"Am I not good at it, or am I not good at all?" STEM gender gaps in higher education*

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Abstract

I study the heterogeneous gender effect of enrolling in a STEM major on college graduation from the initial major, major switch (i.e., a dropout from the initial major and enrollment in a new one), and college dropout without enrolling into another. I leverage administrative data on Colombian high school graduates through their senior and college years to estimate a multistage discrete choice model where individuals: (i) decide to enroll or not in college, (ii) conditional on enrolling, choose an initial major, (iii) decide between graduating, switching majors, or dropping out of college. To the best of my knowledge, this is the first paper that addresses selection on both enrollment and major choice. I find that for all students, enrolling in a STEM major reduces college completion and increases major switch and dropout rates. The increase in major switch is higher for men, while dropout is higher for women. These gender differences seem to be explained by gaps in self-efficacy.

Keywords: STEM major, gender gaps, unobserved heterogeneity.

JEL-codes: I23, J14, J16, J24.

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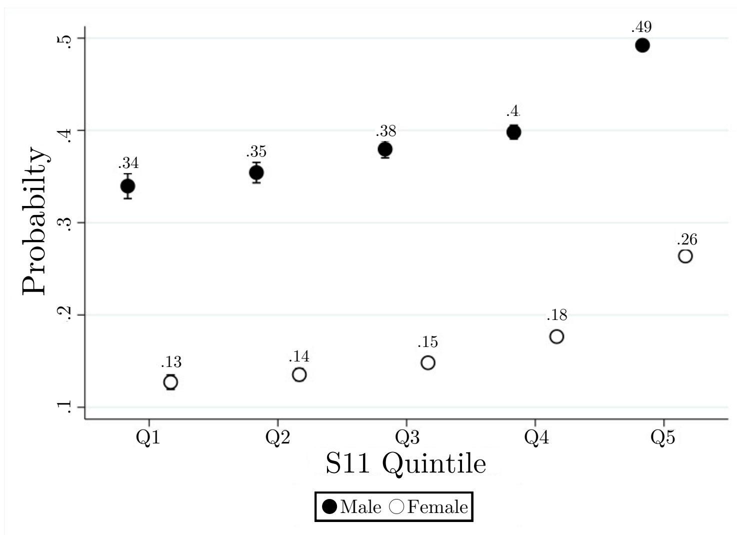
1 Introduction

The gender gaps in higher education start with marked differences in performance on standardized tests in which men considerably outperform women (Saltiel, 2022; Muñoz, 2018). These differences seem to translate into the lack of female representation in STEM majors (Science, Technology, Engineering, and Mathematics). Also, it appears to be an efficiency problem in STEM majors' gender composition. In particular, given limited spots for STEM majors, low-skilled men are filling positions where it would be more efficient to have high-skilled women. This problem is evidenced in Figure 1, where the probability of enrolling in a STEM major for a woman in the highest quintile of the *Saber 11* (S11, the high school exit exam) is even lower than the probability for a man in the lowest quintile.

Figure 1: STEM enrollment rate by gender



Source: Instituto Colombiano para la Evaluación de la Educación (2015); Ministerio de Educación Nacional (2015b). Author's calculations.
Note: N= 558,010. 95% confidence intervals from White-Hubber robust standard errors.

When students apply to college in Colombia, they apply to a specific major. So dropout, even when there is re-enrollment into another major, implies high costs such as loss of human capital, time, and money. Not enrolling or dropping out from a STEM major also means that students will not access its high labor market returns (between 10% and 22%, according to Saltiel (2022)). As STEM majors have greater returns than Colombia's gender wage gap (approximately 9.5% for 2006, according to Hoyos, Ñopo, and Peña (2010)), the lack of female representation could contribute to the wage gap. Therefore, it is important to understand the gender-differentiated effect of enrolling in a STEM major on the probability of graduating from the initial major, switching majors (i.e., a dropout from the initial major and enrollment in a new one), and dropping out without enrolling into another.

I leverage student-level administrative data on high school graduates (cohorts from 2006 to 2008) through their senior and college years to estimate a multistage discrete choice model where individuals: (i) decide to enroll or not in college, (ii) conditional on enrolling, choose an initial major, and (iii) decide between graduating from their initial major, switching major, or dropping out of college. To the best of my knowledge, this is the first paper that models selection on both enrollment and major choice. I implement a control function approach to address the unobserved heterogeneity. For the enrollment decision, I propose the college enrollment rate of the previous cohort of the student's high school as the exclusion restriction. As an exclusion restriction for the major choice, I use the STEM enrollment rate (among those enrolled in college) of the previous cohort of student's high school. For example, for student i that attended high school h in year t, the exclusion restriction for enrollment is high school's h college enrollment rate for the $t-1$ cohort. Similarly, the exclusion restriction for major choice is the number of students from high school's h $t-1$ cohort that enrolled in a STEM major over the number of students that enrolled in college from the same cohort. I assume both exclusion restrictions are exogenous as they both are equilibria of the college admission market (see section 4, Exclusion Restrictions, for further discussion).

I find that enrolling in a STEM major reduces the student's probability of graduating from their initial major and academic achievement (i.e., approved courses rate). In particular, enrolling in a STEM major (relative to other majors) reduces the probability of graduating from the initial major by 13% of the average[1] (that is around 6 percentage points, p.p.). Likewise, it increases the probability of switching majors by 26% of the average (5 p.p.) for women and by 35% for men (7 p.p), and of dropout by 5% for women (2 p.p.) while not affecting the probability for men. In other words, I found that enrolling in a STEM program makes men more likely to switch to another major, while women more likely to quit their studies. Suggestive evidence points to self-efficacy as the mediator for these gender differences (see further discussion in section 2). Presumably, STEM

[1]Note that the average is the unconditional probability of graduating among enrolled students.

enrollment makes men think they are not capable of graduating from STEM but are capable of graduating from another major, while women that they are not capable of graduating from college.

Given the potential role of self-efficacy and the positive results of Porter and Serra (2020), I propose to increase exposure to female professors, who could be seen as role models. This suggestion is reasonably inexpensive and easy to implement. Nevertheless, it leaves a window for an intervention that targets both men and women in STEM programs.

Most of the works on STEM education have focused on understanding the determinants of enrolling in STEM major and how to foster women's participation (Anaya, Stafford, and Zamarro, 2022; Bastarrica, Hitschfeld, Marques Samary, and Simmonds, 2018; Bordon, Canals, and Mizala, 2020; Brenøe and Zölitz, 2020; Chise, Fort, and Monfardini, 2019; Cohen and Kelly, 2020; Dulce-Salcedo, Maldonado, and Sánchez, 2022; Espinosa Borda, Bayona, and Enriquez, 2020; Wegemer, 2019). There are considerably fewer papers that study how enrolling in a STEM major impacts graduation (Fischer, 2017; Griffith, 2010; Saltiel, 2022), which is as important as enrollment because graduation returns are considerably higher. Through a rigorous approach, I identify the unintended gender-differentiated effects of enrolling in a STEM major, a problem that has not been dealt with in the previous literature.

