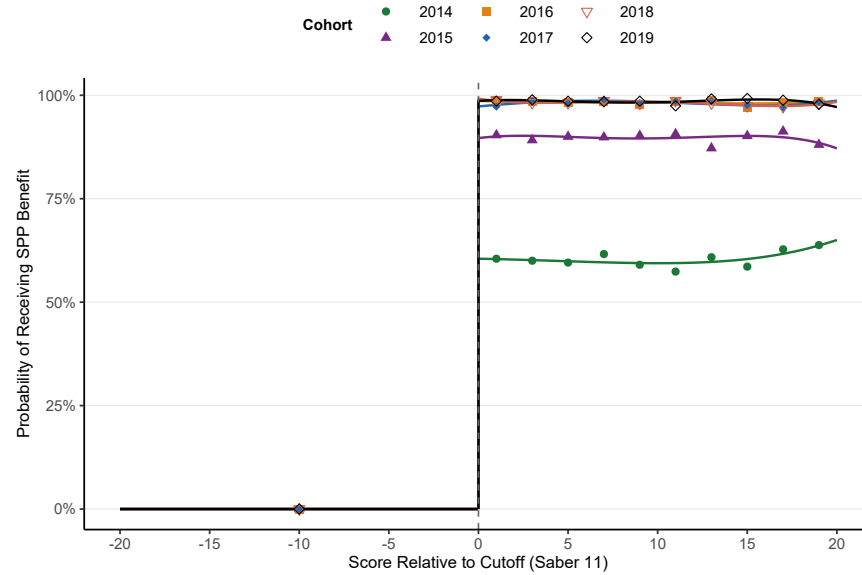
A.2.1 Sharp Assignment at Eligibility Thresholds

Figure [A.3](#) presents the probability of receiving a scholarship benefit as a function of the two running variables, separately for each cohort from 2014 to 2019. Both panels document a sharp and precisely located discontinuity at the eligibility threshold: the probability of receiving the scholarship jumps from near zero just below the cutoff to well above 50 percent just above it, with the transition occurring exactly at the cohort-specific threshold in each case. This pattern holds consistently across all six cohorts and under both the academic *Saber 11* threshold and the socioeconomic SISBEN threshold, confirming that the eligibility rules of both the *Ser Pilo Paga* and *Generación E Excelencia* programs were enforced as specified and that treatment assignment followed a sharp regression discontinuity design in practice. The probability of receiving the benefit does not reach 100 percent above the threshold, reflecting the additional requirement that eligible students gain admission to an accredited high-quality institution. This incomplete take-up is particularly pronounced for the 2014 cohort, for whom the program was announced only after *Saber 11* results were released in October 2014. Many academically and socioeconomically eligible students in that cohort had taken the exam without knowledge of the program and had likely already made postsecondary plans — or decided not to apply at all — by the time they learned of their eligibility. From 2015 onwards, awareness of the program was widespread among prospective applicants, and take-up above the threshold increases accordingly. The sharp pattern is

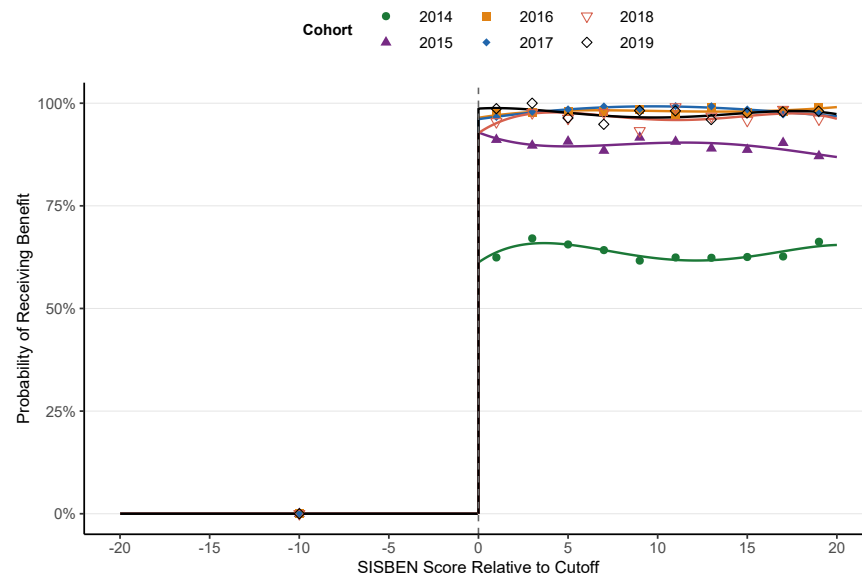


nevertheless sufficient across all cohorts to confirm that crossing the threshold generates a large and discontinuous increase in the probability of receiving financial aid, satisfying the first-stage requirement of the RD design.

