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Abstract

We investigate the gender gap in Economics among bachelor's and master's graduates in Italy between 2010 and 2019. First we establish that being female exerts a negative impact on the choice to major in Economics: at the bachelor level, only 73 women graduate in Economics for every 100 men, with the mathematical content of high school curricula as the key driver of the effect and a persistence of the gap at the master level. Second, within a full menu of major choices, Economics displays the largest gap, followed by STEM and then Business Economics. Third, decomposition analyses expose a unique role for the math background in driving the Economics gender gap relative to other fields. Fourth, a triple difference analysis of a high school reform shows that an increase in the math content of traditionally low math curricula caused an increase in the Economics gender gap among treated students.

JEL Codes: A22, I23, J16.

Keywords: Education Gender Gap, Economics, Higher Education, Business Economics, Major Choice, Major Switching, Mathematics, Stereotypes.

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1 Introduction

"Adams" is the name assigned to an anonymous college that first provided administrative data for a project launched by Claudia Goldin in order to understand why there are so few women majoring in Economics (Goldin, 2015; Avilova and Goldin, 2018). Then and now, at Adams and worldwide, women disproportionately do not major in Economics and, quoting Goldin (2015):

> *Exactly why males decide to major in economics far more so than females [...] remains somewhat of a mystery.*

In OECD countries women attain a higher level of education than men, on average (OECD, 2021). In 2020, 42 percent of women aged 25 to 64 hold a tertiary degree, against 35 percent of men of the same age. In the same year, among the 25- to 34-year old, 52 percent of women are tertiary-educated against 39 percent of men. Thus, the expansion of tertiary education in industrialized countries has largely benefited women. However, the reversal of deeply entrenched gender gaps in education has occurred despite a persistence of visible imbalances in the choice of major. The fact that women are underrepresented in STEM fields has long attracted the attention of scholars, policymakers, and the media, but the presence of similar or even larger gaps in Economics has instead been surfacing much more recently, despite their repercussions for women's occupational and earnings prospects and overall economic efficiency.

The available studies on the gender gap in Economics have thus far mostly focused on the US, so that even less is known about the European case. Yet, a peculiar feature of Economics curricula within the European university system is that they often overlap with those in Business Economics (hereafter, Business), despite the typically lower math intensity and higher marketability of the latter. In the Anglo-Saxon system, instead, the two degrees are usually offered by separate university divisions (namely, schools of arts and sciences for Economics and business schools for Business). The partial overlap, in Europe, between Economics and its likely closest substitute may lend support to the expectation of a narrower gender gap in the former, whose extent calls for an investigation.

The scope of the present paper is to shed new light on why "Adams" outnumber "Eves" among Economics majors in a European context. We base our empirical investigation on the AlmaLaurea dataset, which provides annually administrative and survey information about the near-universe of Italian graduates from the public university system, both at the bachelor and master level. We focus on cohorts graduating between 2010 and 2019, separately for each level. The data include information on field of graduation, high school type and graduation grade, enrollment year, residence, parents' education and occupation, and students' motivations, that we complement with province-level information about macroeconomic indicators such as the fertility rate and the employment rate.

We first present stylized facts to assess the size, time evolution, and geographical distribution of the gender gap in Economics and also in all other fields, with special attention to Business. On average over the period, the raw data reveal that at the bachelor level there are 59.5 female Economics graduates for every 100 male Economics graduates. Since women outnumber men among bachelor's graduates overall, this statistic is weighted by the female proportion of graduates. Thus, the weighted ratio of females to males can be interpreted as a Gender Parity Index (hereafter, GPI), that indicates an underrepresentation of women for values below one and an overrepresentation for values above one.[1]

In the subsequent analysis, we investigate the correlates of observed gaps. We start with logit regressions where the dependent variable is the choice to graduate in Economics, separately at the bachelor and master level, and controls include gender, region of residence and enrollment year fixed effects, and a broad set of covariates. At the bachelor level, we find a significantly negative impact of being female on the probability to graduate in Economics: in the fully controlled specification, the ratio between the likelihood of graduating in Economics among females and the likelihood of graduating in Economics among males, i.e., the estimated GPI, yields 73 women for every 100 men. Among other covariates, the mathematical content of high school curricula carries by far the highest explanatory power both on the choice of majoring in Economics and on the gender gap, while factors such as parents' characteristics and students' motivations only play a marginal role. Thus, the Economics gender gap is largely determined by decisions made by girls early on at age 14, when they choose between high school tracks.

In order to study the decision to major in Economics within a broader perspective accounting for the entire menu of available choices, we also run multivariate logit regressions where the dependent variable is a categorical reflecting four fields. Strikingly we find that, in the fully controlled specification, Economics displays the largest gender gap, followed by STEM (with 79 female graduates for every 100 males) and Business (with 81), while a substantial female overrepresentation occurs in the Humanities (with 140).

At the master level, where fields of graduation also include Finance and the bachelor field is added to previous covariates, we uncover an attenuation in the gender gap in Economics that, however, is driven by a lower probability among males of graduating

[1] The corresponding value of the gender conversion rate employed by Avilova and Goldin (2018) is 1.8, which in terms of the GPI means that for every 100 men majoring in Economics there are 55.5 women. Thus, Italy as a whole with 59.5 women fares only slightly better than Adams College.

in this field, while the probability among females is about the same as the one at the bachelor level. At the same time, graduating in Finance is much more likely among males than among females, which contributes to explain the decreased proportion of graduates in Economics among males. The gender gap is actually reversed in Business, where the probabilities of graduating in the discipline increase among both female and male graduates, but especially among the former. Furthermore, controlling for bachelor choice absorbs the influence of the high school math background, suggesting that early choices on school track are hard to reverse along university careers. To understand the determinants of the discrepancies we detected between the bachelor and master levels, we also look at the decision to switch major in the transition from bachelor to master. Major switches are relatively rare events, as they occur for slightly over 6 percent of the students, with females being almost as likely to switch as males in fully controlled regressions. However, when we zoom in on patterns of switches across different fields—focusing in particular on Economics and Business—we uncover that females are more likely than males to switch from Economics to Business, while the opposite move is very rare.

To dig deeper into the role played by the high school math background, we perform a decomposition analysis, using both the Gelbach (2016) and the Oaxaca (1973) and Blinder (1973) (hereafter, OB) methodologies. The former exercise shows that, uniquely for Economics, the variation of the explained part of the gender gap at the bachelor level is entirely influenced by the high school math background. Consistently, the latter methodology confirms that high school math composes all of the explained part of the gender gap in Economics, with an additional countervailing effect on the unexplained part, which implies that there are unobserved characteristics of female students that actually mitigate the effect of their average lower high school math. In other words, coming from a high math school rather than a low math one is more effective in increasing females' probabilities of graduating in Economics than males' ones.

Lastly, we study the effects of an education reform aimed at increasing the math content of curricula in those high schools that traditionally lacked it. The treatment group is represented by students from traditionally low math schools and we can observe the first and part of the second cohort of post-reform university graduates. A triple difference strategy discloses a post-reform decrease in Economics choices among treated females and a less than compensating rise among treated males, with a negative net treatment effect. This gender heterogeneity in the treatment effect implies a decline in female representation in Economics, while no effect obtains for other fields.

The paper is structured as follows. Section 2 reviews the relevant literature. Section 3 describes the data. Section 4 outlines the empirical strategy. The main results are in Section 5 while Section 6 presents Gelbach and OB decompositions. Section 7 presents a triple difference analysis of a high school reform increasing the math content of traditionally low math schools. Section 8 concludes. An Appendix contains additional figures and tables.

2 Literature review

While gender gaps in college graduation from STEM fields have been widely acknowledged and researched (UNESCO, 2017; Kahn and Ginther, 2018; Bertocchi and Bozzano, 2020; Delaney and Devereux, 2021), the presence of significant gaps in Economics is relatively less explored, despite early accounts such as Dynan and Rouse (1997). In the US, the share of Economics majors who are females is lower than in Chemistry, Mathematics, and Statistics. Moreover, while the highly male-dominated field of Engineering has witnessed an increase in the female share in the past decades, scarce progress has been detected for Economics (Bayer and Rouse, 2016; Avilova and Goldin, 2018). Using Eurostat data for 25 European countries over the period 2013-2018, Megalokonomou et al. (2021) report that, consistent with US data, the Economics GPI has been stable or decreasing over time at around 0.6 on average, which is lower than for Business (1.1). STEM performs worse (0.35), but shows a mild increase over the period. The consequences of a reluctance of girls to enroll in Economics majors affect multiple realms such as their occupational and earnings prospects and their ability to develop a career, including an academic one (Lundberg and Stearns, 2019; Bertocchi, 2020; Lundberg, 2020), as well as overall economic efficiency.

Several explanations for the gender gap in Economics majors have been suggested, including interest in the subject, expected marketability, mathematics aptitudes and training, parents' beliefs and expectations, availability of role models, teaching and assessment methods, grade sensitivity, classroom climate, and representation of women in textbooks. Allgood et al. (2015) review the available research on teaching Economics to undergraduates and conclude that the gap remains an unsolved puzzle. Subsequent contributions include Tonin and Wahba (2015) who, based on UK administrative data, rule out the hypothesis that universities discriminate against female applicants along the admission process, possibly because women are perceived as less competent in the discipline, or out of fear that they are less likely to accept an offer due to the low ranking of Economics in their preferences. Based on a field experiment performed at a US college, where students taking Economics introductory classes were exposed to successful women who had majored in Economics at the same college, a beneficial influence of female role models has been found by Porter and Serra (2020). However, over a panel of US institutions Emerson et al. (2018) find no evidence that female faculty attract female students to Economics majors. The effectiveness of nudges (consisting for instance in encouraging messages) is also controversial, as shown by field experiments conducted in the US: Li (2018) finds a positive effect on female students' probability of majoring in Economics,[2] but Pugatch and Schroeder (2021) report no such effect. Recent papers signal that making introductory courses more attractive represents a promising avenue: using institutional US data Ahlstrom and Asarta (2019) show that persistence in studying Economics for female students increases with this intervention; Bayer at al. (2020) present a case study on a newly designed introductory course—based on innovative teaching methods and content presentation—that nearly achieved a gender balance; Mallory et al. (2021) report about an intervention on the content and structure of an introductory course that greatly reduced the gender gap in the likelihood of continuing on with Economics.

Among the determinants of gender gaps in major choice, the mathematics background —together with the stereotypes associated with female mathematics aptitudes (Guiso et al., 2008)—plays a potentially crucial role, which has been investigated with reference to STEM (Granato, 2018; Card and Payne, 2020; Chise et al., 2021), but not as much to Economics. Exceptions are Emerson et al. (2018), who show that quantitative requirements within college curricula deter women from majoring in Economics, and Ahlstrom and Asarta (2019), who expose a gendered asymmetry in Economics degree selection, such that men's is correlated with math aptitudes, while women's is correlated with both math and verbal ones. The high math intensity content of Economics curricula is stressed by Kahn and Ginther (2018) who, as an alternative to STEM (that is, Science, Technology, Mathematics and Engineering), introduce the taxonomy of GEMP (Geoscience, Economics, Engineering, Math and Computer Science, and Physical Science) vs LPS (Life Science, Psychology, and Social Sciences excluding Economics), based on different mathematical requirements. They also argue that the drivers of gender gaps in mathematical ability are not biological differences but psychological and cultural factors that manifest themselves both at home and at school through negative gender stereotypes proposed by family, teachers, and peers. The fact that high school teachers' negative gender stereotypes cause an increase in the gender gap in math performance is reported by Carlana (2019), while the influence of parents and peers is choosing gender-stereotypical subject (such as literature for girls and math for boys) is explored by Carlana and Corno (2021).

The causal impact on major choice of reforms aimed at increasing the math content of high school curricula has been examined only with reference to STEM. Gorlitz and

[2] The field experiments in Li (2018) and Porter and Serra (2020) were conducted within an ongoing broader research project, the Undergraduate Women in Economics (UWE) Challenge (Avilova and Goldin, 2018).

Gravert (2018) and Biewen and Schwerter (2021) show that a German reform led to asymmetric gendered effects, with females reacting less than males or even negatively. Joensen and Nielsen (2016) and De Philippis (2021) reach contrasting conclusions on the effect of programs targeting high ability students, respectively in Denmark and the UK: while the latter's results align with those previously reported for Germany, the former report a shift for females toward more math intensive fields.

The literature on the determinants of college major choice is surveyed by Patnaik et al. (2020), while Zafar (2013) focuses on the involved gender gap to show that males care about pecuniary outcomes in the workplace more than females. Anelli and Peri (2015) relate gender differences in major choice to differences in psychological attitudes towards competition and altruism: since women tend to be less competitive and more altruistic, they are driven to more socially oriented majors (Education, Social Sciences) rather than profit oriented ones (Engineering, Business). Anelli and Peri (2019) find evidence of an influence of high school experience, with male students being more likely to choose high-paid majors if they attended high school classes with a large male share, while class gender composition is not so important for women. They also suggest that recommendation of college majors by teachers—which is very gender-biased—exerts a strong impact of students' choice. A role for self-confidence is suggested by Bordón et al. (2020), who find that males apply to selective programs even when they are marginal candidates, while equally qualified female candidates tend to apply less often to these programs.

Turning to major switches, Astorne-Figari and Speer (2019) discover that students switch to majors where their gender is more represented, so that females tend to switch to female-heavy majors. Moreover, women are more likely to leave STEM fields for less competitive majors. Kugler et al. (2020) show that women switch out of a major more often than men only when they experience a combination of low grades on the one hand and, on the other, a prevalence of men or else a major's reputation for being stereotypically male-oriented. Emerson and McGoldrick (2019) concentrate on major switching into and out of Economics within the course of US four-year degrees and find that females from other majors are less likely than males to switch into Economics.