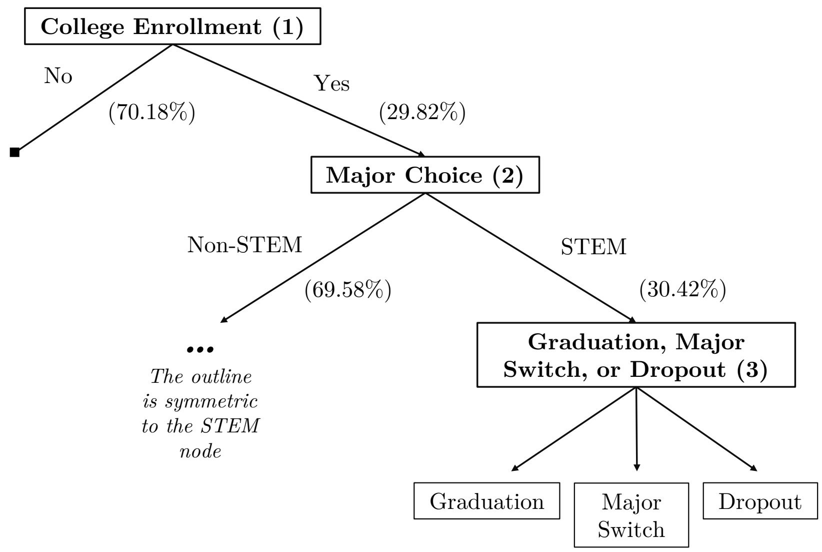
This paper is organized into six sections. The following section describes the potential mechanisms behind the gender differences in the impact of STEM enrollment on graduation, major switch, and dropout. In section 3, I describe the data and characterize the students in my sample. In section 4, I describe the empirical strategy, in section 5 the results, and in section 6, the conclusion.

2 Mechanisms

In Colombia, the college enrollment process starts by taking the S11. S11 is a standardized test that high school seniors take at the end of the academic year. The exam is not mandatory to obtain a high-school degree, but it is to enroll in post-secondary education. However, more than 90% of students take the test, including those that do not seek a degree in higher education (Londoño-Vélez, Rodríguez, and Sánchez, 2020).

Once a student takes the S11, the higher education decision process begins. I propose a sequential discrete choice model (see Figure 2) where students rationally make decisions. First, students decide to enroll or not in college.[2] Second, conditional on enrolling, they choose a major between STEM, Business, and Others. Finally, they decide whether to graduate from their initial major, switch majors, or dropout of college.

Figure 2: Discrete choice model



Note: The "non-STEM" category is divided in two categories, Business and Others. The choice structure of the "non-STEM" nodes is symmetric to the "STEM" node. Among those who enrolled in college, 24.29% enrolled in a Business major and 45.29% in Others (i.e., not STEM nor Business). Also, among the college students, 49.76% graduated from their initial major, 18.93% dropped out from their initial major and enrolled in a new one (switched majors), and 31.32% dropout from college.

The objective of this paper is to inquire about the gender-differentiated effect of enrolling in a STEM major on graduation, major switch, and dropout. Therefore, I delve into the possible mechanisms of this relationship through suggestive evidence. The previous literature has documented several differentiated factors by gender that could impact the graduation of students in STEM majors. I discuss those that are related to gender differences in initial cognitive skills, female students' minority status, risk aversion, and responsiveness to grades.

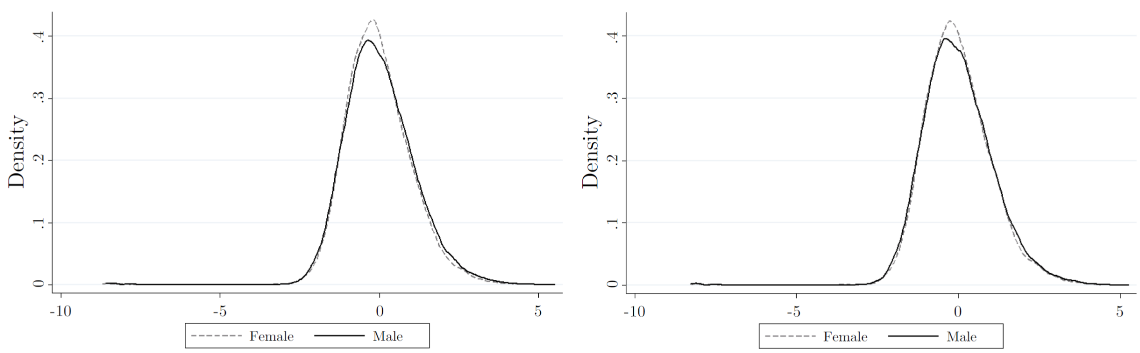
[2] I only consider four or more year educational programs as college. In Colombia, educational programs of one or two years are considered technical or technological (i.e., not college-level degrees).

Gender Differences in Skills

As mentioned before, there are marked differences in the performance in standardized tests where men outscore women considerably (Saltiel, 2022; Muñoz, 2018). In Figure 3, I present the conditional distribution of skills by gender for STEM majors. The p-value of the Smirnov-Kolmogorov test ($H0$ equal distributions across genders) is zero for both skills. That is, with a 95% confidence, the distributions are different. In particular, it can be observed that the distribution for women has a higher concentration at the mean and a right tail with lower mass (i.e., the maximum value for men is 5 SD while for women it is 4 SD in both skills). The mean for quantitative reasoning is statistically higher for man, while the reading skills is not different ($\alpha = 5\%$). Even so, the difference in quantitative reasoning is economically negligible (0.01 SD). This suggests that STEM majors are not a setting where women dropout at higher rates because they are less skilled.