FIGURE A.3: Probability of Receiving Scholarship Benefit at Eligibility Thresholds, by Cohort



(A) Academic *Saber 11* threshold.



(B) Socioeconomic SISBEN threshold.

Notes: Each panel plots the probability of receiving a scholarship benefit as a function of the score relative to the cohort-specific eligibility cutoff. Panel (a) uses the *Saber 11* academic threshold as the running variable, with the sample restricted to SISBEN-eligible students. Panel (b) uses the SISBEN socioeconomic threshold as the running variable, with the sample restricted to academically eligible students. Each line corresponds to a cohort from 2014 to 2019, covering both the *Ser Pilo Paga* (2014–2017) and *Generación E Excelencia* (2018–2019) programs.



A.2.2 Manipulation Tests

To test whether students or administrators could have manipulated their scores to cross the eligibility thresholds, Figures A.4 and A.5 report the results of density continuity tests for the academic *Saber 11* and socioeconomic SISBEN running variables, implemented using the `rddensity` procedure of Cattaneo et al. (2020) with automatic bandwidth selection.

For the academic *Saber 11* threshold, the density appears smooth on either side of the cutoff in most cohorts, with p-values of 0.444, 0.706, 0.475, and 0.648 for the 2014, 2016, 2017, and 2019 cohorts respectively, providing no evidence of manipulation in those years. The 2015 and 2018 cohorts yield p-values of 0.001 and 0.014 respectively, indicating a statistically significant discontinuity in the density at the threshold in those two years. Manipulation of the *Saber 11* score is unlikely given the high standards of security and reliability with which the exam is administered and graded by ICFES, and the nature of the discontinuity does not suggest strategic bunching from below. The source of the density discontinuity in those two cohorts is unclear, and I do not offer a definitive explanation.

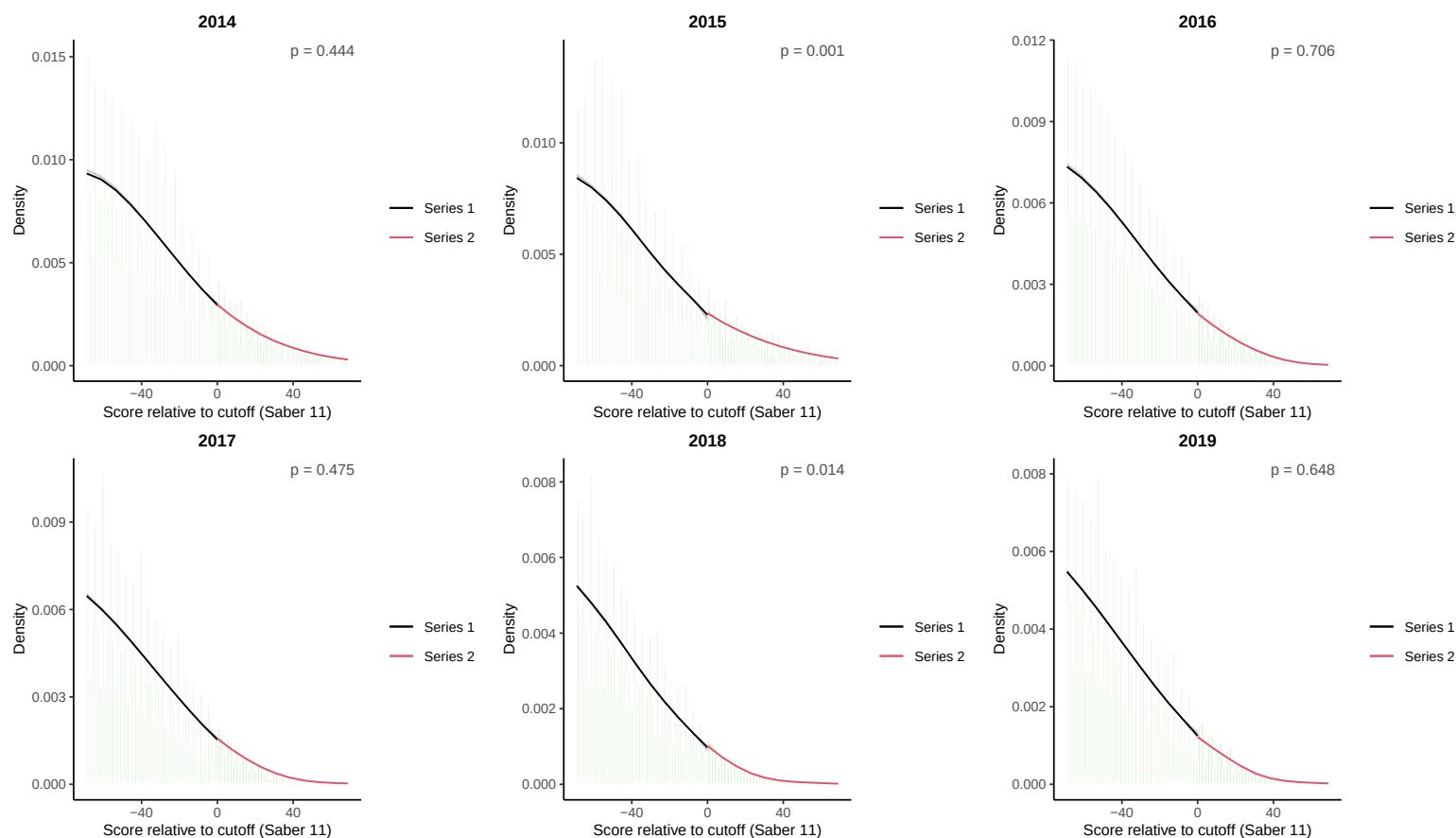
For the socioeconomic SISBEN threshold, p-values are 0.635, 0.481, 0.138, 0.324, and 0.427 for the 2014 and 2016–2019 cohorts respectively, providing no evidence of manipulation in those years. The 2015 cohort yields a p-value of 0.001. One possible explanation is that, following the announcement of the program in late 2014, some households may have sought to update their SISBEN registration in order to obtain a score that would qualify them for the benefit. However, this pattern is not systematic across cohorts, and the isolated rejection in 2015 does not undermine the validity of the design more broadly.