The next three papers investigate the specific choice between Economics, Business, and related majors within a European institutional context. Aina et al. (2020) find that, after their first year in college, female students are more likely than male to switch from Economics to Business but less likely to do the opposite, despite the absence of differences in students' pre-enrollment characteristics. Within an Economics bachelor program, Arnold (2020) examines differences in major choice among Economics subfields and shows that female students are strongly underrepresented in Finance and overrepresented in Accounting. Zölitz and Feld (2021) investigate how the gender composition of peers affects women's and men's choices within business schools. They find evidence of gender segregation, as women assigned to teaching sections with more female peers are less likely to choose male-dominated majors (like Finance) and more likely to choose female-dominated ones (like Marketing). Men instead, when exposed to more female peers, are more likely to choose male-dominated majors and less likely to choose female-dominated ones.

3 Data and descriptive statistics

We use stacked cross-sectional data from the AlmaLaurea survey on the 2010 to 2019 cohorts of graduates from Italian public universities (the *Profilo dei Laureati* survey).[3] The coverage of the survey increases during the period, from 57 to 78 universities, from 192,358 to 280,230 respondents, and from 67 to 90 percent of all Italian graduates.[4] We focus on two degree levels, bachelor and master, using two separate datasets. The first concerns the population of students who graduated from either a three-year degree program (called *Laurea*, corresponding to a bachelor's degree) or from a six- or five-year degree program (called *Laurea magistrale a ciclo unico*, equivalent to a single cycle master's degree), both accessible with a high school diploma. The second dataset comprises students who graduated from a two-year program at the master level, accessible after obtaining a bachelor's degree. The bachelor sample, with 1,489,048 respondents, is larger than the master's sample, which comprises 230,240 respondents. It is smaller because, naturally, some students end their education at the bachelor level, others move to universities not included in the AlmaLaurea dataset, and practically all those who attend six- and five-year programs do not subsequently enroll in master's degree programs.[5] For these reasons combined, the master sample includes 644,231 respondents. We further restrict it to the 230,240 master's graduates for whom we have administrative information about the field they graduated in at the bachelor level. The gender composition of our two samples is quite similar: female students are about 60 percent of the total population at the bachelor level and 58 percent at the master level. The female component is slightly

[3] Aggregate data can be accessed from the AlmaLaurea website at `https://www2.almalaurea.it/cgi-php/universita/statistiche/tendine.php?LANG=it&config=profilo`. While we are the first to use these data to study the decision to major in Economics, Granato (2018) and Chise et al. (2021) have used them for the case of STEM.

[4] We include respondents who graduated starting in 2010 and enrolled after 2005 at age up to 25 for the bachelor level and up to 28 for the master. We exclude respondents with a foreign high school diploma.

[5] The fields within the six-year programs are Medicine and Dentistry, and within five-year programs are Pharmacy, Law, Primary Education, Veterinary, Architecture, Chemistry.

above average within the six-and five-year degree programs, which can partly explain the small fall of the female share at the master level.

As mentioned above, our rich dataset includes both administrative and survey information. The former are provided by universities. The latter derive from students' responses, upon graduation, to a detailed questionnaire concerning the level of education of both parents and their last occupation, students' expectations and motivations on their studies and future jobs, characteristics of students' educational career, both at high school and university, and place of residence.

We split upper secondary schools according to the relative weight of the mathematical, scientific or technological content of their curricula, to build a binary variable, denominated High School Math, that takes value one when the content is relatively high, and zero otherwise.[6] Among university fields, we separately consider Economics and its potential closer substitutes, that is Business[7] and Finance (the latter is present as a separate major only at the master level), while we group the other disciplines into two macro-fields: STEM and Humanities.[8] In the transition between the bachelor's and the master's degree, students can switch across majors subject to a number of constraints that vary at the university level (e.g., admission tests, applications for admission, supplementary course work).[9]

Finally, we extract yearly data on fertility and employment rates at a province level from the ISTAT database[10] and merge them with AlmaLaurea data on the basis of the province of residence and the year of enrollment. We employ the fertility rate as a proxy for women's sexual emancipation (see Braga and Checchi, 2008) while the employment rate is meant to measure the extent to which available labor resources are being used.

Table A1 in the Appendix presents variable definitions and Tables A2 and A3 summary statistics, separately for the bachelor and master datasets. Table 1 summarizes the distribution of female and male graduates across fields at the two degree levels. At each

[6]Italy has three main tracks of upper secondary schools: Lyceums, Technical, and Vocational (see Bertocchi and Spagat, 1997 and Brunello and Checchi, 2007). Tracking starts at age 14. Following AlmaLaurea main disaggregation, High School Math takes value one when the student attended a lyceum with a scientific curriculum (*Liceo scientifico*) or a technical or vocational school, and zero otherwise.

[7]Business majors include a broad range of subjects such as Management, Accounting, Marketing, Organizational Studies, Finance, etc. At the master level only, Finance is formally considered a separate major.

[8]Since our focus is on Economics and Business, we allocate all other subjects to only two broadly defined fields. STEM takes value one when the student graduates in Science (Physics and Mathematics), Engineering, Architecture, Chemistry, Pharmaceutics, Biology, Geology, Medicine or Veterinary, and zero otherwise. Humanities takes value one when the student graduates in Political Science, Sociology, Literature and Languages, Law, Teachers Training, Psychology, Physical Education or Defence Sciences, and zero otherwise.

[9]Switches during the course of a degree are possible but even more constrained. Information about them is not provided by AlmaLaurea.

[10]Data can be downloaded from `https://dati.istat.it/`.

Table 1: Distribution of female and male graduates, by field and degree level

		Economics	Business	Finance	STEM	Humanities	Total	Obs.
Bachelor	Females	2.53	8.08		38.12	51.27	100	899,385
	Males	4.25	12.43		53.86	29.46	100	589,663
Master	Females	2.58	13.15	0.58	30.38	53.31	100	133,309
	Males	3.41	15.71	1.28	55.41	24.18	100	96,931

Note: Shares are computed at each degree level as graduates in each field of each gender over all graduates of the same gender. The samples comprise 1,489,048 students at the bachelor level and 230,240 students at the master level. Females are 60 percent of all students at the bachelor level and 58 percent at the master level.

level, shares are the ratio of the number of students of each gender in a given field to the total number of students of the same gender. The table reveals that the share of women graduating in Economics is much smaller than that of men, both at the bachelor and master levels. It is almost 1.8 percentage points lower (2.5 vs 4.3) at the bachelor level and 0.8 percentage points lower (2.6 vs 3.4) at the master level. The gap appears to shrink at the master level, but the share of women remains about the same at the two levels and the reduction is due to a lower relative presence of men. At the same time, the degree in Finance, which is offered only at the master level, absorbs a population of male students that more than compensates for their decreased presence in Economics, while it attracts a much smaller component of female students. The latter's share is about 0.7 percentage points lower (0.6 vs 1.3) than among males.

The share of graduates in Business is also lower among females than among males, but this field presents two differences with respect to Economics. One is that gender gaps are smaller at both levels. The other is that students of both genders are more likely to graduate in Business at the master than at the bachelor level, but the increase of females, with their share rising from 8.1 to 13.2, is stronger that of males. The STEM and Humanities macro-fields also present some interesting features. One is that, as is well known, female students graduate in STEM subjects in much lower proportions than males. Table 1 shows that this concerns both levels. However, among females, the share of graduates in a STEM discipline further decreases at the master level, while it increases among male students. Humanities, instead, is characterized by the two symmetrically opposed characteristics: relatively more women graduate in the Humanities at the bachelor level, and their proportion increases at the master level, while that of men decreases.

To better visualize differences in graduation rates among females and males in each field, we rely on the GPI, already defined as the share of graduates in each field among females divided by the same share among males, which can also be read as the ratio of

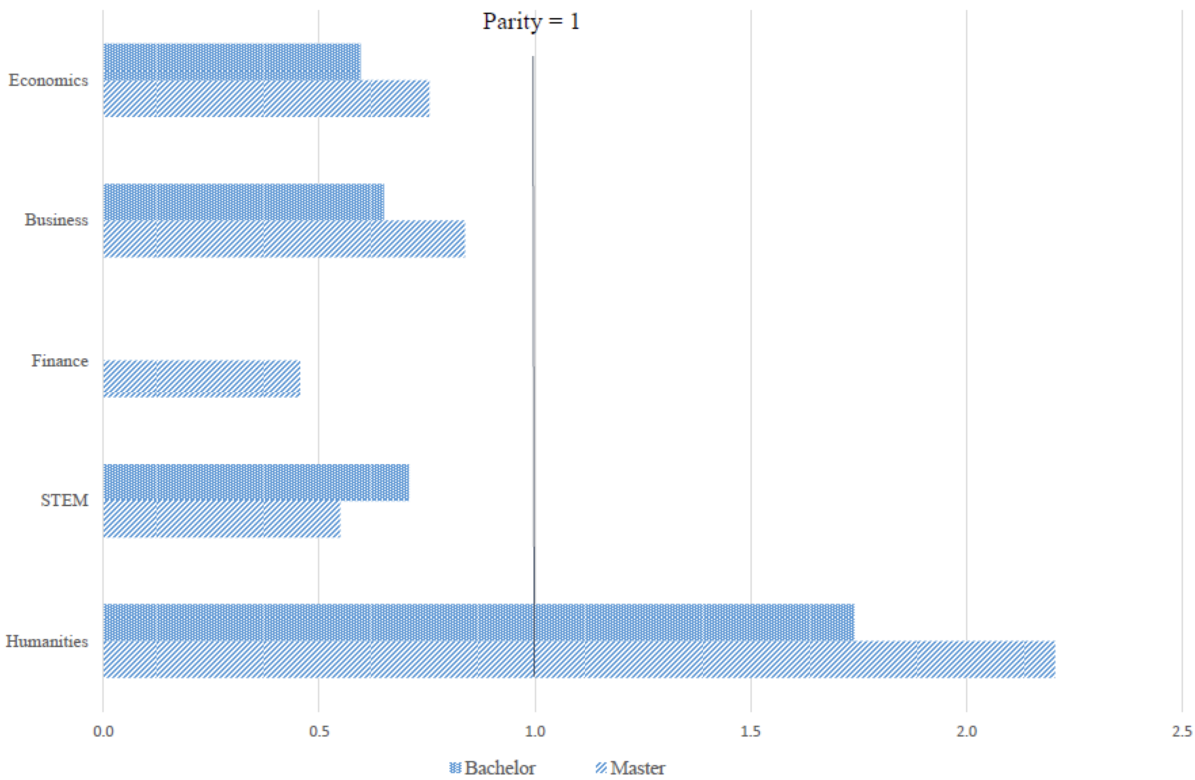

Figure 1: Gender Parity Index, by field and degree level

Note: $\mathrm{GPI_j}$ = (Share of Graduates in $\mathrm{Field_j}$ among Females)/(Share of Graduates in $\mathrm{Field_j}$ among Males), with j = Economics, Business, Finance, STEM, Humanities. Parity corresponds to the GPI taking value 1. Distances between the vertical line, corresponding to unity, and GPI values represent gender gaps.

females to males in each field divided by the overall ratio of females to males.[11] Gender gaps are the difference between unity and the value of the GPI. The index is computed separately at the bachelor and master levels and the resulting values are depicted in Figure 1.

The lower frequency among females of graduates in Economics, Business, Finance, and STEM, and the higher frequency in Humanities, are evidenced in Figure 1. Gender gaps can be visualized as the distance between the vertical line, corresponding to unity, and each value of the GPI. The largest gaps are in Economics at the bachelor level and in Finance at the master level. For instance, among Economics bachelors the index is equal

[11]The GPI is defined as:

$$\mathrm{GPI}_j = \frac{\left(\dfrac{\text{Female Graduates in Field}_j}{\text{All Female Graduates}}\right)}{\left(\dfrac{\text{Male Graduates in Field}_j}{\text{All Male Graduates}}\right)} = \frac{\left(\dfrac{\text{Female Graduates in Field}_j}{\text{Male Graduates in Field}_j}\right)}{\left(\dfrac{\text{All Female Graduates}}{\text{All Male Graduates}}\right)}$$

with j= Economics, Business, Finance, STEM, Humanities. The reciprocal of the index corresponds to the conversion rate of Avilova and Goldin (2018).

to 0.595, which means that for every 100 male graduates in Economics there are 59.5 women. The position of females is more favorable in Business (where the index is 0.650) and even more so in STEM (0.708), while a reversal of the gap occurs for the Humanities (1.740).

As shown in Figures A1 and A2, the distribution of female and male students across fields varies with time and space, but the above mentioned stylized facts are persistent and widespread across areas. To be noticed is that, during the sample period, for Economics bachelors the weighted share of males is increasing, while that of females is relatively flat. Further inspection of the summary statistics in Tables A2 and A3 reveals that females are much more likely than males to attend a high school with a low math content and to obtain a higher exit grade. Females are also slightly more likely than males to undertake a single cycle degree and slightly less likely to switch across fields.

4 Empirical strategy

Separately for the bachelor and master level, we start by estimating the determinants of the decision to graduate in Economics, rather than in another field, with a logit specification which can be formally outlined as follows:

$$Economics^{*}_{iyp} = \beta_0 + \alpha_y + \gamma_r + \beta_1 Female_i + X^{'}_{i}\beta_2 + Z^{'}_{yp}\beta_3 + \epsilon_{iyp} \tag{1}$$

where $Economics^{*}_{iyp}$ is a latent variable and $Economics_{iyp}$ is a binary variable observed according to the rule:

$$\begin{cases} Economics_{iyp} = 1 \text{ if } Economics^{*}_{iyp} > 0 \\ Economics_{iyp} = 0 \text{ if } Economics^{*}_{iyp} \leq 0 \end{cases}$$

where $Economics_{iyp}$ takes value one if student i enrolled in year y and residing in province p at time of enrollment graduates in Economics, and zero if the student graduates in another field. We control for enrollment year and region of residence at enrollment fixed effects, respectively α_y and γ_r, in order to capture unobserved characteristics that vary at such levels.[12] The key regressor is $Female_i$, a binary variable taking value one if student i is female, and zero if male. The coefficient β_1 will capture the impact of gender on the probability to graduate in Economics rather than in any other field. X_i includes

[12] We refer to enrollment year rather than graduation year, since the time of enrollment is more likely to influence subsequent choices. For the same reason we refer to the region of residence at enrollment rather than graduation. Individual characteristics are entered at a province level, where provinces are the next smaller administrative units relative to regions.

other individual characteristics: namely, the mathematical content of the high school curriculum, the high school exit grade, mothers' and fathers' education and occupation, and cultural and work-related motivations regarding the degree choice. For the master level specification, X_i also includes the bachelor level field of study (Economics, Business, STEM, and Humanities).[13] Z_{yp} includes two province level macroeconomic indicators: the fertility rate and employment rate, both measured in the year of enrollment. The error ϵ_{iyp} is clustered at the university level, in order to avoid to overstate the estimator precision due to correlation within clusters.