Figure 3: Conditional distribution of skills by gender for STEM students

(a) Quantitative reasoning (b) Reading



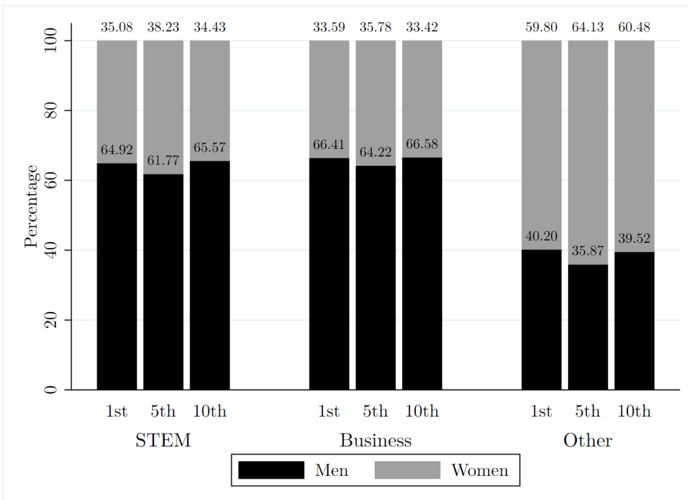
Source: Instituto Colombiano para la Evaluación de la Educación (2015); Ministerio de Educación Nacional (2015b). Author's calculations.
Note: N= 50,617. Skills measures have mean zero and are obtained through a measurement system using S11 information. See the section 4 for further detail. For quantitative reasoning, I use mathematics, physics, and chemistry scores, while for reading, language, English, philosophy, and social sciences scores. Skills distributions are conditional on age at S11, socioeconomic stratum, mother's education, and S11 semester fixed effects.

Women's Minority Status

Shan (2022) studies the impacts of study groups' gender composition for college students in an introductory economics course. The author finds that being assigned to a study group in which the student is part of a minority increases the women's probability of dropping out by 10 p.p., while not affecting men. She suggests that the minority status might be harming women's self-efficacy and reducing their interactions with other classmates.

In Figure 4, I present the average gender composition of the cohorts by major for the first, fifth, and tenth semesters. Women are considered a minority only in STEM majors, as they represent 35.9% of the students in the first semester. Similarly, as the percentage of women increases, the minority status does not exacerbate over time, it diminishes. Nevertheless, the minority status of women may reduce their self-efficacy and interactions, leading to an increase in their dropout as suggested by Shan (2022).

Figure 4: Gender composition by major and semesters enrolled



Source: Instituto Colombiano para la Evaluación de la Educación (2015); Ministerio de Educación Nacional (2015b). Author's calculations.
Note: N= 166,418.

Figure 4 shows that conditional on enrolling in a STEM major, men dropout at higher rates than women. As in STEM men do not outperform women's skills (see Figure 3), men's higher dropout rates might be related to a higher selection in STEM enrollment for women. This could translate into higher dropout rates for men. Because of this, the previous descriptive statistic reasonably captures results influenced by non-observed factors and not necessarily the causal effect of major choice.

Gender Differences in Risk Aversion and Responsiveness to Grades

There is a strong positive relationship between skills and STEM enrollment (see Figure 1). Then it is reasonable that STEM majors are, on average, more skilled than students in other majors. Fischer

(2017) shows that having more high-ability classmates makes women more likely to dropout from a STEM major while it does not affect men. The author theorizes that grades are the mechanism behind these gender differences.

Enrolling in a STEM major reduces academic achievement, even conditional on skills and major choice (see section 5 for further discussion). Then, based on Fischer (2017), I theorize that after receiving bad grades in STEM courses, students update their self-efficacy beliefs about their capacity to graduate from their current major. In particular, they might see themselves as less capable of graduating. This could translate into a lower graduation rate for female and male STEM majors.

Women are more responsive to grades and risk aversion than men (as cited by Fischer (2017)). So it is reasonable that women and men react differently to the negative impact on academic achievement. Presumably, these could lead to a more substantial decrease in women's self-efficacy (relative to men). That could lead men to think they are not capable of graduating from STEM but are capable of graduating from another major, while women that they are not capable of graduating from college.

To conclude the discussion of the mechanisms, self-efficacy seems to be a key factor for dropout. Factors such as minority status, low academic achievement, risk aversion, and responsiveness to grades might be making STEM students more vulnerable, especially women. Unfortunately, I cannot test this hypothesis empirically since I do not have a measure of self-efficacy in my data.

3 Data

The data from S11 contains administrative information at the student level for all high school graduates in Colombia. The Colombian Institute for the Evaluation of Education (ICFES, by its name in Spanish) is an independent government entity ascribed to the National Ministry of Education. The ICFES is in charge of the design and implementation of the S11 test (Instituto Colombiano para la Evaluación de la Educación, 2020). During the period of interest, Spring 2006 to Spring 2008, the test scores are comparable even though they do not have a defined maximum score. Also, S11 evaluated the components of mathematics, physics, chemistry, biology, philosophy, language, and English, and collected socioeconomic information from the students (Instituto Colombiano para la Evaluación de la Educación, 2014, 2019).

S11 is not a mandatory requirement to obtain a high school degree, but it is to enroll in a higher education program. However, each secondary academic institution must "present all of its students [in the last school year to the S11], except under exceptional circumstances" (Ministerio de Educación Nacional, 2015a). Therefore, the S11 is taken by the majority of high school senior students, including those that are not seeking a degree in higher education.[3]

Once the students enroll in a higher education program, their information is reported every semester by the university to the System for the Prevention of Dropout from Higher Education (SPADIES, by its name in Spanish). The SPADIES is a module of the National System of Higher Education Information (SNIES, by its name in Spanish) created in 1998 by the Universidad de Los Andes in bidding with the Ministry of Education. Moreover, reporting the information is mandatory since 2007 (Ministerio de Educación Nacional, 2006). As a result, I constrain my sample to those students that could have enrolled in higher education from the Fall semester of 2006. Given that I have SPADIES information until the first semester of 2015, this paper includes five different cohorts of students whose higher education decisions have been observed for at least seven years.[4]

The objective of the SPADIES is to monitor the academic and socioeconomic conditions of the students to establish the determinants of dropout, characterize the potential population at risk, and design and implement strategies to keep students enrolled (Ministerio de Educación Nacional, 2014, 2020b). Then, the SPADIES contains longitudinal national administrative information for all students that enrolled in a higher education program, independently if they finished their program or not (Ministerio de Educación Nacional, 2014, 2020b).

The union of the S11 and SPADIES data was realized by a group of engineers in charge of providing the data. They claimed to have used ids, names, and time-invariant characteristics (e.g., birth date and place) to implement a probabilistic match. In Online Appendix A, I describe the elimination of anomalous observations and the definition of the final sample based on the availability of information. It is worth mentioning that the data that I received is properly anonymized to preserve the privacy of the individuals. Then it is not possible for me to directly verify the quality of the matches between datasets.

[3] S11 is administered twice a year around March and October. Most of the students only take it once, when they are required to by their high schools. In fact, 94.17% take the exam once or twice.

[4] The information of the Fall 2006 and Spring 2007 is only used to construct the exclusion restrictions for the Fall 2007 and Spring 2008 cohorts.