Taken together, the density tests provide broad support for the identifying assumptions of the RD design. The isolated rejections in the 2015 cohort under both running variables, and in the 2018 cohort under the *Saber 11* threshold, do not point to a systematic pattern of manipulation and are inconsistent with the mechanisms through which strategic score inflation would operate. The results reported here are moreover broadly consistent with the manipulation tests conducted in Londoño-Vélez et al. (2020) and Londoño-Vélez et al. (2025) for the same cohorts of these programs, which find no evidence of systematic manipulation



around either threshold.

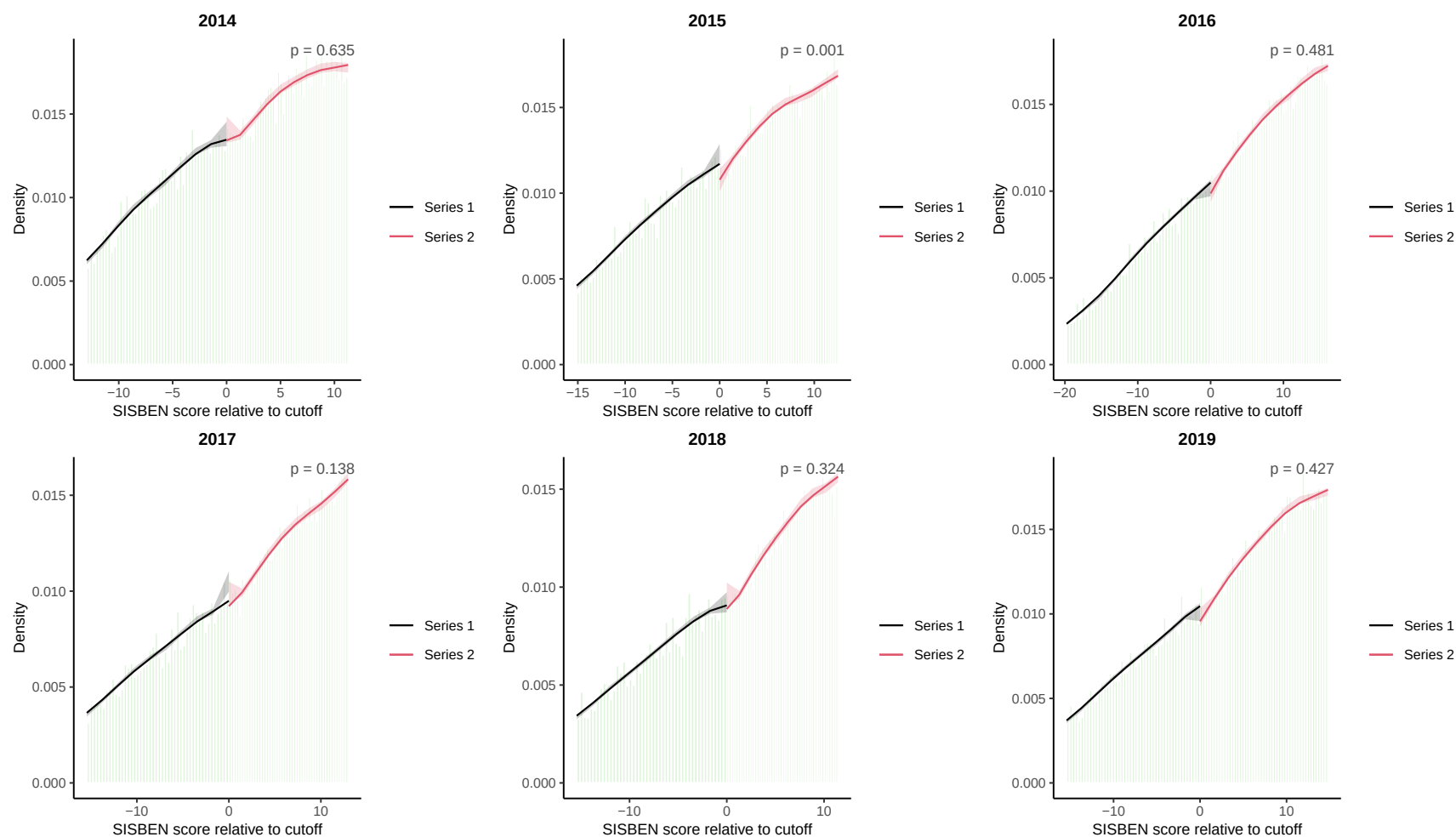
FIGURE A.4: Density Continuity Test: Academic *Saber 11* Threshold, by Cohort