In order to investigate all the available field choices besides Economics, we also estimate a multinomial logit version of Equation (1) where the dependent variable is a categorical capturing whether a student graduates in Economics, Business, STEM, Humanities or at the master level Finance. Formally, we generalize Equation (1) and estimate a system of equations, three at the bachelor level and four at the master level (that is, one for each category relative to the reference category).[14]

To estimate the probability to switch across fields between the bachelor and master levels, and test whether females are more or less likely than males to change field of study, we use a logit specification, analogous to Equation (1), where the dependent variable takes value one if student i enrolled in year y and residing in province p switches across fields between the bachelor and master level, and zero otherwise. To map the directions of switches of female and male students across each field we employ a multinomial logit model at the master level that comprises interactions between gender and the field of the bachelor's degree. With them, we shall be able to disentangle the gender gap in the probability of switching to/from each field.

5 Main results

5.1 Bachelor level

We start by estimating Equation (1), where the dependent variable is a binary capturing whether a student graduates in Economics as opposed to any other field, using logit regressions over the bachelor dataset. For a number of alternative specifications (one for each row), Table 2 reports the estimated GPI, i.e., the ratio of females' to males' probabilities of graduating in Economics. Probabilities for each gender are computed as

[13]Information about the exit grade at the bachelor level is not used because of missing observations and often inaccurate self-reporting.

[14]We test the assumption of Independence of Irrelevant Alternatives with the method proposed by Hausman and McFadden (1984), both at the bachelor and master level. Since results do not reject the assumption, multinomial logit regressions are the preferred specifications.

Table 2: Gender parity in Economics - Bachelor level

		GPI	Observations
(1)	Female	0.593***	1,489,037
		(0.026)	
(2)	High School Math	0.732***	1,489,037
		(0.033)	
(3)	High School Grade	0.591***	1,488,779
		(0.029)	
(4)	Parents	0.590***	1,248,393
		(0.026)	
(5)	Motivations	0.605***	1,385,955
		(0.028)	
(6)	Macro Indicators	0.593***	1,478,378
		(0.033)	
(7)	Full	0.730***	1,235,522
		(0.026)	

Note: Logit estimates. The dependent variable is a binary that takes value one if a student graduates in Economics, and zero if a student graduates in another field. The GPI is the ratio of the probability of females to the probability of males to graduate in the field and equals 1 when they are equal. All models include enrollment year and region of residence fixed effects. Model 1 also includes Female. High School Math, High School Grade, Parents, Motivations, and Macro Indicators are added one at a time to Models 2 to 6. Model 7 includes all controls. Robust standard errors clustered at the university level in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

predictive margins for the Female dummy.

The results disclose the presence of a sizeable gender gap among Economics graduates: the index takes a value of 0.593—well below the value of one corresponding to parity—in the first parsimonious specification where gender is the only control besides enrollment year and region of residence fixed effects (Model 1),[15] and increases to 0.730 in the full specification (Model 7). The GPI value of 0.730 means that, everything else given, there are 73 women for every 100 men among Economics graduates. The fact that the gender gap in Economics shrinks but does not disappear after all controls are included indicates that the latter do carry an explanatory power, while at the same time a sizeable portion of the gap—corresponding to the 27 missing women for every 100 male graduates in Economics—remains unexplained even after including them. In Models 2-7, as we add to gender and fixed effects the other sets of controls (initially one at a time, and then all together in Model 7),[16] we uncover that the gap is largely driven by the mathematical content of high school curricula: in Model 2, controlling only for gender and the variable High School Math leads to a value of the index equal to 0.732, while the contribution of

[15]The reported value of 0.593 corresponds to the ratio between the predictive margin for females, 0.025 (the probability of a female student of graduating in Economics), and the predictive margin for males, 0.043 (the corresponding male probability).

[16]For continuous variables, i.e., High School Grade and the Macro Indicators, we compute margins respectively at the values 60, 80, and 100 for the former and 25, 50, and 75 for the latter.

the other controls is limited.[17]

Table A4 presents variants where interactions between gender and other controls are added one at a time to the full specification. The heterogeneous effect of the High School Math variable is confirmed when the latter is interacted with gender in the full specification (Model 1): the value of the GPI is only 0.460 for Economics graduates with low math background, while women are much more represented, with a value of 0.785, among those with high math background. However, it should be kept in mind that women are much less likely than men to come from a high math track. Table A4 continues with models with interactions between gender and the other controls. Some interesting effects emerge, for instance, when the Female dummy is interacted with the grade obtained at graduation from high school (High School Grade, in Model 2): the index is only 0.463 among Economics graduates with a low grade, and increases to 0.702 and 1.062 respectively as the grade increases to an intermediate and high level. In other words, among Economics graduates with a high grade women are overrepresented. Thus, while girls are less likely to have a high math background, which contributes to widen the gap, they are more likely to exit high school with high grades, which exerts the opposite effect. However, as it will be seen in more detail in Section 6, grades do not contribute to explain the whole gap as much as the math background. Using information about parents' education (Models 3 and 4 for mothers' and fathers' respectively) and occupation (Models 5 and 6), we uncover that females are relatively more likely to graduate in Economics when parents, and especially mothers, hold a low level of education. The influence of parents' occupation is instead not so clear-cut. Even though the declared motivations of the choice of field, either cultural or work-related, display limited variation (as shown in Table A2), their interaction with gender does matter: the gap is smaller (in fact, reversed) when cultural concerns are deemed less important (Model 7) and when concerns regarding jobs prospects (Model 8) are more so. Lastly, some heterogeneities emerge also in terms of macro indicators, with a larger gender gap being associated with higher fertility (Model 9) and lower employment rates (Model 10).

In Table 3 we broaden our perspective by investigating in full depth the available choices besides Economics, again at the bachelor level. To this end, we run multinomial logit regressions using as dependent variable a categorical for the following four fields: Economics, Business, STEM, and Humanities. A first general finding is that the GPI

[17] Robustness checks leading to very similar results include running all regressions (i) over a balanced sample; (ii) using linear probability models in place of logit and multinomial logit; and (iii) confining the sample to three-year graduates. The third check yields a larger value of the GPI (0.768 in the full specification), which is attributable to the smaller female representation relative to six- or five-year graduates (14 percent of males go for single cycle degrees vs 17 percent of females, see Table A2). Results are not reported for brevity.

Table 3: Gender parity in all fields - Bachelor level

		GPI in:				
		Economics	Business	STEM	Humanities	Observations
(1)	Female	0.593***	0.650***	0.709***	1.738***	1,489,048
		(0.026)	(0.026)	(0.023)	(0.065)	
(2)	High School Math	0.725***	0.800***	0.807***	1.375***	1,489,048
		(0.032)	(0.029)	(0.022)	(0.040)	
(3)	High School Grade	0.591***	0.660***	0.684***	1.810***	1,488,790
		(0.028)	(0.066)	(0.022)	(0.067)	
(4)	Parents	0.590***	0.646***	0.712***	1.756***	1,248,402
		(0.026)	(0.025)	(0.023)	(0.067)	
(5)	Motivations	0.604***	0.659***	0.707***	1.748***	1,385,965
		(0.028)	(0.027)	(0.023)	(0.063)	
(6)	Macro Indicators	0.593***	0.650***	0.709***	1.739***	1,478,389
		(0.026)	(0.026)	(0.023)	(0.065)	
(7)	Full	0.722***	0.813***	0.787***	1.422***	1,235,531
		(0.034)	(0.030)	(0.021)	(0.039)	

Note: Multinomial logit estimates. The dependent variable is a categorical capturing whether a student graduates in Economics, Business, STEM, or Humanities. The GPI is the ratio of the probability of females to the probability of males to graduate in any field and equals 1 when they are equal. All models include enrollment year and region of residence fixed effects. Model 1 also includes Female. High School Math, High School Grade, Parents, Motivations, and Macro Indicators are added one at a time to Models 2 to 6. Model 7 includes all controls. Robust standard errors clustered at the university level in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

values in Economics, from the baseline to the fully controlled regressions, are remarkably similar to those of Table 2. This, and the results of Hausman-McFadden tests we performed on the multinomial regressions, which did not reject the assumption of Irrelevance of Independent Alternatives, support our choice of the multinomial logit specification. Moreover, strikingly, the table also reveals that Economics always displays the lowest estimated GPI (0.722 in the fully controlled Model 7), followed by STEM (0.787), with Business coming next (0.813), and a reversal in the Humanities (1.422). Again, the role of the math background remains very strong (Model 2), suggesting its role as a mediator of the influence of gender.[18]

Turning to interactions between gender and other controls, Model 1 in Table A6 shows that differences in the math background matter a lot for Economics and Business alike, and much less so for STEM where, perhaps non-intuitively, gaps are slightly smaller among students with a low mathematical background than the opposite.[19] A possible

[18]To capture the mediating effect of High School Math, in Table A5 we first regress High School Math on Female and all controls; next we regress the probability of graduating in a given field on all controls except High School Math, and compare results with the full specification. Model 1 shows that as expected High School Math is strongly correlated with gender. The increase in the index in Model 2b relative to Model 2a confirms that gender is directly and indirectly—through high school choice—affecting the probability of graduating in Economics. Similar results apply to Business, STEM and, with opposite signs, Humanities (Models 3-5).

[19]The importance of high school type for STEM is shown by Granato (2018) over AlmaLaurea data.

Table 4: Gender parity in Economics - Master level

		GPI	Observations
(1)	Female + Bachelor	0.878***	230,240
		(0.036)	
(2)	High School Math	0.885***	230,240
		(0.039)	
(3)	High School Grade	0.866***	229,386
		(0.039)	
(4)	Parents	0.874***	189,032
		(0.039)	
(5)	Motivations	0.867***	210,185
		(0.039)	
(6)	Macro Indicators	0.877***	229,435
		(0.038)	
(7)	Full	0.875***	187,682
		(0.04)	

Note: Logit estimates. The dependent variable is a binary that takes value one if a student graduates in Economics, and zero if a student graduates in another field. The GPI is the ratio of the probability of females to the probability of males to graduate in the field and equals 1 when they are equal. All models include enrollment year and region of residence fixed effects. Model 1 also includes Female and Bachelor Field. High School Math, High School Grade, Parents, Motivations, and Macro Indicators are added one at a time to Models 2 to 6. Model 7 includes all controls. Robust standard errors clustered at the university level in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

explanation is that women with a low mathematical background that choose STEM are strongly motivated. High School Math also exerts a strong influence on the positive gender gap in the Humanities. In this case the gap is smaller among students with a low level of school math because relatively fewer male students graduate in Humanities when the mathematical knowledge from school is high.

5.2 Master level

In Table 4 we reproduce the previous analysis for master's degree graduates. As explained in Section 3, this sample is smaller than the one concerning bachelor graduates. In the logit specifications (Table 4)—where in addition to gender and fixed effects we also always control for the field at the bachelor level—Model 1 shows that for Economics master's graduates the value of the GPI is 0.878, and that women's representation does not change very much as we add the usual controls. Given that the GPI at the bachelor level is 0.722, the representation of women in Economics at the master level does increase, but the rise is almost entirely due to a reduction in the GPI denominator (i.e., the probability that a male student graduates in Economics diminishes), while the numerator (i.e., the probability that a female student graduates in Economics) does not change significantly.[20]

[20]In footnote 17 we show that, due a slight difference in the composition by gender, the value of the GPI in the bachelor sample is slightly higher when we exclude six- and five-year (single cycle) degree graduates. However, that increase is not sufficient to explain the increase in the index in the master

Table 5: Gender parity in all fields - Master level

		GPI in:					
		Economics	Business	Finance	STEM	Humanities	Observations
(1)	Female + Bachelor	0.869***	1.021***	0.605***	0.990***	1.024***	230,240
		(0.037)	(0.011)	(0.045)	(0.002)	(0.003)	
(2)	High School Math	0.879***	1.032***	0.613***	0.993***	1.017***	230,240
		(0.035)	(0.011)	(0.046)	(0.001)	(0.003)	
(3)	High School Grade	0.858***	1.027***	0.568***	0.989***	1.025***	229,386
		(0.037)	(0.012)	(0.042)	(0.002)	(0.004)	
(4)	Parents	0.865***	1.022***	0.584***	0.991***	1.026***	189,032
		(0.038)	(0.011)	(0.034)	(0.002)	(0.004)	
(5)	Motivations	0.856***	1.021***	0.597***	0.991***	1.025***	210,185
		(0.038)	(0.011)	(0.043)	(0.002)	(0.004)	
(6)	Macro Indicators	0.868***	1.021***	0.606***	0.990***	1.024***	229,435
		(0.037)	(0.012)	(0.045)	(0.002)	(0.004)	
(7)	Full	0.865***	1.035***	0.555***	0.993***	1.020***	187,682
		(0.039)	(0.011)	(0.036)	(0.001)	(0.003)	

Note: Multinomial logit estimates The dependent variable is a categorical capturing whether a student graduates in Economics, Business, Finance, STEM, or Humanities. The GPI is the ratio of the probability of females to the probability of males to graduate in any field and equals 1 when the probabilities are equal. All models include enrollment year and region of residence fixed effects. Model 1 also includes enrollment year and region of residence fixed effects, Female, and Bachelor Field. High School Math, High School Grade, Parents, Motivations, and Macro Indicators are added one at a time to Models 2 to 6. Model 7 includes all controls. Robust standard errors clustered at the university level in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Unlike at the bachelor level, the explanatory effect of the high school math content is now negligible (Model 2), as it is mostly absorbed by the field of the bachelor degree.[21] Moreover, in Table A7—where we add interactions between the Female dummy and bachelor field—Model 1 shows that women are least represented (with a value of the GPI of only 0.434) among Economics master's graduates with a bachelor in the Humanities, while their representation doubles among those (few ones) coming from STEM (0.869), and increases even more among those coming from Business (0.926) and Economics (0.986). Hence, gender gaps in Economics at the master level are smaller when the math content of the students' previous bachelor degrees is stronger, i.e., when they come from Economics, Business or STEM, all fields that, in turn, are strongly and positively affected by the math content of the high school curriculum. Heterogeneities in the effects of other controls, particularly motivations, are also reduced relative to the bachelor level.