In Online Appendix A, Table A. 1, I present the differences between the individuals eliminated in the cleaning process of S11 and the individuals in the final sample. This analysis is done using t-mean tests and mean differences standardized by sample size (following Yang and Dalton (2012)). On average, relative to the final sample, individuals eliminated in the cleaning process have more educated mothers, belong to a higher socioeconomic stratum (SES), have lower levels of the System of Identification of Potential Beneficiaries to Social Programs (SISBEN, by its name in Spanish), and are more likely to be in the highest quintile of the S11. This indicates that the individuals eliminated in the cleaning process systematically differ from the final sample students in purchasing power.

On the other hand, for the explanatory variable of interest, the major choice, I manually classified each major following Saltiel (2022). My classification was done based on the Ministry of Education's classification, complemented by the definitions from the Department of Educations Classification of Instructional Programs (CIP) for the U.S. Given that currently there is no classification for the majors in Colombia, this paper provides a measure of the gender gap in the STEM education. Additionally, this allows a more precise comparison of the gender gap in STEM by disaggregating the comparison groups. For example, the classification allows me to separate biology from the rest of the STEM majors and to separate the non-STEM majors into business, social sciences, health, and others.[5] Besides, this non-binary classification is useful in the context of the model proposed given that there is substantial heterogeneity in the returns to non-STEM majors. This makes it relevant to differentiate the comparisons with non-STEM majors of high returns (e.g., business) from those with lower returns (e.g., social sciences).

The outcome is the decision to graduate from their initial major, switch majors or dropout of college.[6] I define major switch as the definitive transit from one major to another. In other words, major switch is a dropout from the initial major followed by enrollment in a different major, regardless of graduation/dropout from the new major. Meanwhile, dropout is a definitive exit from the higher education system without attempting a second major. This distinction between major

[5] STEM includes majors such as mathematics, statistics, engineering, computer sciences, and biology. Business includes business administration, finance, accounting, taxation, marketing, and international business. Social sciences include economics, anthropology, political science, law, and history. Health includes medicine, nursing, physical therapy, and veterinary. Finally, come majors that are not classified in any of the previously mentioned groups are physical training, nutrition, military sciences, arts, design, literature, and criminology.

[6] As Ministerio de Educación Nacional (2020a), I classified as droppout the absence of at least two consecutive semesters until my last semester of SPADIES (Spring 2015).

switch and dropout is made so that, in the model, students are allowed to make an erroneous major decision and be able to correct it further on. It is worth mentioning that I am unable to study the dropout or culmination of a major for those students that switched majors due to limitations in the available periods in the SPADIES.

In Panel A of Table 1, I characterize my sample. The average age of the students when taking the S11 is 18 years, 54% are women, and 79% come from schools that begin the academic year in the Spring semester (calendar A).[7] Additionally, 60% of students have mothers with at least secondary education, 12% works, and 79% belong to the two SES (out of six SES). Finally, the students live in a household with, on average, 4 other people, 69% report living in a house their family own, and 68% belong to the lowest levels of SISBEN.

Table 1: Sociodemographic characteristics and educational outcomes

	N. Obs.	Mean	SD	Min.	Max.
A. Sociodemographic characteristics					
Age at S11	558,010	18.07	4.36	12	78
Gender: Female	558,010	0.54	0.5	0	1
HS calendar: A	558,010	0.79	0.41	0	1
Mother's education: Some HS or more	558,010	0.6	0.49	0	1
Worked during HS	558,010	0.12	0.33	0	1
SES<3	558,010	0.79	0.41	0	1
HH size	103,730	4.56	1.69	1	12
Own house	558,010	0.69	0.46	0	1
SISBEN<5	103,730	0.68	0.47	0	1
B. Educational outcomes					
N. of classmates	166,418	0.76	1.81	0	27
Graduation	166,418	0.5	0.5	0	1
Major switch	166,418	0.2	0.39	0	1
Dropout	166,418	0.31	0.46	0	1
Rate of approved courses	166,418	0.84	0.26	0	1

Source: Instituto Colombiano para la Evaluación de la Educación (2015); Ministerio de Educación Nacional (2015b). Author's calculations.
Note: Changes in the sample size in sociodemographic characteristics are due to certain periods in which ICFES did not collect such information. N. of classmates is the number of students from the same high school cohort that enroll in the same college.

Table 2 presents a difference in means (standardized by sample size following Yang and Dalton (2012) and non-standardized with t-tests) by gender. In Panel A, it is observed that the sociodemographic characteristics are marginally different between men and women. In particular,

[7]High schools with Calendar A start the academic year in Spring and finish in Fall, while the others start in Fall and finish in Spring. All public schools are Calendar A, and, on average, students from Calendar A schools are more vulnerable than the others.

standardized differences are of a small magnitude. Regarding the educational decisions (Panel B), there are four aspects to highlight. First, just as with other standardized tests, in the S11 there is a gender gap in which men obtain higher scores than women. In particular, a woman has a probability lower by 4.6 percentage points (p.p) of being in the highest quintile of the test than a man. Second, a woman has a probability 1.6 p.p. higher of enrolling in college than a man.