Notes: Estimated density and 95% CI from `rddensity` (Cattaneo, Jansson & Ma, 2020). Automatic bandwidth selection. P-values for H0: no discontinuity in the density at the cutoff.

Notes: Estimated density and 95 percent confidence intervals from `rddensity` (Cattaneo et al., 2020) with automatic bandwidth selection. Each panel corresponds to a cohort from 2014 to 2019. The p-value reported in each panel tests the null hypothesis of no discontinuity in the density at the cohort-specific *Saber 11* eligibility threshold. The sample is restricted to SISBEN-eligible students.

FIGURE A.5: Density Continuity Test: Socioeconomic SISBEN Threshold, by Cohort



Notes: Estimated density and 95% CI from `rddensity` (Cattaneo, Jansson & Ma, 2020). Automatic bandwidth selection. P-values for H_0 : no discontinuity in the density at the cutoff.

Notes: Estimated density and 95 percent confidence intervals from `rddensity` (Cattaneo et al., 2020) with automatic bandwidth selection. Each panel corresponds to a cohort from 2014 to 2019. The p-value reported in each panel tests the null hypothesis of no discontinuity in the density at the SISBEN socioeconomic eligibility threshold. The sample is restricted to academically eligible students.



A.3 Effects on the always takers population

The conditional estimates presented in the main text reflect a combination of two distinct behavioral responses: field-of-study adjustments by students who would have enrolled regardless of financial aid, and initial enrollment decisions by students newly induced into higher education by the scholarship. This appendix presents two exercises aimed at isolating the effects on the always-taker population.

A.3.1 Lee Bounds

The first exercise applies the bounding approach of [Lee \(2009\)](#) to construct sharp bounds on the intensive-margin effects on field-of-study choice. The Lee bounds address the selection problem introduced by conditioning on enrollment without requiring assumptions about the identity of always-takers. The procedure trims the outcome distribution on the side of the threshold with the larger enrollment effect, under the assumption that the complier population — students induced into enrollment by eligibility — is a random subset of enrollees on that side. The resulting lower and upper bounds bracket the average treatment effect for always-takers under this monotonicity assumption.

The implementation of the Lee bounds within the RD framework proceeds in two steps. First, I estimate the optimal bandwidth for each cohort and running variable using `rdrobust`, and restrict the sample to observations within that bandwidth on each side of the threshold. This ensures that the trimming procedure operates on the same local sample used for the main RD estimates, maintaining comparability between the bounds and the point estimates reported in the main text. Second, within this bandwidth-restricted sample, I compute the trimming proportion as the ratio of the estimated extensive-margin enrollment effect to the enrollment rate on the right side of the threshold, following [Lee \(2009\)](#). Since the outcome variables are binary indicators for field and track enrollment, the trimming proportion is bounded above by one, and I apply the standard correction $p = \min\{1, \hat{\Delta}/\bar{y}_R\}$, where $\hat{\Delta}$ is the estimated enrollment effect and $\bar{y}_R$ is the mean enrollment rate on the right side of the threshold within the bandwidth. The bounds are computed separately for each cohort,



running variable, and field–track combination.