In Table 5 we detail the available choices besides Economics at the master level. Here we have the new entry, Finance, which is kept distinct from Business and Economics and is based on a quantitative curriculum; this makes it similar to Economics, while it likely shares with Business career prospects. The results from Table 4 for the dichotomous choice of Economics are confirmed, with a reduced gender gap relative to the bachelor

sample, which necessarily excludes six- and five-year (single cycle) degree graduates.

[21]The same regressions of Table 3 run without the variable Bachelor Field (not reported for brevity) show strong and significant coefficients on the variable High School Math.

level. For Business the gap is even slightly reversed (the GPI is 1.021 in Model 1). However, this tendency toward parity is contrasted by the very low female representation emerging for Finance (with 0.605 in the baseline). Turning to STEM, the gap is still present, is attenuated relatively to the bachelor level, and remains lower than that in Economics. Lastly, the reverse gap in the Humanities is also smaller than in the bachelor level, with a near equal gender representation. As a result, in the full specification (Model 7) women are slightly more represented in Business than in the Humanities.[22]

The takeaway is that, at the master level, we observe a lower probability among males of graduating in Economics that leads to an increase in the female representation in the field; a substantially higher probability of men graduating in Finance relatively to women; and a reversal of the gender gap in Business due to an increase in the presence of graduates in this field that is stronger among women. Furthermore, controlling for bachelor choice absorbs the influence of the high school math background, meaning that decisions made early on by girls, possibly under the influence of negative gendered stereotypes, turn out to be hard to reverse during their educational career.

5.3 Switches in choice of field

The evidence produced so far suggests that gender gaps in Economics, as well as in other fields, do exhibit variation across the bachelor and master level, which in turn calls for an investigation on the determinants of switches across fields. We use the same dataset used in the previous sub-section in order to perform it. To be noticed is that, in order to define switches, we use the same classification of major choices into four fields at the bachelor level (Economics, Business, STEM, and Humanities) and five fields at the master level (in which we include Finance) that we employed so far.[23]

As shown in the summary statistics (Table A3), switches are relatively rare events for both genders (involving 7 and 6 percent of males and females respectively). In Table A8 we start by looking at gender gaps in the probability of switching from/to any field, by estimating with a logit a version of Equation (1) where the dependent variable is the probability to switch. The estimated GPI (0.977 in the full regression of Model 7) confirms that females are almost as likely to switch as males when controls—especially the high school math content—are added. More generally, our results show that students switch more when their mathematical knowledge from school is higher, and that once this variable is controlled for, women switch almost as much as men. The role of high school math is also apparent when interacted with gender (Table A9): when the math

[22]Interactions effects for the master level multinomial logit are discussed in the next sub-section.

[23]Therefore, switches within the latter two groups—which comprise several majors—will not be considered.

background is low, women are less likely to switch than men, while the opposite occurs for a high math background.

In Table A10 we zoom in on patterns of switches across different fields, in fully controlled specifications. The table adds interactions between gender and the other controls to the multinomial logit full specification in Table 5 and, in Model 1, starts by interacting the Female dummy with the bachelor field. Thus, Model 1 allows to assess gender gaps in the probability of a switch across each combination of fields of origin and destination. Movements between Economics and its closest substitutes reveal that women are relatively more likely than men to move from Economics to Business[24] (with an index of 1.109), and that men are almost twice as likely as women to switch from Economics and Business to Finance (index values are, respectively, 0.592 and 0.520).[25] Regarding movements towards Economics, women with a Business bachelor's degree are less likely than men to switch to it (0.912). Women are also less likely than men to move to Economics when their bachelor's degree is in STEM (0.848) and less than half as likely as men when their bachelor's degree is in the Humanities (0.457). Model 2 further dissects switch patterns by adding a further interaction term between gender and High School Math. As previously mentioned, the influence of the latter fades after controlling for the bachelor's degree, the only exception being represented by Finance, where a stronger math background appears to be encouraging also for women. A similar attenuation is observed for the gendered impact of motivations and the other controls.

6 The role of the high school math background

The purpose of this section is to dig deeper into the role played by the high school math background. To this end, to estimate the importance of covariates in explaining the gender gaps in each field, we perform a decomposition analysis using both the Gelbach (2016) and the OB methodologies. The Gelbach method quantifies how much of the change in the coefficient on the dummy for gender—from a baseline regression including only gender to a full regression with all variables and fixed effects—is influenced by each covariate. The OB method computes the correlations between the explained and unexplained parts of the gender gap with the independent variables. The explained component concerns differences in the mean values of covariates within the groups, while

[24]However, the observed reversal in the gap for Business is less due to movements from Economics (which involve small numbers) than to the fact that more women choose not to switch out of Business and to switch from Humanities to Business.

[25]Emerson and McGoldrick (2019) and Aina et al. (2020) find similar results with reference to switches occurring before the bachelor's degree is obtained, respectively using a sample of US institutions and administrative data from the Italian University Ministry.

Table 6: Gelbach decomposition - Bachelor level

	(1)	(2)	(3)	(4)
	Economics	Business	STEM	Humanities
Δ Female Coefficient	-0.006***	-0.022***	-0.054***	0.081***
	(0.000)	(0.002)	(0.004)	(0.004)
High School Math	-0.006***	-0.020***	-0.063***	0.089***
	(0.001)	(0.001)	(0.002)	(0.003)
High School Grade	0.000	-0.001**	0.016***	-0.015***
	(0.000)	(0.001)	(0.001)	(0.001)
Mother Education	0.000*	0.001***	-0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Father Education	0.000	0.000***	-0.003***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Mother Work	0.000***	0.000***	-0.001***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Father Work	-0.000***	-0.001***	0.001***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Motivations Culture	-0.000***	-0.001***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Motivations Jobs	-0.000***	-0.001***	-0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Fertility	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Employment	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)

Note: OLS estimates. The dependent variables are binary variables that take value one if a student graduates in each specific field, and zero otherwise. All models include enrollment year and region of residence fixed effects. The number of observations in all models is 1,235,531. Robust standard errors clustered at the university level in parentheses: *** p <0.01, ** p <0.05, * p <0.1.

the unexplained part concerns group differences in the effects of the independent variables.

6.1 Gelbach decomposition

For the Gelbach decomposition analysis in Table 6, we use a linear probability model (OLS), with the dependent variable being the binary indicating whether the student graduates in a given field. Results are reported in terms of coefficients and models are presented by column. At the bachelor level, concerning Economics, Model 1 shows that the explained variation (Δ) of the coefficient on Female is entirely influenced by students' mathematical knowledge from high school, without any other factor significantly affecting it. Mathematical knowledge from high school is also important for Business, although less than for Economics (Model 2). In this case, High School Math influences about 91 percent of the variation in the Female coefficient, while the remaining part is affected by other covariates. Interestingly, mathematical knowledge from high school also influences most of the—positive and negative—gender gaps in Humanities and STEM.[26] Thus, Economics is unique in displaying high school math as an exclusive determinant of the variation in the Female coefficient.

Turning to the master level, Table A11 shows that the whole gender gap in Economics is now explained by the field of the bachelor's degree which, confirming the findings of Section 5.2 above, absorbs much of the indirect effect of High School Math. A similar result applies to Finance: also in this case, the whole gap is influenced by the bachelor's degree (Model 3). The latter explains most of the variation in the gender gap in the Business master's degree but, unlike Economics, not all of it (Model 2). About 87 percent of the gap is affected by the previous degree, but 7 percent of it is directly influenced by students' mathematical knowledge from high school. This result confirms the importance of High School Math for the (few) students who shift between fields from the bachelor to the master level. In this case, students who shift to Business from bachelor's degrees with low mathematical content in the Humanities find that the move is facilitated by the mathematical knowledge gained while at high school. Moreover, students' motivations concerning employment opportunities provided by a Business degree contribute to determine the variation in the gender coefficient, although in a small measure. Gender gaps at the master level in STEM and Humanities are also almost entirely influenced by the field of the bachelor's degree (Models 4 and 5). However, although in a much smaller measure, in both cases the math content of the high school curriculum also matters.

6.2 Oaxaca-Blinder decomposition

When we decompose gender gaps (now obtained with logit regressions) with the OB method, results are fully consistent with the findings from the Gelbach decomposition, but some further insights do emerge. As expected, in Table 7, Model 1, all of the explained part of the gap in Economics at the bachelor level is related to students' mathematical knowledge from high school. However, the OB decomposition shows that this knowledge also affects the unexplained part of the gap, in this case with a positive sign. Hence, as most of the explained lower graduation rates of females in Economics are related to a lower mean value of the High School Math variable in the female group, coming from a high math school rather than a low math one is more effective in increasing females' probabilities of graduating in Economics than in increasing males' ones. Similarly, High School Grade is uncorrelated with the explained part of the gap, but it is strongly corre-

[26] In both cases, father's education has a three times stronger influence on the respective gender gaps than mother's education. Our results for STEM confirm those by Chise et al. (2021) over AlmaLaurea data.

Table 7: Oaxaca-Blinder decomposition - Bachelor level

	(1)	(2)	(3)	(4)
	Economics	Business	STEM	Humanities
Difference	-0.017***	-0.044***	-0.160***	0.221***
	(0.002)	(0.001)	(0.014)	(0.010)
Explained	-0.008***	-0.025***	-0.056***	0.078***
	(0.001)	(0.003)	(0.003)	(0.003)
High School Math	-0.008***	-0.023***	-0.066***	0.086***
	(0.001)	(0.002)	(0.003)	(0.003)
High School Grade	0.000	-0.001**	0.017***	-0.016***
	(0.000)	(0.001)	(0.002)	(0.002)
Mother Education	0.000*	0.001***	-0.001***	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Father Education	0.000	0.000***	-0.004***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)
Mother Work	0.000***	0.000***	-0.001***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Father Work	-0.000***	-0.001***	0.001***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Motivations Culture	-0.000***	-0.001***	0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Motivations Jobs	-0.000***	-0.001***	-0.001***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Fertility	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Employment	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Unexplained	-0.010***	-0.018***	-0.104***	0.144***
	(0.002)	(0.003)	(0.012)	(0.001)
High School Math	0.008***	0.019***	-0.045***	0.051***
	(0.001)	(0.002)	(0.007)	(0.005)
High School Grade	0.040***	0.137***	-0.333***	0.179***
	(0.005)	(0.015)	(0.034)	(0.030)
Mother Education	0.000	0.000	-0.001	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Father Education	0.000	0.000	-0.002***	0.002***
	(0.000)	(0.000)	(0.000)	(0.000)
Mother Work	0.000	-0.001***	-0.003*	0.002
	(0.000)	(0.000)	(0.001)	(0.002)
Father Work	0.000	0.000	-0.007**	0.001
	(0.000)	(0.001)	(0.003)	(0.003)
Motivations Culture	-0.009***	-0.031***	0.038***	-0.001
	(0.002)	(0.003)	(0.007)	(0.011)
Motivations Jobs	0.011***	0.022***	-0.038***	0.068***
	(0.001)	(0.003)	(0.007)	(0.004)
Fertility	0.001	-0.002	-0.002	0.000
	(0.001)	(0.002)	(0.007)	(0.006)
Employment	0.004	0.033***	-0.057	0.015
	(0.004)	(0.001)	(0.057)	(0.041)
Intercept	-0.042***	-0.150***	0.384***	-0.202***
	(0.010)	(0.03)	(0.082)	(0.065)

Note: Logit estimates. The dependent variables are binary variables that take value one if a student graduates in each specific field, and zero otherwise. All models include enrollment year and region of residence fixed effects. The number of observations in all models is 1,235,531. Robust standard errors clustered at the university level in parentheses: *** p <0.01, ** p <0.05, * p <0.1.

lated with the unexplained part of it and, also in this case, its effect is to close the gap.[27] Similar findings apply to Business (Model 2) where, again, coming from a high math school increases females' probabilities of graduating in Business more than it increases males' ones.

Interestingly, the effect of mathematical knowledge from high school on the unexplained components of the gender gaps in Economics and Business are reversed in STEM and Humanities (Models 3 and 4). In these cases, High School Math is also strongly correlated with the explained and unexplained parts of the gaps, but now the correlations with the unexplained parts contribute to widen the two gaps (the first negative and the second positive). Results of the OB decomposition at the master level (Table A12) show that, as with the Gelbach decomposition, bachelor's degrees explain much of the gaps.

7 A triple difference analysis of a high school reform

Starting from the school year 2010-2011, a high school reform (the Gelmini Reform) introduced an increase in the hours of math taught in schools traditionally characterized by a lower math content, while the other schools were unaffected.[28] The first cohort of post-reform students obtained a high school diploma after five years in 2015 and a bachelor's degree starting three years later, that is from the Summer of 2018.[29] Thus, within our 2010-2019 sample period, we can distinguish between graduates coming from each school type, pre- and post-reform, within a quasi-experimental difference-in-differences (DD) approach.[30] Since the post-reform period only includes the first and part of the second

[27] To be noticed is that in Economics the size of the unexplained part is similar to that of the explained part, while in Business the explained part is bigger and, in STEM and Humanities, the unexplained part is smaller.

[28] Previous experimental tracks—namely, *Piano Nazionale per l'Informatica* (PNR) and *Progetto Brocca*, introduced in the 1980s and 1990s respectively—also involved curricula with additional hours of math, but they were implemented only sparsely (Tomasi, 2012; Giacardi and Scoth, 2014). By contrast, the Gelmini Reform took effect simultaneously in the entire country. As a result, in the vast majority of traditionally low math schools the number of weekly hours of math in the first year went from two to three, while it remained at five, for instance, in traditionally high math schools such as *Liceo scientifico* (MIUR, 2011).