Table 2: Sociodemographic characteristics and education outcomes by gender

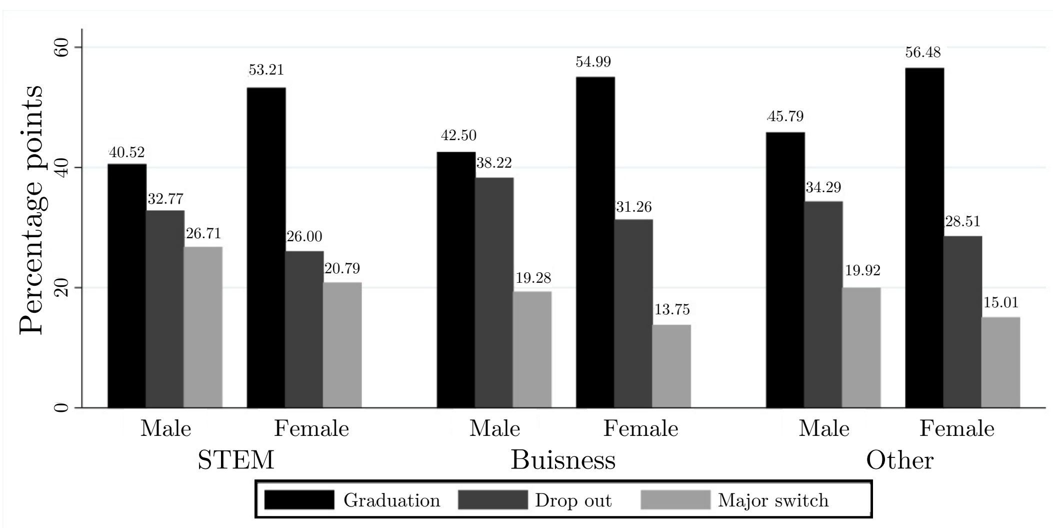
	N. Obs.	**Men**	**Women**	**Difference (Cohen's "d")**
A. Sociodemographic characteristics				
Age at S11	558,010	18.072	18.072	0.000
		(4.127)	(4.548)	(0.000)
HS calendar: A	558,010	0.782	0.793	0.011***
		(0.413)	(0.405)	(0.026)
Mother's education: Some HS or more	558,010	0.600	0.600	0.000
		(0.490)	(0.490)	(0.000)
Worked during HS	558,010	0.126	0.116	-0.010***
		(0.331)	(0.320)	(0.030)
SES<3	558,010	0.798	0.787	-0.011***
		(0.401)	(0.409)	(0.028)
HH size	103,730	4.544	4.575	0.032***
		(1.667)	(1.710)	(0.019)
Own house	558,010	0.691	0.693	0.002
		(0.462)	(0.461)	(0.003)
SISBEN<5	103,730	0.677	0.679	0.002
		(0.467)	(0.467)	(0.003)
B. Educational outcomes				
S11: Quintil 5	558,010	0.227	0.181	-0.046***
		(0.419)	(0.385)	(0.116)
College enrollment	558,010	0.289	0.306	0.016***
		(0.453)	(0.461)	(0.036)
STEM	166,418	0.433	0.198	-0.235***
		(0.496)	(0.399)	(0.529)
Business	166,418	0.206	0.273	0.066***
		(0.405)	(0.445)	(0.155)
Other	166,418	0.36	0.529	0.169***
		(0.480)	(0.499)	(0.344)
N. of classmates	166,418	0.746	0.778	0.032***
		(1.774)	(1.844)	(0.018)
Graduation	166,418	0.428	0.554	0.126***
		(0.495)	(0.497)	(0.254)
Major switch	166,418	0.227	0.158	-0.069***
		(0.419)	(0.365)	(0.177)
Dropout	166,418	0.344	0.288	-0.057***
		(0.475)	(0.453)	(0.123)
% of approved courses	166,418	0.801	0.863	0.061***
		(0.274)	(0.239)	(0.241)

Source: Author's calculations using Saber 11 and SPADIES information..
Note: Statistical significance of t-mean difference tests: *p<0.1, **p<0.05, ***p<0.01. Difference of means standardized following Yang and Dalton (2012) presented with Cohen's d-stastic. Standard errors and Cohen's d-statistic in parenthesis. Changes in the sample size of sociodemographic characteristics are due to certain periods in which ICFES did not collect such information.

Third, STEM is the only field in which there is a considerable sub-representation of women. In particular, conditional on college enrollment, a woman has a probability of choosing a STEM major 23.5 p.p. lower than a man. Finally, unconditionally, women have better results in terms of graduation, major switch, and dropout. Relative to men, women, have probabilities of graduating higher by 12.6 p.p., of switching majors lower by 6.9, and of dropout lower by 5.7 p.p.

Figure 5 shows graduation, major switch, and dropout rates by gender and initial major. In terms of the differences across majors, STEM majors have the lowest graduation and dropout rates, as well as higher major switch rates. The counterfactual to STEM is disaggregated only into Business and Others because Business is the one that presents the biggest unconditional differences (see Online Appendix B) without threatening the stability of the multinomial model. On the other hand, unconditionally, women are ahead of men by 12.69 p.p. in graduation, 5.92 p.p. in major switch, and 6.77 p.p. in dropout in STEM majors. However, this may be driven by the fact that selection into STEM is higher for women than for men.

Figure 5: Graduation, major switch, and dropout rates by gender and initial major



Source: Instituto Colombiano para la Evaluación de la Educación (2015); Ministerio de Educación Nacional (2015b). Author's calculations.
Note: N= 166,418.

4 Methodology

First, I estimate a measurement system to obtain students' quantitative reasoning and reading skills. Then I estimate the multistage discrete choice previously described (see Figure 2) using a control function approach with exclusion restrictions for the enrollment and major decisions.

Measurement System of Latent Skills

In this model, each student has unobserved quantitative reasoning (f^q) and reading (f^r) skills. As in (Saltiel, 2022) skills are unobserved, so I implement a measurement system to estimate the moments of the skills distributions. Following the latent skills literature, I define a dedicated measurement system where S11 test scores are the noisy measures of the desired latent skills (Agostinelli and Wiswall, 2021; Attanasio, Cattan, Fitzsimons, Meghir, and Rubio-Codina, 2020; Cunha and Heckman, 2008; Saltiel, 2022; Urzua, 2008). In particular, each S11 test score is a function of a specific latent skill and a measurement error term.

In the period of interest, I observe eight S11 test scores. I propose that the mathematics, physics, and chemistry S11 scores are a function of quantitative reasoning skills. Let T^q_{ik} be the student's i k-th test score, whose functional form is:

$$T^q_{ik} = \delta^q_{0,k} + lnf^q_i \delta^q_k + e^q_{ik}$$

where $k = \{\text{mathematics, physics, chemistry}\}$ and, as usual in this literature, the measurement error term (e^q_{ik}) is assumed to be independent of the logarithm of quantitative reason skills (lnf^q_i).

Similarly, the language, English, philosophy, and social sciences S11 scores are a function of reading skills. The functional form of the k'-th test score, $T^r_{ik'}$, is:

$$T^r_{ik'} = \delta^r_{0,k'} + lnf^r_i \delta^r_{k'} + e^r_{ik'}$$

where $k' = \{\text{language, English, philosophy, social sciences}\}$ and $e^r_{ik'}$ is assumed to be independent of the logarithm of reading skills (lnf^r_i).

As described by Attanasio et al. (2020), the identification of the measurement system requires localization and scale normalizations. For the location, I set the means of the logarithms of the skills to zero, $E(lnf^q) = E(lnf^r) = 0$. I set the scale of the logarithms of the skills by setting the loading of one test score per skill to 1. In particular, $\delta^q_m = \delta^r_l = 1$, where m indicates mathematics and l language. Also, to identify the covariance between the skills, I set $V(lnf^q) = V(lnf^r) = 1$.

In previous versions of his work, Saltiel (2022) documented a large positive correlation between problem-solving and reading skills in the US. It is reasonable that good communication skills foster learning in other disciplines as it is vital in learning activities such as reading and hearing a class (Alvarez-Marinelli, Berlinski, and Busso, 2021). So I allow for a correlation between quantitative reasoning and reading skills.

I estimate the measurement system by Maximum Likelihood, assuming a joint normal distribution of the skills.[8] To obtain the predicted skills (i.e., one value per student and skill), I use empirical Bayes means. Finally, as expected, I found a 0.9 correlation between quantitative reasoning and reading skills.