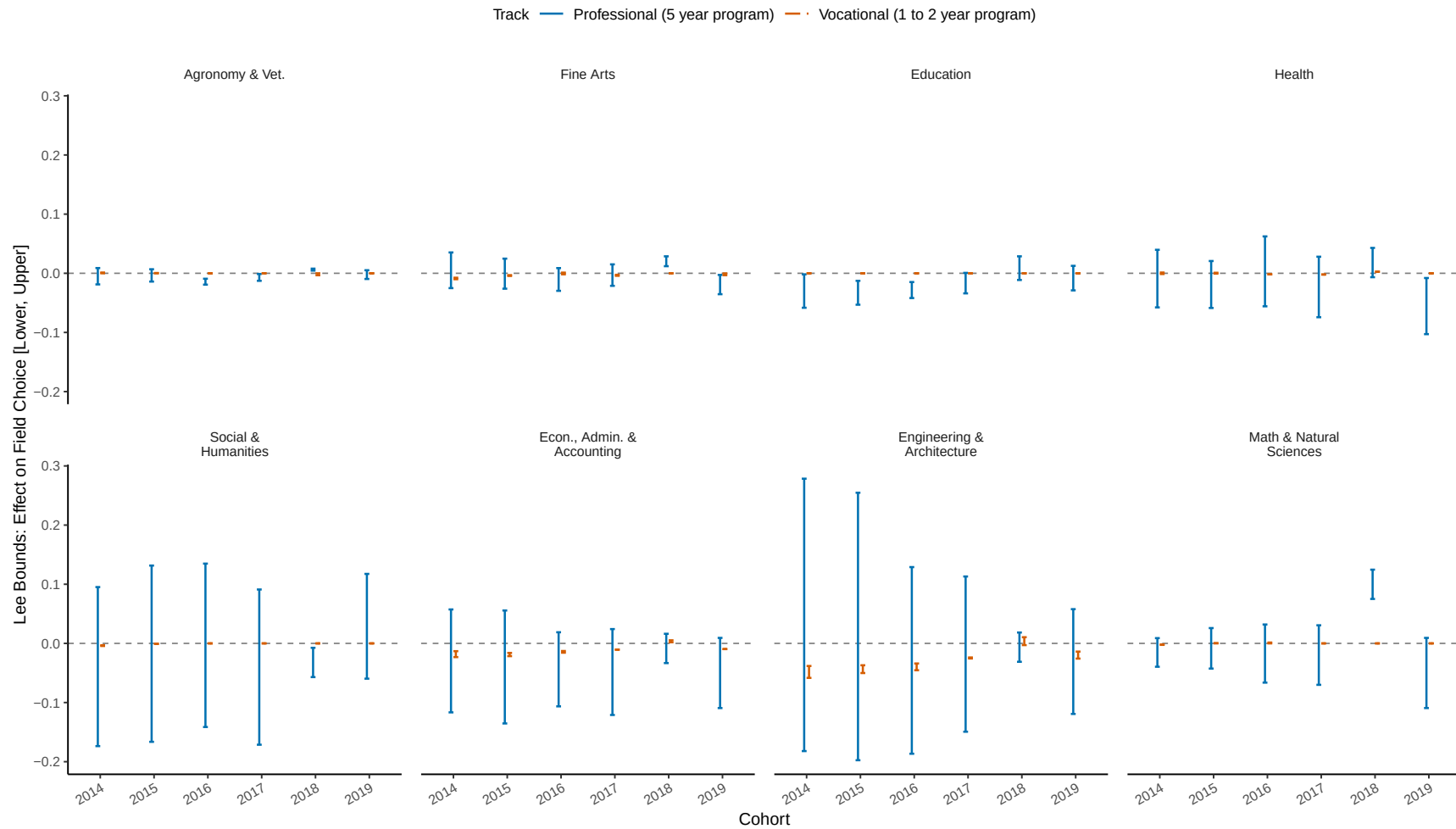
Figures [A.6](#) and [A.7](#) present the Lee bounds for effects on field and track combinations using the academic *Saber 11* and socioeconomic SISBEN thresholds respectively. As expected given the large extensive-margin effects documented in the main results, the bounds are wide in most cohorts and fields, reflecting the substantial share of compliers at the eligibility margin, and for most fields and tracks they are too wide to draw definitive conclusions about the effects on the always-taker population.

A-19



Notes: Lee bounds (Lee, 2009) on the effect of scholarship eligibility on enrollment in each field and track combination, using the academic *Saber 11* threshold as the running variable. The sample is restricted to SISBEN-eligible students. Each panel shows the lower and upper bound of the treatment effect for the always-taker population, separately for professional and vocational tracks. Bounds are constructed by trimming the outcome distribution on the side of the threshold with the larger enrollment share under the monotonicity assumption.

FIGURE A.7: Lee Bounds: Effects on Field and Track Choice, Socioeconomic SISBEN Threshold



Notes: Lee bounds (Lee, 2009) on the effect of scholarship eligibility on enrollment in each field and track combination, using the socioeconomic SISBEN threshold as the running variable. The sample is restricted to academically eligible students. Each panel shows the lower and upper bound of the treatment effect for the always-taker population, separately for professional and vocational tracks. Bounds are constructed by trimming the outcome distribution on the side of the threshold with the larger enrollment share under the monotonicity assumption.