[29] It is crucial to identify pre- and post-reform students by the year of enrollment rather than the year of graduation, because graduation dates in the Italian system are less closely linked to enrollment dates than in other systems. Specifically, the last cohort of pre-reform bachelor students, i.e., those completing their third year in 2016-2017, can regularly complete their degree up to the Spring of 2018. Likewise, the first cohort of post-reform students completing their third year in 2017-2018 can complete their degree up to the Spring of 2019. Therefore, in 2018 the sample includes both pre- and post-reform three-year degree bachelor students, while post-reform graduates from six- or five-year (single cycle) degree programs are not included in the sample. Furthermore, it is quite common for students to complete their degree with a delay, sometimes of several years, as *fuori corso*.

[30] Meghir and Palme (2005) apply a DD to the analysis of a school reform. A DDD is applied by Piopiunik (2014).

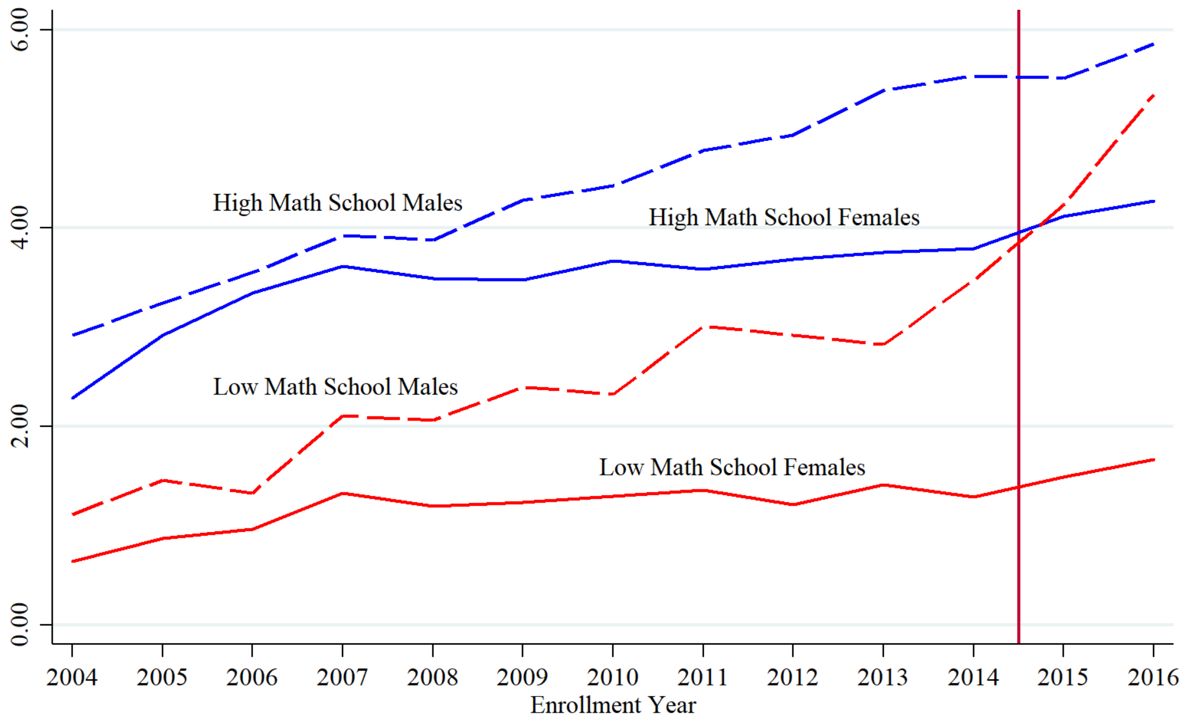

Figure 2: Shares of Economics bachelor's graduates over all bachelor's graduates, by enrollment year, school type and gender

Note: Shares of Economics female bachelors over total female bachelors and Economics male bachelors over total male bachelors, by enrollment year and school type. The vertical line marks the onset of the school reform.

cohort of post-reform graduates, previous analyses over the entire sample still maintain their validity, especially because the reform reduced but did not remove the distinction between high schools in terms of math content.[31] At the same time, however, we can take a first glance at the impact of the reform, at least in the short term, and exploit it in order to identify a potentially causal effect of high school math on major choice.

In our setting, the treatment group is represented by students from traditionally low math schools and the control group is represented by students from high math schools, who were not directly affected by the reform. The treatment is applied to students enrolling at university starting from 2015. In Figure 2 we show the evolution of the shares of Economics bachelor's graduates by school type and gender. Visual inspection reveals that, for females, the shares for the treatment and control groups display parallel trends before and even after 2015, the year the reform takes place. For males, up to 2014, again we observe parallel trends, albeit with a steeper slope compared to females and with a more uneven trend for males from low math schools.[32] After treatment initiation,

[31]According to the Gelmini Reform, low math schools have three weekly hours of math in the first year, against four or five in the high math schools.

[32]Even though an increase in the share of males in low math schools actually starts from 2014, we can rule out an Ashenfelter dip scenario, since by no means cohorts entering high school in 2009 would

we observe a much steeper increase for the latter, i.e., for those affected by the reform.

The above visual evidence can be properly dissected within a triple difference (DDD) approach. After pooling across high school types, pre- and post-reform periods, and gender, the DDD estimator for the choice to graduate in Economics at the bachelor level takes the following form:

$$\begin{aligned} Economics_{stiyp} = {} & \beta_0 + \beta_1 Treat_s + \beta_2 Post_t + \beta_3 Female_i \\ & + \beta_4 (Treat_s * Post_t) + \beta_5 (Treat_s * Female_i) + \beta_6 (Post_t * Female_i) \\ & + \beta_7 (Treat_s * Post_t * Female_i) + \beta_8 y + \gamma_r + X_i^{'} \beta_9 + Z_{yp}^{'} \beta_{10} + \epsilon_{styip} \end{aligned} \tag{2}$$

where the index s indicates the school type and t the period of school enrollment for student i enrolled in year y and residing in province p at time of enrollment. $Treat_s$ is a binary variable that takes value one for traditionally low math schools subject to the reform and zero for traditionally high math schools not affected by the reform, so that β_1 measures pre-reform differences between treated and control groups of male students; $Post_t$ is a binary variable that takes value zero up to 2014 and one from 2015; the interaction $Treat_s * Post_t$ captures the effect of the reform on male students, so that β_4 represents the DD estimate for the treatment effect on males. The key coefficient β_7 identifies the effect of the triple interaction term $Treat_s * Post_t * Female_i$, that represents the difference between females and males in the treatment effect. Thus, the DD estimate of the causal impact of the treatment on females is $\beta_4 + \beta_7$. Variants of the baseline DDD estimator described so far also include a linear enrollment year trend y, region of residence at enrollment fixed effects γ_r, other individual characteristics X_i, and macroeconomic indicators Z_{yp}, as described for Equation (1). The error ϵ_{styip} is clustered at the university level. For ease of interpretation of the multiple interaction terms, we estimate Equation (2) using OLS.

The absence of differential pre-treatment trends, as documented in Figure 2, suggests that outcomes would have been the same for each school type/gender in the absence of treatment, which lends plausibility to the model's key identifying assumption. Identification of the reform's effects would be hampered if other major provisions had complemented the increase in math hours in treated schools. However, while the reform did imply a general reorganization of school tracks, it did not alter their distinction along the math content dimension. Likewise, the reform did decrease the total number of hours being taught, but it did so for both types of schools, again lending plausibility to our approach. Furthermore, the reform did not address gender issues, so that it did not

have been able to access the new curriculum after their first year. The new curriculum was only made available for the cohort entering high school in 2010.

introduce other innovations that could explain its gendered effects.

Table 8: The treatment effect of the high school reform on the treated in all fields

		DDD in GPI				
		Economics	Business	STEM	Humanities	Observations
(1)	Baseline	-0.113**	-0.015	0.045	0.002	1,488,972
		(0.043)	(0.029)	(0.035)	(0.043)	
(2)	Trend	-0.109**	-0.014	0.045	0.002	1,488,972
		(0.043)	(0.029)	(0.035)	(0.043)	
(3)	Trend + Region	-0.100**	-0.016	0.046	0.002	1,488,972
		(0.043)	(0.028)	(0.036)	(0.044)	
(4)	Full	-0.118**	-0.028	0.018	0.066	1,235,467
		(0.043)	(0.029)	(0.035)	(0.042)	

Note: OLS estimates. The dependent variables are binary variables that take value one if a student graduates in each specific field, and zero otherwise. The GPI is the ratio of the probability of females to the probability of males to graduate in the field and equals 1 when the probabilities are equal. Model 1 is the DDD baseline estimator. Model 2 adds a linear enrollment year trend. Model 3 further adds region of residence fixed effects. Model 4 further adds High School Grade, Parents, Motivations, and Macro Indicators. Robust standard errors clustered at the university level in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 8 presents our DDD estimates. Each entry represents the estimated DDD in the probability of a woman graduating in a given field relative to that of a man, expressed as a change in the GPI. Column 1 starts by looking at results for the choice to graduate in Economics for four alternative specifications, one for each row. For the baseline specification (Model 1), the table indicates for the treated a decline in the estimated Gender Parity Index. In the following three rows we test the robustness of our result to alternative specifications, by sequentially adding a linear enrollment year trend (Model 2), region of residence at enrollment fixed effects (Model 3), and individual characteristics and macroeconomic indicators in the fully controlled Model 4. Reassuringly, the magnitude of the reduction of the index as well as its statistical significance remain similar across all specifications, confirming the robustness of the baseline result. In order to shed light on the mechanisms behind the decline in the GPI, an alternative presentation of the same results is provided for Economics in Table A13 (where the four specifications in Table 8 are presented by column and OLS coefficients are displayed). The table reveals that the GPI decline happens by way both of an increase in the male probability of graduating in Economics and a decrease in the female one since, in all specifications, the coefficient on $Treat * Post$ (i.e., β_4) representing the effect of the reform on males is positive, the coefficient on $Treat * Post * Female$ (i.e., β_7) representing the gender difference in the treatment effect is negative, and their cumulative effect (i.e., $\beta_4 + \beta_7$) representing the treatment effect on females turns negative.[33]

[33] When we replicate the analysis for Economics after splitting the sample by macro-region of residence at university enrollment, we discover that the negative effect on the GPI (as well as the effects on the female and male probabilities) vanishes in the North-West, where experimental, often math intensive

To convey an idea of magnitudes, when the above coefficients are used to compute the predicted numbers of Economics graduates, it turns out that for the first post-reform cohort of 2015 we obtain 307 treated males against a counterfactual of 241, and 489 treated females against a counterfactual of 588, with a fall in the latter more than compensating for the rise in the former. Figure A3 portrays these results for the full specification (Model 4 in Tables 8 and A13). The dotted lines depict the counterfactual evolution of the treated female and male shares had it followed that of the untreated, by showing what would have happened to low math graduates in the absence of the reform. The fact that the counterfactual line for low math school males lies below the observed one is evidence of a positive treatment effect on males, while for low math school females we observe a negative treatment effect, with the counterfactual lying above the observed line. In the next three columns of Table 8 we report analogous DDD estimates for Business, STEM, and the Humanities. Strikingly, the estimates show a zero (placebo) effect on the GPI, making the impact of the reform—and particularly its heterogeneous gendered effect—a unique feature of Economics.[34]

To conclude, for Economics, the causal impact of an increase in the math content of traditionally low math curricula is an increase in the gender gap, by making the field more attractive for males and less for females through the negative net treatment effect on students from low math schools.[35] Especially after accounting for the evidence from previous sections—that indicates that females from traditionally high math schools do take Economics in higher proportions than females from low math schools—this conclusion is puzzling and does raise an immediate question: why is that females are further discouraged to take Economics after being exposed to more math while males are encouraged? Since we are able to observe only the first and part of the second cohort of post-reform graduates, one possible answer rests on a slower reaction of girls relative to boys to the new curricula, possibly because of girls' more limited appreciation of the potentialities of the renewed content, or else because of girls' higher psychological barriers in confronting it. A second answer relies on the potential, lingering effect of stereotypes induced by the preponderance of girls in low math schools, that can in turn result in

curricula were likely more widespread prior to the reform. In the Center, the decline in the GPI is mostly determined by the decline in the female probability, since the effect on the male one is positive but not significant. Results for the North-East and the South are in line with the aggregate results. Tables are omitted for brevity.

[34]For Business the reform bears no influence on either gender, while it increases both male and female enrollment in the Humanities and decreases both in STEM, suggesting that exposing to more math students of either gender that had opted for a traditionally low math school made their field choice even more radical.

[35]Within a DD analysis of a German reform aimed at increasing math intensity, Gorlitz and Gravert (2018) and Biewen and Schwerter (2021) obtain similarly gendered results for STEM. The former find an increase in STEM enrollment for males but not females, while the latter find no effect on STEM enrollment for males and a decrease for females.

negative peer pressure. A third, more general consideration is that being imposed more math within a traditionally low math curriculum does not sort the same effect on girls as choosing a high math curriculum in the first place. Future research into the medium- and long-term effects of the reform should investigate whether its negative short-term effect on gender parity in Economics shall die out or even reverse over time, and should explore the mechanisms driving such effects.

8 Conclusion

The causes and consequences of women's underrepresentation in STEM fields are widely researched and debated, but the low female presence in Economics is much less recognized, especially in Europe. Over Italian data we investigate whether women study Economics as much as men and, if not, why. Differently from the Anglo-Saxon system, in the European system, including the Italian one, Economics and Business are usually taught together in the same departments. This institutional setting calls for a joint investigation of major choice that we also extend to all other fields.

Using the AlmaLaurea dataset on Italian graduates from 2010 to 2019, after controlling for the characteristics of students and their families and for region and time fixed effects we find that only 73 females graduate in Economics for every 100 males. At the master level, the fully controlled gap is attenuated, with 87 women graduating in Economics for every 100 men, but this convergence is due to a reduced representation of men in Economics, rather than to a higher presence of women. Hence, the Economics gender gap in Italy is similar to that reported for other countries and even larger than that in STEM, while the gap in Business is significantly smaller despite the partial overlap of the curricula.