Online Appendix C shows an approximation of the validity of the predicted skills. Figure C.1 shows that quantitative reasoning and reading skills have what Bernal, Giannola, and Nores (2020) call a well-behaved distribution (i.e., symmetric, with thin tails, and without bunching). Similarly, skills and sociodemographic characteristics are correlated in the expected directions (see Table C.2). Skills are positively correlated with being in the 5th quintile of Saber 11, the mother's education, and the family's house ownership, and negatively with being female, age, working before college, and being in the low SES and SISBEN levels.

College Enrollment

Once students finish high school, they decide whether to enroll in college based on their skills and sociodemographic characteristics. Let I^*_{i1} be the latent utility that i receives from enrolling into college (relative to not enrolling). I^*_{i1} depends on observed and unobserved student characteristics as follows:

$$I^*_{i1} = x_i\delta_1 + z_{i1}\gamma_1 + lnf_i\alpha_1 + u_{i1} \tag{1}$$

where x_i is a vector that contains an intercept, the student's gender, age at S11, SES, mothers'

[8] For the optimization, I use quasi-Newtonian methods.

education, and fixed effects of the semester when the student took the S11 (e.g., Spring 2008 and Fall 2008). z_{i1}, the exclusion restriction, is the college enrollment rate of the previous cohort of the student's i high school. lnf_i is a vector with both latent skills and their interactions with the student's gender, and u_{i1} is an idiosyncratic error term.

As skills are not observed, I use the predicted logarithm of the skills. Also, I define I_i as the observed binary enrollment decision such that if $I^*_{i1} > 0$, then $I_i = 1$.

Finally, for the enrollment equation (1), I estimate a Probit. I define the enrollment control function with these results, CF_{i1}. CF_{i1} is the predicted probability of enrolling for those with $I_{i1} = 1$ and it is not defined for those with $I_{i1} = 0$.

Major Choice

Conditional on enrolling into college, students choose an initial major, m_1, from the set of possible majors $M_1 = \{\text{STEM (S), Business (B), Others (O)}\}$. Let $I^*_{i2,m1}$ be the latent utility student i derives from choosing major m_1 relative to Others. $I^*_{i2,m1}$ depends on observed and unobserved characteristics as:

$$I^*_{i2,m_1} = x_i\delta_{2,m1} + z_{i2}\gamma_{2,m1} + lnf_i\alpha_{2,m1} + CF_{i1}\pi_{2,m1} + u_{i2,m1} \tag{2}$$

where u_{i2,m_1} is an idiosyncratic error term and z_{i2} is the STEM enrollment rate (among those enrolled in college) of the previous cohort of student's i high school. That is, for a student who graduated from high school h in year t, z_{i2} is the number of students enrolled in a STEM major that graduated from h in $t-1$ over the number of students from h in $t-1$ that went to college.

I include CF_{i1} as a regressor in equation (2) to control for the selection induced by the non-random truncation in the major choice ($E(u_{2,m1}u_1) \neq 0$).[9] Also, define C_i as a set of three dummies (one per major) that capture the observed major decisions. For a particular major m_1, if $m_1 = \arg\max_{m_1 \in M_1} I^*_{i2,m1}$, then $C_i^{m1} = 1$.

Finally, I estimate the major choice equation (2) with a multinomial Probit on the sample of enrolled students (i.e., $I_i = 1$). To reduce the computational cost of the estimation, $\forall m1, m1' \quad st. \quad m1 \neq m1'$, I set $cov(u_{2,m1}, u_{2,m1'}) = 1$. Note that the normalization implies the in-

[9]Note that the major choice is not observed for those students that decide not to enroll in college, $I_{i1} = 0$.

dependence of irrelevant alternatives assumption. Additionally, I define the second control function (CF_{i2}) as the predicted probabilities of enrolling into a STEM and Business majors.

Graduation, Major Switch, or Dropout

Once students choose their initial major m_1, they choose between graduating from that major, switching majors, or dropping out of college without re-enrollment in a new major. Let $Y^*_{i,m2}$ be the latent utility that i gets from choosing the alternative $m1 \in M_2 = \{$graduation, major switch, dropout$\}$. The functional form of $Y^*_{i,m2}$ is:

$$Y^*_{i,m2} = C_i\beta_{m2} + x_i\delta_{3,m2} + lnf_i\alpha_{3,m2} + CF_{i1}\pi^1_{3,m2} + CF_{i2}\pi^2_{3,m2} + u_{i3,m2} \tag{3}$$

where C_i is a vector of binary indicators of enrollment in STEM and Business (C_i^S and C_i^B) and their interactions with the student's gender, and u_{i3,m_2} is an idiosyncratic error term. Note that the inclusion of CF_{i1} addresses the selection from college enrollment ($E(u_{3,m_2}u_1) \neq 0$), while the inclusion of CF_{i2} from major choice ($E(u_{3,m_2}u_{2,m_1}) \neq 0$).

Let D_i be a set of three binary dummies that capture the graduation, major switch, and dropout decision. For a particular choice m_2, if $m_2 = \arg\max_{m_2 \in M_2} \left\{Y^*_{im_2}\right\}$, then $D_i^{m_2} = 1$.

I estimate equation (3) with a multinomial Probit on the sample of enrolled students (i.e., $I_i = 1$). Then, the effect of enrolling in a STEM major on the probability of choosing m_2 is $Pr\left(D_i^{m_2} = 1 | C_i^S = 1, x, lnf, CF\right) - Pr\left(D_i^{m_2} = 1 | C_i^{\_S} = 1, x, lnf, CF\right)$, where $\_S = \{B, O\}$. As for equation 2, I set $\forall m2, m2' \quad st. \quad m2 \neq m2', \quad cov(u_{3,m2}, u_{3,m2'}) = 1$ (i.e., assume independence of irrelevant alternatives).

Finally, note that the estimations of equations (1), (2), and (3) are sequential, and each one includes results from all previous stages, including the measurement system. To compute valid standard errors, I implement a bootstrap where each iteration estimates the equation of interest and all the previous stages.

Exclusion Restrictions

The j-th exclusion restriction z_{ij} is valid if its (i) relevant (i.e., predicts decision made in stage j) and (ii) does not affect other decisions through something different than j stage's decision. z_{i1} is valid if (i) $Cov(z_1, I) \neq 0$, (ii) $Cov(z_1, u_{2,m_1}) = 0$, and $Cov(z_1, u_{3,m_2}) = 0$, while z_{i2} is valid if (i) $Cov(z_2, C^{m_1}) \neq 0$ and (ii) $Cov(z_2, u_{3,m_2}) = 0$

For the enrollment decision, I propose the college enrollment rate of the previous cohort of the student's high school as the exclusion restriction (z_{i1}). As older students might be perceived as role models or even provide younger students with information (e.g., about the application process or financial aid), it is reasonable that z_{i1} affects enrollment. Also, z_{i1} is the past equilibrium of the college admissions market. As it is an equilibrium, it is plausible that students' preferences and decisions could not affect it.