Two patterns are nonetheless discernible. First, in engineering, architecture and urbanism, the bounds for vocational track enrollment remain negative across the 2014–2017 cohorts under both the *Saber 11* and SISBEN thresholds, suggesting that the reduction in vocational engineering enrollment documented in the main results is not entirely driven by the choices of newly induced entrants and is at least partly attributable to always-takers switching away from vocational programs. The bounds for professional engineering enrollment are too wide to draw analogous conclusions on that margin. Second, in education sciences, the upper bound for professional track enrollment is negative for most early cohorts under both the *Saber 11* and SISBEN thresholds, indicating that the decline in education enrollment is not fully explained by the decisions of students newly induced into higher education, and that always-takers also reduced their enrollment in professional education programs. Beyond these two patterns, the bounds for all remaining fields are wide enough to include zero under both identification strategies, and the Lee bounds exercise does not allow further conclusions about the always-taker effects in those fields.

A.4 Predicted Always-Taker Sample

The second exercise directly approximates the always-taker population using a machine learning model trained on pre-program data. The identifying assumption is that the 2013 cohort of *Saber 11* takers — for whom no scholarship program existed — enrolled in higher education based solely on their own resources, preferences, and academic preparation, without any induced entry from financial aid. The enrollment decisions of this cohort therefore reflect the counterfactual enrollment behavior that would have prevailed in the absence of the program, and a model trained to predict enrollment in this cohort can be used to identify students in subsequent cohorts who would have enrolled regardless of scholarship eligibility.

Concretely, I train a gradient boosted tree model (XGBoost) on the 2013 cohort to predict the binary outcome of higher education enrollment as a function of observable student characteristics, including standardized *Saber 11* subject scores, SISBEN score, gender, rurality, ethnicity, socioeconomic stratum dummies, household size, rooms in the household, department of residence, and parental education. The model also incorporates interaction



terms between academic scores and stratum and parental education, allowing the predicted enrollment probability to vary flexibly with the joint distribution of academic ability and socioeconomic background. The data are split into training (70 percent), validation (20 percent), and test (10 percent) sets, stratified by the enrollment outcome, and class imbalance is addressed by weighting observations inversely proportional to their class frequency.

The trained model is then applied to predict enrollment probabilities for each student in the 2014–2019 cohorts. A key step in translating these predicted probabilities into an always-taker classification is the choice of threshold. Rather than using a fixed probability cutoff such as 0.5, which would be arbitrary in this context, I anchor the threshold to the 2013 baseline enrollment rate $\bar{p}$ — the share of students who enrolled in higher education before the program existed. The intuition is straightforward: in the absence of the scholarship, the share of students who would have enrolled in any given cohort should be approximately equal to the pre-program enrollment rate, under the assumption that the underlying distribution of enrollment propensities is stable across cohorts. I therefore classify as predicted always-takers the top $\bar{p}$ fraction of students in each cohort by predicted enrollment probability — that is, students whose predicted probability exceeds the $(1 - \bar{p})$ quantile of the predicted probability distribution within their cohort. This ensures that the size of the predicted always-taker subsample in each post-program cohort matches the counterfactual enrollment rate that would have prevailed in the absence of the scholarship, rather than reflecting an arbitrary probability cutoff. The RD estimates for field and track choices are then re-estimated on this predicted always-taker subsample using both the academic *Saber 11* threshold and the socioeconomic SISBEN threshold as running variables.