We find a significant impact of the mathematical knowledge acquired at high school on the probability of graduating at the bachelor level in all fields, but this impact is particularly strong on Economics. Decomposition analysis also shows that, only for Economics, the explained part of the gender gap exclusively depends on high school math, trumping family background, other students' characteristics, and even students' declared motivations for the choice of field. Since the Italian school system starts tracking at 14, and girls are strongly underrepresented in schools with curricula requiring more hours of math, their disadvantage in accessing Economics majors is a deeply rooted one. At the master level, the explained part of the gender gap is instead mostly affected by the field of the bachelor's degree which, again uniquely for Economics, entirely absorbs the effect of high school math. Our analysis of major switches shows that they are a relatively rare event in general and particularly for women moving to Economics. Thus, those choices made early on by girls prove very hard to reverse and persistently limit their subsequent options at university, with life-long consequences for their labor market outcomes. Policy interventions aimed at closing the gender gap in Economics need either to target very young girl, or else to remove tracking at such a young age.

Furthermore, when decomposing the gender gap in Economics, not only do we find a significant impact of the high school math background on its explained part but also a strong, and somewhat surprisingly, positive effect on its unexplained component, which means that female students who opt for a high math school increase their probability of graduating in Economics more than males that make the same choice.

Lastly, a triple difference analysis of a high school reform aimed at intensifying the math content of curricula in traditionally low math schools reveals a negative treatment effect of the reform on gender parity in Economics, since males as a result are more attracted toward this field while for females the opposite occurs, with a negative net treatment effect on the number of students from low math schools who graduate in Economics. This finding suggests a crucial role for gendered differences in preferences in shaping major choice and that imposing more math within a traditionally low math curriculum does not sort the same effect on girls as choosing a high math curriculum in the first place. However, since we can observe the effect of the reform only through a restricted end-of-sample window, this finding may be limited to the short term, calling for future research into the medium- and long-term impact of policy reforms.

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APPENDIX

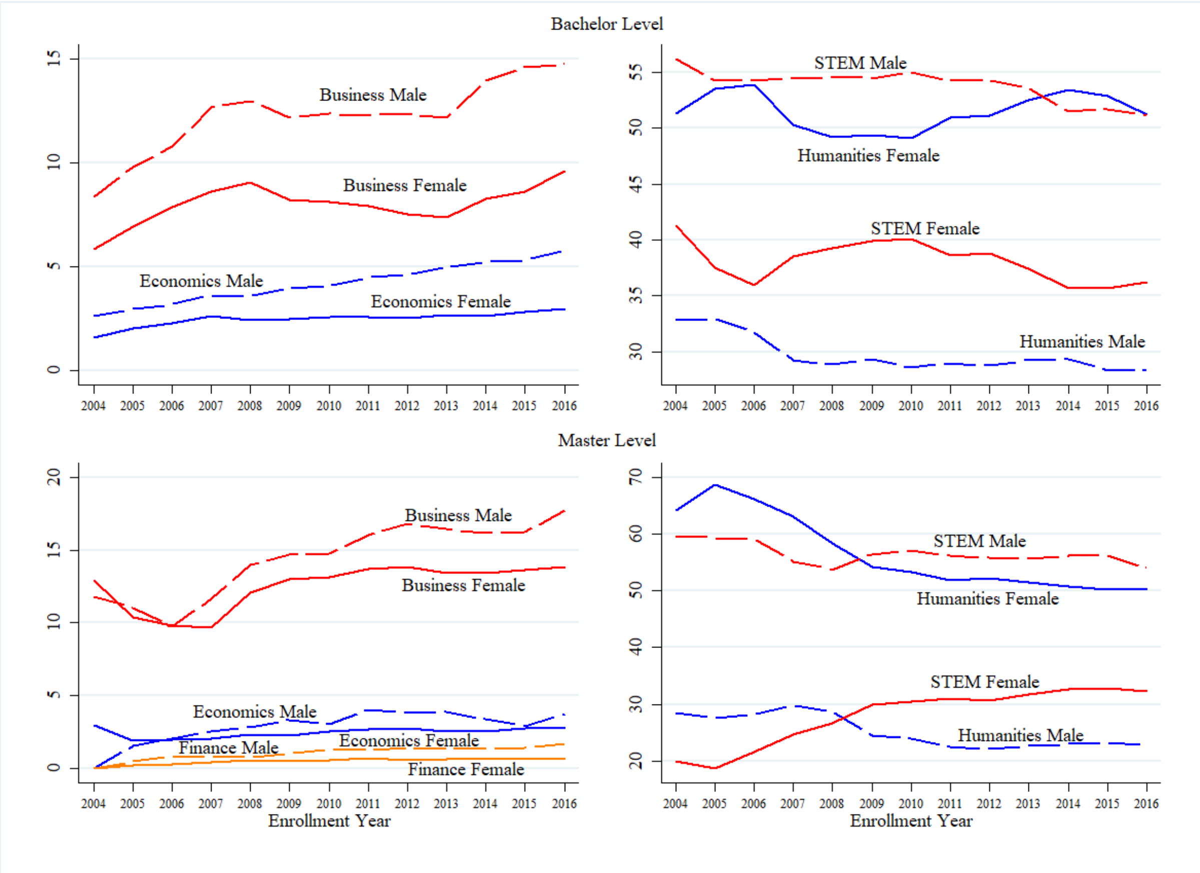

Figure A1: Share of graduates, by enrollment year, field, gender and degree level

Note: Shares of females over total females and males over total males, by enrollment year, field and degree level. Vertical axes scales differ.

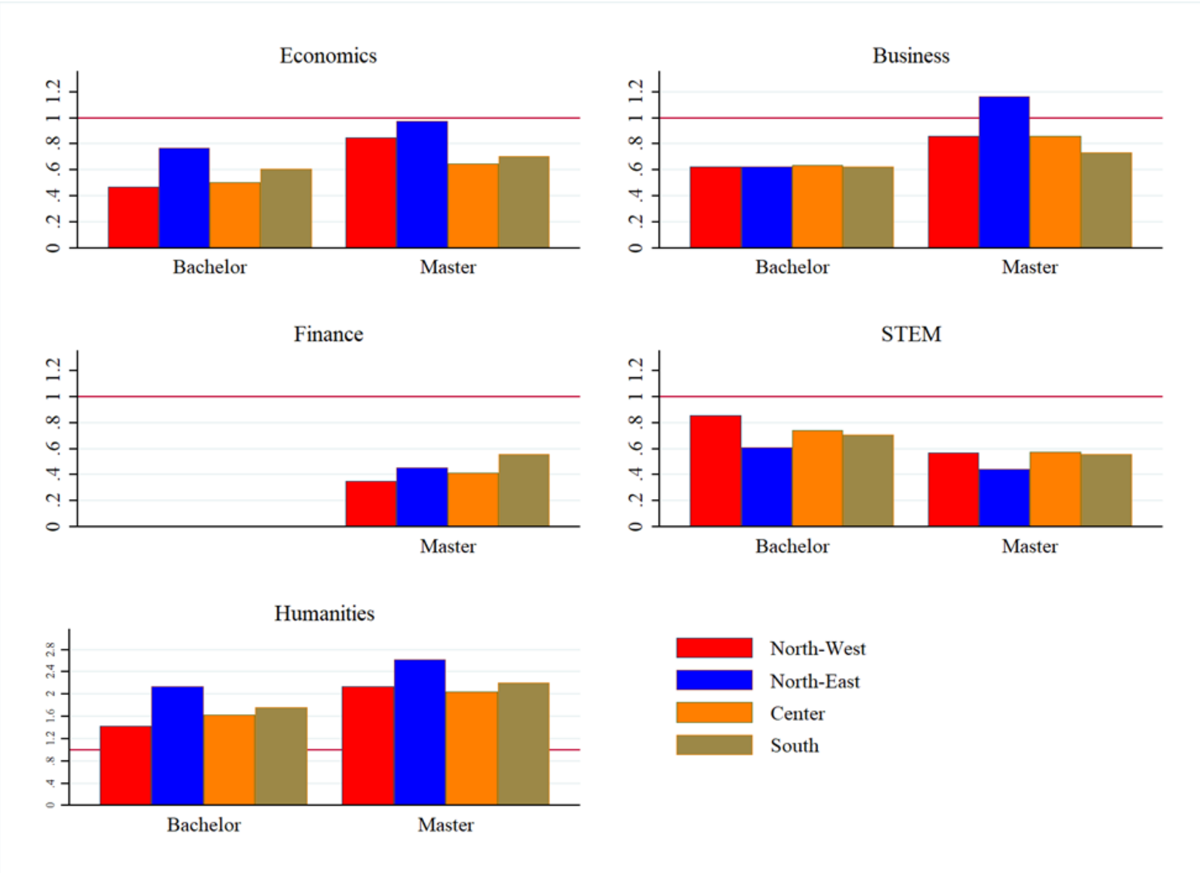

Figure A2: Gender Parity Index, by field, degree level and macro-region

Note: Shares of females over total females and males over total males, by field, degree level and macro-region. Vertical axes scales differ.

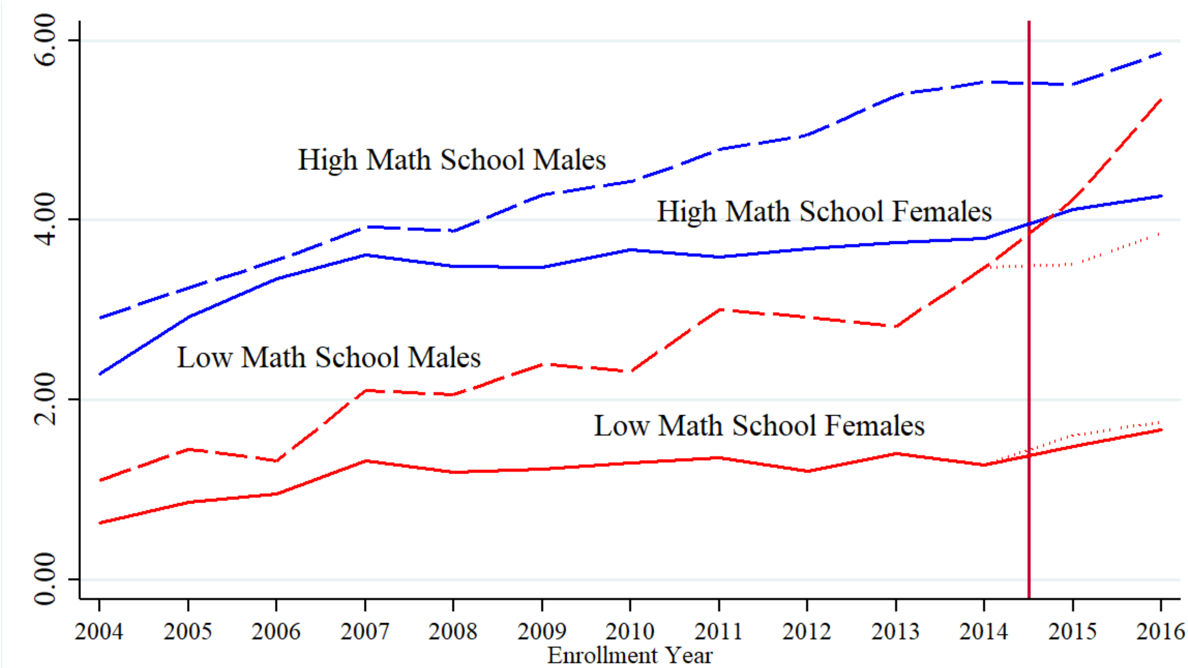

Figure A3: Estimated probabilities of graduating in Economics at the bachelor level, by enrollment year, school type and gender

Note: Probabilities are computed as predictive margins from Model 4 of Tables 8 and A13. Dotted lines depict the counterfactual evolution of the probabilities for treated females and males. The vertical line marks the onset of the school reform.

Table A1: Variable description

Variable	Description
Female	Binary variable taking value 1 if female, 0 if male. Source: AlmaLaurea (AL).
Economics Bachelor Business Bachelor STEM Bachelor Humanities Bachelor	Binary variables that take value one if the respondent graduated in each specific bachelor field, and zero otherwise. Source: AL.
Economics Master Business Master Finance Master STEM Master Humanities Master	Binary variables that take value one if the respondent graduated in each specific master field, and zero otherwise. Source: AL.
Single Cycle Degree	Binary variable taking value 1 if the respondent graduated in a six- or five-year degree program, and 0 otherwise. Source: AL.
High School Math	Binary variable taking value 1 if the respondent attended a high school with high mathematical content, and 0 otherwise. Source: AL.
Switch	Binary variable taking value 1 if the respondent switched across fields between the bachelor and master level, and 0 otherwise. Source: AL.
High School Grade	Continuous variable representing the high school exit grade, ranging from 60 to 100. Source: AL.
Mother Education: Low Intermediate High	Binary variables representing the mother's education level. The education level is low if the mother completed no more than lower secondary school, intermediate if she completed high school, high if she gained a higher degree. Source: AL.
Father Education: Low Intermediate High	Binary variables representing the father's education level. The education level is low if the father completed no more than lower secondary school, intermediate if he completed high school, high if he gained a higher degree. Source: AL.
Mother Work: Homemaker Blue Collar Employee Self-Employed Manager Entrepreneur	Binary variables representing the mother's latest occupation. Source: AL.
Father Work: Homemaker Blue Collar Employee Self-Employed Manager Entrepreneur	Binary variables representing the father's latest occupation. Source: AL.
Motivations Culture	Binary variable taking value 1 if the respondent declares to be interested in the field for cultural reasons. Source: AL.
Motivations Jobs	Binary variable taking value 1 if the respondent declares to be interested in the field for work-related reasons. Source: AL.
Fertility	Continuous variable representing the fertility rate in the province of residence in the year of enrollment of the respondent. It is obtained by dividing the number of live births by the number of women between age 15 and 49 (multiplied by 1,000) at the province level. Source: ISTAT.
Employment	Continuous variable representing the employment rate in the province of residence in the year of enrollment of the respondent. It is calculated as the ratio of the employed to the working age population (multiplied by 100) at the province level. Source: ISTAT.