For the validity of z_{i1}, I assume that students from different cohorts within the same high school interact. Additionally, I assume that, conditional on S11 semester fixed effects, SES, and mothers' education, z_{i1} does not capture structural factors (e.g., an increase in openings or financial aid, or socks to family's income).

As an exclusion restriction for the major choice, I use the STEM enrollment rate (among those enrolled in college) of the previous cohort of student's high school (z_{i2}). This exclusion restriction is reasonably relevant in settings in which high schools have a focus on, for example, knowledge in humanities or sciences. Either because it is an explicit focus with vocational guidance programs, or implicit with accomplished professors in certain fields. In the previous scenario, it is reasonable that the major choice of older students is related to the major choice of the younger ones. Just as with the previous stage, z_{i2} plausibly only affects the students' decisions through the major choice, given that it is an equilibrium of the college admissions market.

Identification Assumptions. Advantages and Limitations

The control function approach described before aims to solve the selection issues from omitted variable bias present in this context. In this methodology, the assumption of conditional independence is required for the identification of causal effects. By including the exclusion restrictions in every stage, the assumptions are reduced to identification in non-finite order (as cited in Saltiel (2022)). Chamberlain (1986) says that the non-finite order assumption requires that at least one continuous variable in the model has a non-finite domain.[10] This assumption is plausible in large samples like mine because of the central limit theorem.

[10] See Chamberlain (1986); Heckman, Humphries, and Veramendi (2016) for more detail.

On the other hand, my approach has three main advantages. First, the identification does not completely depend on the relevance of the exclusion restrictions. As mentioned before, in case that the exclusion restrictions have relevance or exogeneity issues, the identification assumption is analogous to a matching assumption. Second, the measurement system reduces the noise from standardized tests. Finally, the implementation of control functions is considerably less computationally costly that the full-information Maximum Likelihood through a Roy model.

However, latent skills must be estimated, so there may persist a measurement error. Given the measurement error, because of the problem of incidental parameters, all Maximum Likelihood estimators would be inconsistent. This problem usually creates an attenuation bias in linear models, while the direction of the bias is unclear in a multinomial model. It is worth mentioning that the Heckman, Pinto, and Savelyev (2013) correction is only proposed for Ordinary Least Squares estimations. Therefore, I cannot implement this correction in my original model. Nevertheless, I estimated a binary version of the sequential choice model using Linear Probability Models and the Heckman et al. (2013) correction. My results are robust to this correction (results available upon request).

5 Results

College Enrollment

Table 3 shows that reading skills and mothers' education positively affect the probability of enrolling in college. On the other hand, quantitative reasoning skills appear to have a negative effect and are statistically significant with a 99% confidence, although economically negligible. In particular, for women, an increase of 0.1 SD in quantitative reasoning skills reduces the probability of enrolling in university by 0.25 p.p., which corresponds to 0.8% of the average. These results can be accounted for by the high correlation (0.99) between skills. It is worth mentioning that, just as what is found by Saltiel (2022) for the U.S., reading skills are a better predictor of college enrollment for men than for women. In terms of the exclusion restriction, an increase of 5 p.p. in the enrollment rate of the students' high school previous cohort increases the probability of enrollment by 2.26 p.p. This effect is statistically significant with a 99% confidence at represents 35.56% of the effect of the mother's education. Therefore, it is plausible that the exclusion restriction is relevant.

Table 3: Average marginal effects of the first and second stages: Enrollment into higher education and major choice

VARIABLES	**College Enrollment**	**Major Choice** STEM	Business	Other
Quantitative reasoning: Women	-0.024***	0.232***	-0.050***	-0.182***
	(0.005)	(0.009)	(0.008)	(0.009)
Reading: Women	0.134***	-0.180***	0.019**	0.161***
	(0.004)	(0.009)	(0.008)	(0.009)
Quantitative reasoning: Men	-0.065***	0.695***	-0.242***	-0.454***
	(0.009)	(0.035)	(0.017)	(0.026)
Reading: Men	0.173***	-0.665***	0.214***	0.451***
	(0.009)	(0.036)	(0.018)	(0.027)
Mother's education: Some HS or more	0.057***	-0.009**	-0.002	0.011***
	(0.001)	(0.004)	(0.003)	(0.004)
Exclusion Restriction	0.451***	0.188***	-0.110***	-0.078***
	(0.003)	(0.010)	(0.010)	(0.011)
Control Function 1		-0.011	0.017*	-0.005
		(0.010)	(0.009)	(0.011)
N. Obs.	558,010	166,418	166,418	166,418

Source: Instituto Colombiano para la Evaluación de la Educación (2015); Ministerio de Educación Nacional (2015b). Author's calculations.
Note: Univariate and multinomial probit estimations. Bootstrap standard errors with 1,000 repetitions in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Major Choice

The probability of choosing a STEM major increases with quantitative reasoning skills and decreases with reading skills (see Table 3). Likewise to the enrollment into university, quantitative reasoning skills predict in higher magnitude the choice for men than for women. This last pattern reappears for the major choice of Business and Others with reading skills. It is worth noting that the effects between skills cancel each other for men.

In terms of the exclusion restriction, an increase of 5 p.p. in the STEM enrollment rate (among enrolled) of the student's high school previous cohort increases the probability of enrolling in a STEM major by 0.94 p.p and reduces the probability of enrolling into a Business and Others major by 0.39 p.p. These effects are statistically significant with a 99% confidence. Also, the effect on STEM enrollment represents a 25.7% of the effect of a 0.1 SD increase in reading skills of men, while the effect on Business enrollment an 8.6%. In consequence, the exclusion restriction is relevant.

Graduation, Major Switch, or Dropout

Enrolling in a STEM major makes students systematically more likely to not graduate from their first major. I find that enrolling in a STEM major has statistically ($\alpha = 1\%$) and economically significant effects on the probabilities of graduation, major switch, and dropout. For graduation, the effects are similar and statistically equal across gender ($\alpha = 5\%$). STEM enrollment reduces graduation probability by 6.4 p.p. and 6.6 p.p. for women, and between 5.6 p.p. and 6.7 p.p. for men (see Table 4). Theses effects correspond to a reduction between 11.2% and 13.5% of the average.

For major switch, the effects are larger relative to Business than to Other majors. I find that enrolling in a STEM major increases major switch by 5.9 p.p. with respect to Business and 4.9 p.p. with respect to Others (31.2% and 25.9% of the average, respectively) for women. Likewise, it increases major switch between 6.7 p.p. with respect to Business and 7.9 p.p. respect to Others (35.6% and 41.8% of the average) for men. The differences in the effects by gender are relatively favorable for women.