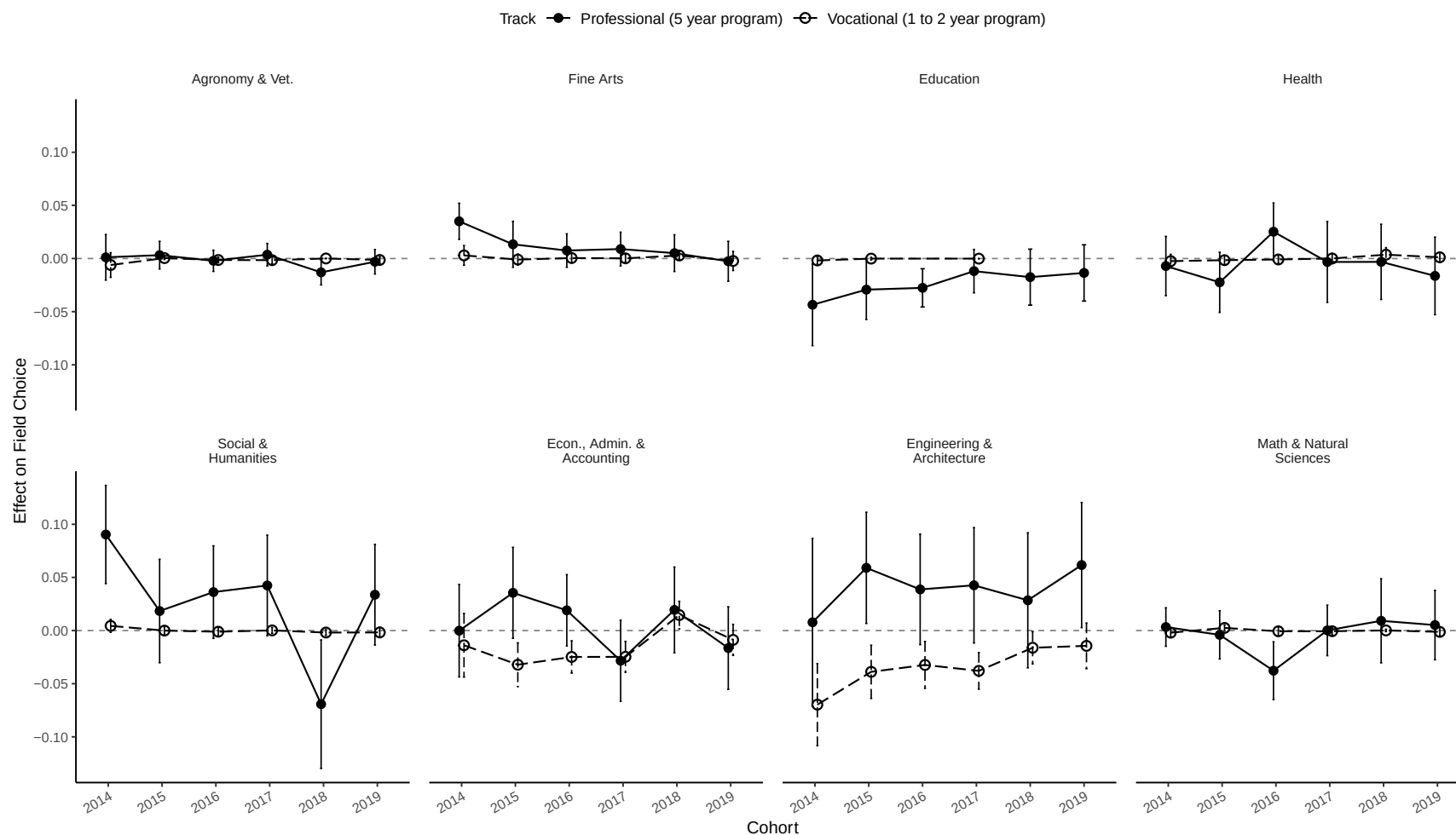
Figures [A.8](#) and [A.9](#) present the results under the academic *Saber 11* and socioeconomic SISBEN thresholds respectively. Before interpreting the estimates, it is important to acknowledge that the predicted always-taker classification is imperfect by construction. The XGBoost model achieves a ROC-AUC of approximately 0.80 on the held-out test set, with sensitivity of around 40 percent and specificity of around 89 percent at the chosen threshold, implying that the predicted always-taker subsample captures a meaningful but incomplete share of true always-takers while also including some misclassified compliers. The exercise



should therefore be interpreted not as a precise decomposition of the treatment effect, but rather as suggestive evidence on whether students who were likely to enroll regardless of the scholarship also appear to have adjusted their field and track choices in response to eligibility.