Table A2: Descriptive statistics - Bachelor level

	Males			Females		
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Economics Bachelor	588,967	0.043	0.202	900,081	0.025	0.157
Business Bachelor		0.124	0.330		0.081	0.273
STEM Bachelor		0.539	0.499		0.381	0.486
Humanities Bachelor		0.295	0.456		0.513	0.500
Single Cycle Degree	588,967	0.143	0.350	900,081	0.169	0.375
High School Math	588,967	0.836	0.370	900,081	0.543	0.498
High School Grade	588,836	79.877	12.202	900,081	82.676	11.803
Mother Education Low	531,878	0.258	0.438	833,619	0.321	0.467
Mother Education Intermediate		0.517	0.500		0.501	0.500
Mother Education High		0.225	0.418		0.178	0.382
Father Education Low	533,062	0.283	0.451	831,235	0.359	0.480
Father Education Intermediate		0.471	0.499		0.453	0.498
Father Education High		0.246	0.431		0.188	0.390
Mother Work Homemaker	524,298	0.245	0.431	821,668	0.270	0.444
Mother Work Blue Collar		0.089	0.285		0.113	0.316
Mother Work Employee		0.458	0.498		0.420	0.494
Mother Work Self-Employed		0.133	0.340		0.136	0.343
Mother Work Manager		0.059	0.235		0.046	0.210
Mother Work Entrepreneur		0.016	0.126		0.014	0.118
Father Work Homemaker	503,463	0.005	0.067	780,465	0.005	0.0073
Father Work Blue Collar		0.157	0.364		0.202	0.401
Father Work Employee		0.297	0.457		0.286	0.452
Father Work Self-Employed		0.319	0.466		0.330	0.470
Father Work Manager		0.168	0.374		0.130	0.336
Father Work Entrepreneur		0.054	0.227		0.047	0.213
Motivations Culture	542,049	0.973	0.161	845,988	0.983	0.131
Motivations Jobs	541,785	0.877	0.328	845,522	0.869	0.337
Fertility	588,967	0.241	0.137	900,081	0.241	0.137
Employment	584,823	56.066	10.548	893,566	55.883	10.561

Table A3: Descriptive statistics - Master level

	Males			Females		
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.
Economics Master	96,927	0.034	0.182	133,313	0.026	0.158
Business Master		0.157	0.364		0.132	0.338
Finance Master		0.013	0.113		0.006	0.076
STEM Master		0.554	0.497		0.304	0.460
Humanities Master		0.242	0.428		0.533	0.499
Economics Bachelor	96,927	0.052	0.222	133,313	0.038	0.191
Business Bachelor		0.146	0.353		0.114	0.318
STEM Bachelor		0.554	0.497		0.304	0.460
Humanities Bachelor		0.249	0.432		0.544	0.498
Switch	96,927	0.070	0.256	133,313	0.058	0.234
High School Math	96,927	0.857	0.350	133,313	0.551	0.497
High School Grade	96,464	82.494	12.350	132,922	85.149	11.698
Mother Education Low	86,438	0.269	0.444	120,601	0.318	0.466
Mother Education Intermediate		0.508	0.5		0.499	0.5
Mother Education High		0.222	0.416		0.183	0.387
Father Education Low	86,597	0.284	0.451	120,431	0.344	0.475
Father Education Intermediate		0.471	0.499		0.459	0.498
Father Education High		0.245	0.43		0.197	0.398
Mother Work Homemaker	85,666	0.264	0.441	119,216	0.293	0.455
Mother Work Blue Collar		0.087	0.281		0.098	0.298
Mother Work Employee		0.461	0.498		0.427	0.495
Mother Work Self-Employed		0.115	0.319		0.120	0.325
Mother Work Manager		0.059	0.235		0.049	0.215
Mother Work Entrepreneur		0.014	0.117		0.013	0.114
Father Work Homemaker	81,545	0.005	0.067	112,234	0.006	0.077
Father Work Blue Collar		0.155	0.361		0.185	0.389
Father Work Employee		0.314	0.464		0.303	0.460
Father Work Self-Employed		0.296	0.456		0.316	0.465
Father Work Manager		0.181	0.385		0.144	0.351
Father Work Entrepreneur		0.050	0.219		0.045	0.208
Motivations Culture	87,971	0.971	0.169	122,565	0.976	0.154
Motivations Jobs	87,915	0.890	0.313	122,510	0.859	0.348
Fertility	96,927	0.277	0.138	133,313	0.271	0.140
Employment	96,655	55.614	10.793	132,780	54.484	10.886

Table A4: Gender parity in Economics - Bachelor level - Interactions

	Female Interacted With:		GPI	
(1)	High School Math	No	0.460***	(0.018)
		Yes	0.785***	(0.038)
(2)	High School Grade	Low	0.463***	(0.026)
		Intermediate	0.702***	(0.036)
		High	1.062***	(0.078)
(3)	Mother Education	Low	0.867***	(0.049)
		Intermediate	0.698***	(0.031)
		High	0.608***	(0.028)
(4)	Father Education	Low	0.823***	(0.044)
		Intermediate	0.705***	(0.036)
		High	0.639***	(0.026)
(5)	Mother Work	Homemaker	0.772***	(0.033)
		Blue Collar	0.905***	(0.061)
		Employee	0.671***	(0.036)
		Self-Employed	0.762***	(0.034)
		Manager	0.578***	(0.028)
		Entrepreneur	0.705***	(0.058)
(6)	Father Work	Homemaker	0.620***	(0.068)
		Blue Collar	0.862***	(0.048)
		Employee	0.672***	(0.033)
		Self-Employed	0.740***	(0.035)
		Manager	0.660***	(0.033)
		Entrepreneur	0.713***	(0.040)
(7)	Motivations Culture	Low	1.014***	(0.073)
		High	0.721***	(0.035)
(8)	Motivations Jobs	Low	0.408***	(0.025)
		High	0.753***	(0.036)
(9)	Fertility	Low	0.780***	(0.039)
		Intermediate	0.757***	(0.037)
		High	0.691***	(0.034)
(10)	Employment	Low	0.715***	(0.034)
		Intermediate	0.738***	(0.042)
		High	0.743***	(0.047)

Note: Logit estimates. The dependent variable is a binary that takes value one if a student graduates in Economics, and zero if a student graduates in another field. The GPI is the ratio of the weighted probability of females to the weighted probability of males to graduate in the field and equals 1 when the weighted probabilities are equal. All models include enrollment year and region of residence fixed effects, Female, High School Math, High School Grade, Parents, Motivations, and Macro Indicators. The number of observations in all models is 1,235,522. Robust standard errors clustered at the university level in parentheses: *** p <0.01, ** p <0.05, * p <0.1.

Table A5: Mediation analysis - Bachelor level

		GPI								
		High School Math	Economics		Business		STEM		Humanities	
(1)	Full	0.643*** (0.004)								
(2a)	Full Without High School Math		0.595*** (0.027)							
(2b)	Full			0.714*** (0.032)						
(3a)	Full Without High School Math				0.665*** (0.028)					
(3b)	Full					0.808*** (0.033)				
(4a)	Full Without High School Math						0.689*** (0.022)			
(4b)	Full							0.791*** (0.022)		
(5a)	Full Without High School Math								1.815*** (0.064)	
(5b)	Full									1.414*** (0.036)
	R-squared	0.1069	0.088	0.0116	0.0213	0.0315	0.0591	0.0964	0.0969	0.1721

Note: OLS estimates. Column headers indicate the dependent variables of each model. Model 1 reports the GPI from regressing High School Math on Female, controls and enrollment year and region of residence fixed effects. The controls are High School Math, High School Grade, Parents, Motivations, and Macro Indicators. Each pair of subsequent models reports the GPI from regressing each Bachelor Field on Female, controls and enrollment year and region of residence fixed effects, without (a) and with (b) High School Math. The GPI is the ratio of the weighted probability of females to the weighted probability of males to graduate in any field and equals 1 when the weighted probabilities are equal. The number of observations in all models is 1,235,531. Robust standard errors clustered at the university level in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A6: Gender parity in all fields - Bachelor level - Interactions

			Estimated GPI							
	Female Interacted With:		Economics		Business		STEM		Humanities	
(1)	High School Math	No	0.459***	(0.018)	0.560***	(0.018)	0.838***	(0.027)	1.178***	(0.022)
		Yes	0.786***	(0.038)	0.869***	(0.038)	0.791***	(0.021)	1.664***	(0.063)
(2)	High School Grade	Low	0.484***	(0.027)	0.531***	(0.019)	0.923***	(0.038)	1.246***	(0.033)
		Intermediate	0.687***	(0.034)	0.791***	(0.028)	0.791***	(0.022)	1.413***	(0.039)
		High	1.046***	(0.073)	1.262***	(0.074)	0.727***	(0.074)	1.725***	(0.075)
(3)	Mother Education	Low	0.858***	(0.048)	0.928***	(0.037)	0.715***	(0.023)	1.503***	(0.048)
		Intermediate	0.691***	(0.030)	0.783***	(0.030)	0.790***	(0.022)	1.423***	(0.039)
		High	0.599***	(0.026)	0.711***	(0.026)	0.872***	(0.019)	1.336***	(0.032)
(4)	Father Education	Low	0.815***	(0.023)	0.901***	(0.037)	0.724***	(0.042)	1.473***	(0.046)
		Intermediate	0.698***	(0.022)	0.787***	(0.030)	0.785***	(0.035)	1.439***	(0.039)
		High	0.629***	(0.019)	0.723***	(0.026)	0.876***	(0.025)	1.331***	(0.032)
(5)	Mother Work	Homemaker	0.763***	(0.032)	0.837***	(0.032)	0.741***	(0.025)	1.492***	(0.043)
		Blue Collar	0.895***	(0.059)	0.978***	(0.045)	0.701***	(0.024)	1.514***	(0.052)
		Employee	0.665***	(0.035)	0.763***	(0.031)	0.812***	(0.024)	1.403***	(0.039)
		Self-Employed	0.753***	(0.032)	0.829***	(0.033)	0.665***	(0.021)	1.387***	(0.038)
		Manager	0.571***	(0.026)	0.723***	(0.032)	0.892***	(0.022)	1.289***	(0.031)
		Entrepreneur	0.693***	(0.056)	0.802***	(0.032)	0.781***	(0.029)	1.475***	(0.052)
(6)	Father Work	Homemaker	0.619***	(0.068)	0.809***	(0.084)	0.824***	(0.045)	1.299***	(0.050)
		Blue Collar	0.854***	(0.046)	0.932***	(0.040)	0.712***	(0.023)	1.501***	(0.048)
		Employee	0.666***	(0.032)	0.775***	(0.031)	0.802***	(0.020)	1.400***	(0.038)
		Self-Employed	0.731***	(0.034)	0.822***	(0.030)	0.790***	(0.021)	1.415***	(0.040)
		Manager	0.652***	(0.032)	0.737***	(0.031)	0.842***	(0.021)	1.389***	(0.036)
		Entrepreneur	0.698***	(0.038)	0.770***	(0.028)	0.770***	(0.077)	1.544***	(0.046)
(7)	Motivations Culture	Low	0.995***	(0.070)	1.166***	(0.055)	0.707***	(0.022)	1.369***	(0.058)
		High	0.713***	(0.033)	0.802***	(0.030)	0.788***	(0.021)	1.425***	(0.038)
(8)	Motivations Jobs	Low	0.425***	(0.027)	0.547***	(0.025)	0.865***	(0.025)	1.130***	(0.017)
		High	0.742***	(0.035)	0.827***	(0.031)	0.779***	(0.021)	1.510***	(0.047)
(9)	Fertility	Low	0.770***	(0.037)	0.845***	(0.032)	0.784***	(0.019)	1.413***	(0.036)
		Intermediate	0.749***	(0.035)	0.830***	(0.030)	0.785***	(0.020)	1.417***	(0.037)
		High	0.684***	(0.033)	0.783***	(0.030)	0.789***	(0.025)	1.430***	(0.045)
(10)	Employment	Low	0.711***	(0.034)	0.771***	(0.037)	0.798***	(0.028)	1.441***	(0.045)
		Intermediate	0.728***	(0.041)	0.832***	(0.033)	0.782***	(0.023)	1.413***	(0.043)
		High	0.732***	(0.046)	0.845***	(0.037)	0.778***	(0.026)	1.407***	(0.048)

Note: Multinomial logit estimates. The dependent variable is a categorical capturing whether a student graduates in Economics, Business, STEM, or Humanities. The GPI is the ratio of the weighted probability of females to the weighted probability of males to graduate in any field and equals 1 when the weighted probabilities are equal. All models include enrollment year and region of residence fixed effects, Female, High School Math, High School Grade, Parents, Motivations, and Macro Indicators. The number of observations in all models is 1,235,522. Robust standard errors clustered at the university level in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A7: Gender parity in Economics - Master level - Interactions