On the probability of dropping out, the effects differ more relative to Business than to Other majors. I find an increase of 1.7 p.p. (5.4% of the average) for women when comparing STEM with other majors, and a reduction of 2.3 p.p. (7.4% of the average) for men when comparing STEM with Business. The remaining effects are not statistically significant from zero with a 99% confidence. In this case the differences by gender are favorable for men and correspond to 5.4% and 7.3% of the unconditional probability of dropping out, respectively.

Finally, the results differentiated by gender appear to indicate that there are no differences in graduation. Nevertheless, men are more likely to switch majors, while women more likely to dropout. It is worth mentioning that the results are robust to a change in the disaggregation of STEM's counterfactual (ie., with Social Sciences instead of Business), and to the measurement error correction proposed by Heckman et al. (2013) on a sequence of binary choices (results available upon request).

Table 4: Average marginal effects on graduation, major switch, and dropout

VARIABLES	Graduation: STEM vs Business	Graduation: STEM vs Other	Major switch: STEM vs Business	Major switch: STEM vs Other	Dropout: STEM vs Business	Dropout: STEM vs Other
STEM: Women	-0.064***	-0.066***	0.059***	0.049***	0.005	0.017***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)
STEM: Men	-0.056***	-0.067***	0.079***	0.067***	-0.023***	0.000
	(0.004)	(0.003)	(0.005)	(0.004)	(0.005)	(0.005)
Quantitative reasoning: Women	-0.298***		0.083***		0.215***	
	(0.034)		(0.015)		(0.023)	
Reading: Women	0.348***		-0.109***		-0.239***	
	(0.033)		(0.015)		(0.023)	
Quantitative reasoning: Men	-0.588***		0.048		0.540***	
	(0.074)		(0.048)		(0.069)	
Reading: Men	0.666***		-0.082*		-0.584***	
	(0.073)		(0.050)		(0.070)	
Control Function 1	0.205***		0.156***		-0.361***	
	(0.032)		(0.014)		(0.021)	
Control Functions 2:						
STEM	2.632***		-0.858***		-1.774***	
	(0.209)		(0.128)		(0.187)	
Business	3.864***		-1.409***		-2.455***	
	(0.447)		(0.281)		(0.373)	
Unconditional mean	0.498		0.189		0.313	
N. Obs.	166,418		166,418		166,418	

Source: Instituto Colombiano para la Evaluación de la Educación (2015); Ministerio de Educación Nacional (2015b). Author's calculations.
Note: Multinomial Probit estimation. Bootstrap standard errors with 400 repetitions in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

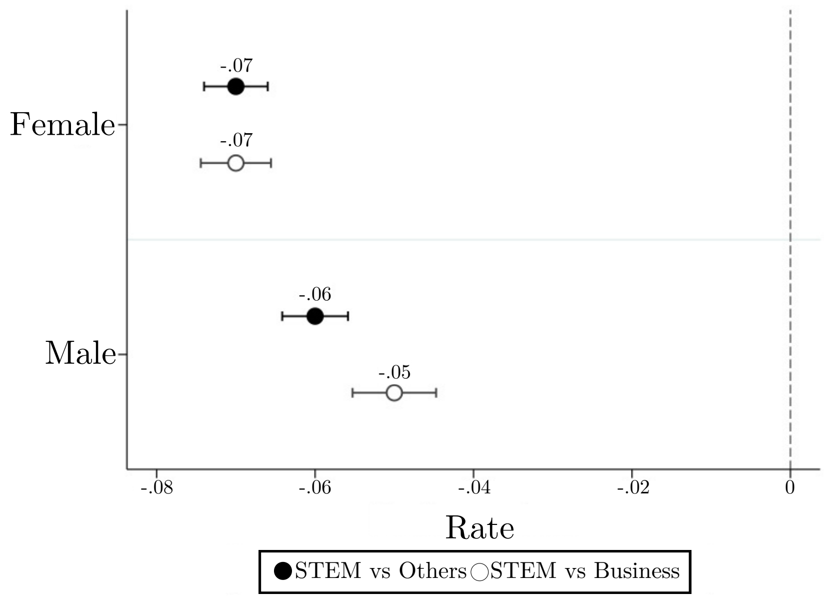
Academic Achievement

To analyze if enrolling in a STEM major impacts academic achievement, I estimate a control function model in which students (i) decide to enroll or not in college, (ii) conditional on enrolling, choose an initial major, and (iii) I observe their fraction of approved courses in their first semester. Given that the first two stages of the model are the same as in the main model, I use the same exclusion restrictions described in the methodology section.

Enrolling in a STEM major reduces academic achievement for men and women (see Figure 6), and the effect is higher for women. Enrolling in a STEM major relative to Business reduces academic achievement by of 6.8 p.p. (0.26 SD) for women and 5.1 p.p. (0.2 SD) for men. The effects are significant and different between them with 99% confidence. On the other hand, enrolling in a

STEM major relative to others reduces academic achievement in the same amount for women and men, around 7 p.p. (0.28 SD).

Figure 6: Effects of STEM enrollment on academic achievement



Source: Instituto Colombiano para la Evaluación de la Educación (2015); Ministerio de Educación Nacional (2015b). Author's calculations.
Note: N= 716,879. The estimation includes three stages: (i) college enrollment and (ii) major choice, as described for Table 4's results, and (iii) an Ordinary Less Squares estimation of the effect of STEM enrollment on the rate of the approved courses. Academic achievement is measured as the rate of approved courses. That is the number of approved courses over the number of courses taken. 95% confidence intervals based on Bootstrap standard errors with 400 repetitions.

6 Conclusion

Dropout from STEM majors restricts access to a labor market with higher returns than the gender wage gap documented by Hoyos et al. (2010) for Colombia in 2006. Therefore, it is relevant to understand the gender-differentiated effects of enrolling in a STEM major on the probabilities of graduation, major switch, and dropout.

In this paper, I propose a decision model in which individuals (i) decide to enroll or not into college, (ii) conditionally on enrolling, they choose an initial major, and (iii) they choose between graduating from their initial major, switch majors, or dropping out from college. I address the selection problem from this model through a control function. For the enrollment decision, I propose the college enrollment rate of the previous cohort of the student's high school as the exclusion restriction. As an exclusion restriction for the major choice, I use the STEM enrollment rate (among those enrolled in college) of the previous cohort of student's high school. I claim that the exclusion of the college admission market.

In conclusion, I found that enrolling in a STEM major makes students more likely to not graduate. In particular, I found that enrolling in a STEM program makes men more likely to switch to another major, while women more likely to quit their studies. Additionally, I hypothesize that the results are associated with gender differences in self-efficacy. Given my and Porter and Serra (2020)'s results, I propose to increase the exposure to female professors in introductory courses. I expect that higher exposure to successful female professors improves female students' self-efficacy by allowing them to identify the professors as role models.

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