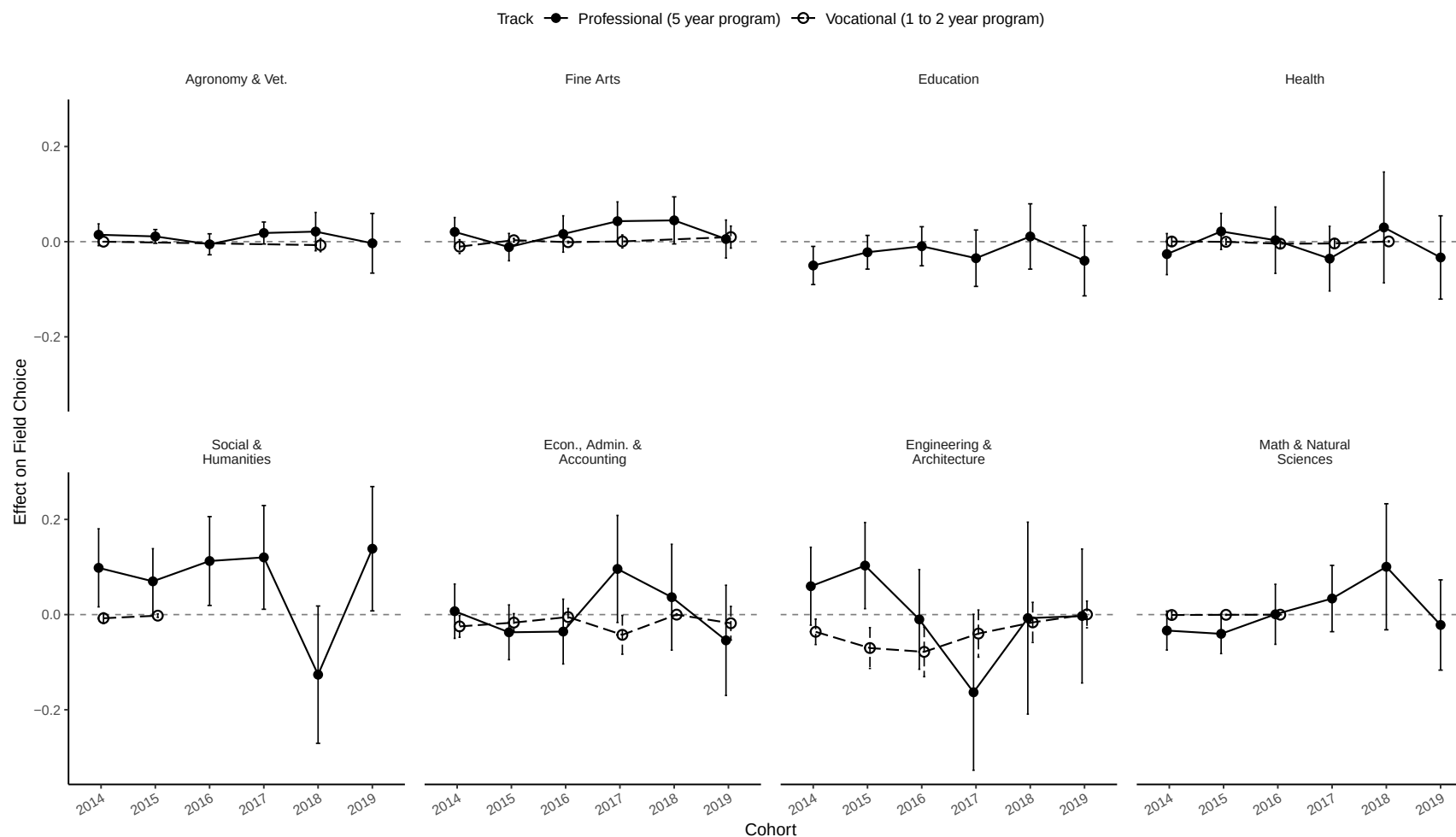
With this caveat in mind, the *Saber 11*-based estimates in Figure A.8 suggest that among students most likely to be always-takers, eligibility is associated with some of the same patterns documented in the main results. Negative effects on vocational engineering enrollment are visible across the 2014–2016 cohorts, negative effects on professional education enrollment appear in the same period, and positive effects on professional fine arts and social and human sciences enrollment are visible in the early cohorts. The SISBEN-based estimates in Figure A.9 are considerably noisier given the smaller effective sample sizes near the socioeconomic threshold, and most estimates are not statistically distinguishable from zero, though the directional patterns are broadly consistent with the *Saber 11* results for the 2014 and 2015 cohorts. To the extent that the model captures at least part of the always-taker population, these patterns suggest that the reallocation of students away from vocational engineering and education programs and toward social sciences and fine arts professional programs is not driven exclusively by the choices of newly induced entrants, and that always-takers were also making different enrollment decisions at the field and track level in response to eligibility.

FIGURE A.8: Effects on Field and Track Choice: Predicted Always-Taker Sample, Academic *Saber 11* Threshold



Notes: RD ITT estimates of the effect of scholarship eligibility on enrollment in each field and track combination, using the academic *Saber 11* threshold as the running variable. The sample is restricted to students classified as predicted always-takers based on the XGBoost model trained on the 2013 pre-program cohort, as described in the text. Filled and open circles represent point estimates for professional and vocational tracks respectively. Bars represent 95 percent robust confidence intervals.

FIGURE A.9: Effects on Field and Track Choice: Predicted Always-Taker Sample, Socioeconomic SISBEN Threshold



Notes: RD ITT estimates of the effect of scholarship eligibility on enrollment in each field and track combination, using the socioeconomic SISBEN threshold as the running variable. The sample is restricted to students classified as predicted always-takers based on the XGBoost model trained on the 2013 pre-program cohort, as described in the text. Filled and open circles represent point estimates for professional and vocational tracks respectively. Bars represent 95 percent robust confidence intervals.