			GPI			
			Economics Bachelor	Business Bachelor	STEM Bachelor	Humanities Bachelor
(1)	Female Interacted With Bachelor		0.986*** (0.042)	0.926*** (0.061)	0.869*** (0.026)	0.434*** (0.039)
Female and Bachelor Interacted With:						
(2)	High School Math	No	1.048*** (0.059)	1.012*** (0.116)	0.957*** (0.289)	0.462*** (0.046)
		Yes	0.976*** (0.045)	0.913*** (0.058)	0.856*** (0.261)	0.414*** (0.042)
(3)	High School Grade	Low	1.002*** (0.046)	0.947*** (0.074)	0.895*** (0.280)	0.444*** (0.047)
		Intermediate	0.988*** (0.040)	0.929*** (0.060)	0.876*** (0.266)	0.434*** (0.039)
		High	0.975*** (0.054)	0.911*** (0.073)	0.857*** (0.259)	0.425*** (0.042)
(4)	Mother Education	Low	0.971*** (0.055)	0.908*** (0.058)	0.840*** (0.243)	0.421*** (0.043)
		Intermediate	0.967*** (0.043)	0.903*** (0.068)	0.835*** (0.259)	0.420*** (0.037)
		High	1.073*** (0.065)	1.052*** (0.110)	0.989*** (0.309)	0.497*** (0.062)
(5)	Father Education	Low	0.988*** (0.048)	0.930*** (0.059)	0.869*** (0.261)	0.434*** (0.044)
		Intermediate	1.000*** (0.046)	0.947*** (0.068)	0.890***(0.266)	0.443*** (0.035)
		High	0.974*** (0.058)	0.903*** (0.093)	0.854*** (0.275)	0.424*** (0.055)
(6)	Mother Work	Homemaker	0.983*** (0.054)	0.924*** (0.063)	0.861*** (0.245)	0.431*** (0.041)
		Blue Collar	1.063*** (0.101)	1.035*** (0.125)	0.972*** (0.300)	0.485*** (0.078)
		Employee	0.985*** (0.051)	0.928*** (0.094)	0.871*** (0.282)	0.435*** (0.048)
		Self-Employed	0.909*** (0.057)	0.822*** (0.062)	0.765*** (0.238)	0.383*** (0.039)
		Manager	1.105*** (0.097)	1.095*** (0.143)	1.058*** (0.319)	0.525*** (0.087)
		Entrepreneur	1.062*** (0.149)	1.032*** (0.199)	0.975*** (0.350)	0.490*** (0.105)
(7)	Father Work	Homemaker	0.634*** (0.132)	0.476*** (0.131)	0.416** (0.195)	0.213*** (0.071)
		Blue Collar	0.965*** (0.062)	0.901*** (0.075)	0.831*** (0.246)	0.417*** (0.048)
		Employee	1.014*** (0.053)	0.967*** (0.101)	0.905*** (0.282)	0.452*** (0.051)
		Self-Employed	0.961*** (0.043)	0.888*** (0.053)	0.828*** (0.253)	0.415*** (0.039)
		Manager	1.041*** (0.063)	1.007*** (0.096)	0.948*** (0.295)	0.475*** (0.051)
		Entrepreneur	0.998*** (0.086)	0.949*** (0.099)	0.878*** (0.289)	0.440*** (0.041)
(8)	Motivations Culture	Low	1.084*** (1.084)	1.076*** (1.076)	1.028*** (1.028)	0.512*** (0.096)
		High	0.983*** (0.983)	0.921***(0.921)	0.865*** (0.865)	0.431*** (0.039)
(9)	Motivations Jobs	Low	0.953*** (0.075)	0.888*** (0.095)	0.819*** (0.232)	0.410*** (0.048)
		High	0.988*** (0.043)	0.928*** (0.063)	0.876*** (0.269)	0.440*** (0.044)
(10)	Fertility	Low	0.998*** (0.042)	0.944*** (0.065)	0.887*** (0.270)	0.443*** (0.040)
		Intermediate	0.984*** (0.041)	0.924*** (0.062)	0.867*** (0.265)	0.433*** (0.040)
		High	0.976*** (0.045)	0.913*** (0.067)	0.855*** (0.263)	0.427*** (0.042)
(11)	Employment	Low	1.009*** (0.047)	0.956*** (0.068)	0.899*** (0.271)	0.449*** (0.039)
		Intermediate	0.969*** (0.041)	0.901*** (0.063)	0.844*** (0.262)	0.421*** (0.042)
		High	0.960*** (0.043)	0.891*** (0.066)	0.834*** (0.261)	0.415*** (0.044)

Note: Logit estimates. The dependent variable is a binary that takes value one if a student graduates in Economics, and zero if a student graduates in another field. The GPI is the ratio of the weighted probability of females to the weighted probability of males to graduate in the field and equals 1 when the weighted probabilities are equal. All models include enrollment year and region of residence fixed effects, Female, High School Math, High School Grade, Parents, Motivations, Macro Indicators, and Bachelor Field. The number of observations in all models is 187,622. Robust standard errors clustered at the university level in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A8: Gender parity in field switching

		GPI in Switch	Observations
(1)	Female	0.835*** (0.054)	230,240
(2)	High School Math	0.942*** (0.052)	230,240
(3)	High School Grade	0.847*** (0.057)	229,386
(4)	Parents	0.839*** (0.055)	189,032
(5)	Motivations	0.856*** (0.057)	210,185
(6) ,	Macro Indicators	0.837*** (0.054)	229,435
(7)	Full	0.977*** (0.056)	187,682

Note: Logit estimates. The dependent variable is a binary that takes value one if a student switches, and zero otherwise. The GPI is the ratio of the probability of females to the probability of males to switch and equals 1 when the probabilities are equal. All models include enrollment year and region of residence fixed effects. Model 1 also includes Female. High School Math, High School Grade, Parents, Motivations, and Macro Indicators are added one at a time to Models 2 to 6. Model 7 includes all controls. Robust standard errors clustered at the university level in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A9: Gender parity in field switching - Interactions

	Female Interacted With:		GPI	
(1)	High School Math	No	0.702***	(0.057)
		Yes	1.042***	(0.060)
(2)	High School Grade	Low	0.607***	(0.045)
		Intermediate	0.925***	(0.055)
		High	1.428***	(0.118)
(3)	Mother Education	Low	1.101***	(0.072)
		Intermediate	0.952***	(0.057)
		High	0.867***	(0.054)
(4)	Father Education	Low	1.054***	(0.068)
		Intermediate	0.942***	(0.061)
		High	0.943***	(0.060)
(5)	Mother Work	Homemaker	0.987***	(0.059)
		Blue Collar	1.194***	(0.101)
		Employee	0.936***	(0.054)
		Self-Employed	0.949***	(0.080)
		Manager	0.939***	(0.105)
		Entrepreneur	1.070***	(0.125)
(6)	Father Work	Homemaker	0.721***	(0.185)
		Blue Collar	1.094***	(0.070)
		Employee	0.903***	(0.062)
		Self-Employed	1.002***	(0.066)
		Manager	0.929***	(0.067)
		Entrepreneur	1.046***	(0.067)
(7)	Motivations Culture	Low	0.892***	(0.117)
		High	0.979***	(0.057)
(8)	Motivations Jobs	Low	0.744***	(0.062)
		High	0.993***	(0.059)
(9)	Fertility	Low	1.007***	(0.061)
		Intermediate	0.975***	(0.057)
		High	0.956***	(0.059)
(10)	Employment	Low	0.879***	(0.059)
		Intermediate	1.025***	(0.064)
		High	1.057***	(0.072)

Note: Logit estimates. The dependent variable is a binary that takes value one if a student switches, and zero otherwise. The GPI is the ratio of the probability of females to the probability of males to switch and equals 1 when the probabilities are equal. All models include enrollment year and region of residence fixed effects, Female, High School Math, High School Grade, Parents, Motivations, and Macro Indicators. The number of observations in all models is 187,622. Robust standard errors clustered at the university level in parentheses: *** p <0.01, ** p <0.05, * p <0.1.

Table A10: Gender parity in all fields - Master level - Interactions

			GPI											
			Economics				Business				Finance			
			Economics Bachelor	Business Bachelor	STEM Bachelor	Human. Bachelor	Economics Bachelor	Business Bachelor	STEM Bachelor	Human. Bachelor	Economics Bachelor	Business Bachelor	STEM Bachelor	Human. Bachelor
(1)	Female Inter.		0.981***	0.912***	0.848***	0.457***	1.109***	1.034***	0.895***	0.928***	0.592***	0.520***	1.069***	0.112*
	With Bachelor		(0.041)	(0.061)	(0.251)	(0.043)	(0.037)	(0.008)	(0.140)	(0.113)	(0.058)	(0.049)	(0.187)	(0.060)
Female and Bachelor Interacted With:														
(2)	High Sch. Math	No	1.027***	0.957***	0.873***	0.492***	1.112***	1.038***	0.882***	0.966***	0.481***	0.421***	0.852***	0.099*
			(0.064)	(0.119)	(0.267)	(0.054)	(0.059)	(0.119)	(0.189)	(0.154)	(0.073)	(0.085)	(0.223)	(0.052)
		Yes	0.973***	0.905***	0.842***	0.441***	1.109***	1.034***	0.898***	0.914***	0.614***	0.537***	1.117***	0.121*
			(0.045)	(0.057)	(0.253)	(0.046)	(0.037)	(0.008)	(0.140)	(0.105)	(0.070)	(0.052)	(0.197)	(0.067)
(3)	High Sch. Grade	Low	0.996***	0.944***	0.756***	0.453***	1.075***	1.023***	0.761***	0.884***	0.560***	0.503***	0.882***	0.105*
			(0.047)	(0.077)	(0.267)	(0.052)	(0.042)	(0.010)	(0.189)	(0.138)	(0.101)	(0.083)	(0.223)	(0.060)
		Interm.	0.983***	0.916***	0.828***	0.457***	1.104***	1.033***	0.868***	0.927***	0.585***	0.516***	1.020***	0.112*
			(0.040)	(0.061)	(0.267)	(0.043)	(0.036)	(0.008)	(0.189)	(0.114)	(0.064)	(0.052)	(0.223)	(0.060)
		High	0.972***	0.890***	0.907***	0.460***	1.136***	1.044***	0.990***	0.972***	0.611***	0.531***	1.180***	0.119*
			(0.056)	(0.075)	(0.253)	(0.052)	(0.046)	(0.011)	(0.140)	(0.125)	(0.060)	(0.059)	(0.197)	(0.062)
(4)	Mother Educ.	Low	0.968***	0.907***	0.943***	0.424***	1.096***	1.029***	0.997***	0.866***	0.660***	0.586***	1.354***	0.121*
			(0.054)	(0.057)	(0.282)	’(0.052)	(0.044)	(0.010)	(0.189)	(0.105)	(0.072)	(0.081)	(0.266)	(0.068)
		Interm.	0.962***	0.882***	0.826***	0.454***	1.132***	1.040***	0.906***	0.956***	0.580***	0.504***	1.038***	0.111*
			(0.043)	(0.068)	(0.259)	(0.045)	(0.037)	(0.010)	(0.189)	(0.118)	(0.075)	(0.049)	(0.195)	(0.059)
		High	1.069***	1.040***	0.789***	0.515***	1.048***	1.020***	0.716***	0.895***	0.519***	0.477***	0.785***	0.100*
			(0.067)	(0.067)	(0.242)	’(0.066)	(0.046)	(0.011)	(0.140)	(0.149)	(0.080)	(0.083)	(0.204)	(0.056)
(5)	Father Educ.	Low	0.990***	0.927***	0.833***	0.439***	1.100***	1.032***	0.858***	0.876***	0.591***	0.521***	1.009***	0.106*
			(0.047)	(0.058)	(0.267)	(0.052)	(0.039)	(0.010)	(0.189)	(0.119)	(0.072)	(0.066)	(0.266)	(0.076)
		Interm.	0.995***	0.934***	0.861***	0.464***	1.101***	1.032***	0.894***	0.924***	0.580***	0.516***	1.055***	0.111*
			(0.046)	(0.070)	(0.243)	(0.043)	(0.039)	(0.010)	(0.189)	(0.114)	(0.071)	(0.057)	(0.266)	(0.064)
		High	0.964***	0.882***	0.853***	0.466***	1.123***	1.037***	0.948***	0.987***	0.618***	0.542***	1.182***	0.125*
			(0.058)	(0.093)	(0.283)	(0.061)	(0.054)	(0.011)	(0.140)	(0.132)	(0.077)	(0.061)	(0.204)	(0.064)
(6)	Mother Work	Homem.	0.987***	0.943***	0.876***	0.413***	1.068***	1.020***	0.878***	0.798***	0.679***	0.618***	1.255***	0.117*
			(0.056)	(0.066)	(0.265)	(0.044)	(0.041)	(0.009)	(0.160)	(0.102)	(0.098)	(0.090)	(0.247)	(0.066)
		Blue	1.041***	1.002***	1.113***	0.548***	1.075***	1.028***	1.061***	1.006***	0.662***	0.608***	1.462***	0.143*
		Collar	(0.104)	(0.125)	(0.369)	(0.106)	(0.065)	(0.013)	(0.253)	(0.170)	(0.107)	(0.107)	(0.422)	(0.085)
		Empl.	0.977***	0.905***	0.811***	0.467***	1.123***	1.038***	0.872***	0.959***	0.573***	0.502***	0.998***	0.112*
			(0.052)	(0.096)	(0.262)	(0.053)	(0.042)	(0.011)	(0.153)	(0.116)	(0.057)	(0.042)	(0.201)	(0.059)
		Self	0.912***	0.793***	0.816***	0.418***	1.213***	1.061***	1.012***	0.992***	0.468***	0.388***	0.868***	0.086*
		Empl.	(0.058)	(0.060)	(0.258)	(0.057)	(0.054)	(0.013)	(0.228)	(0.173)	(0.075)	(0.056)	(0.269)	(0.046)
		Manager	1.108***	1.094***	0.779**	0.492***	1.029***	1.016***	0.670***	0.806***	0.469***	0.440***	0.684**	0.084
			(0.100)	(0.149)	(0.354)	(0.102)	(0.064)	(0.016)	(0.238)	(0.215)	(0.104)	(0.082)	(0.269)	(0.053)
		Entrepr.	1.038***	0.999***	0.912*	0.608***	1.052***	1.021***	0.863*	1.108***	0.474***	0.449**	0.9	0.117
			(0.146)	(0.199)	(0.478)	(0.198)	(0.099)	(0.022)	(0.487)	(0.385)	(0.180)	(0.184)	(0.635)	(0.087)
(7)	Father Work	Homem.	0.629***	0.431***	0.811	0.348*	1.615***	1.151***	2.018	1.653*	0.687*	0.475	1.999	0.169
			(0.124)	(0.115)	(0.660)	(0.202)	(0.259)	(0.062)	(1.315)	(0.864)	(0.399)	(0.330)	(1.866)	(0.171)
		Blue	0.967***	0.901***	0.950***	0.419***	1.116***	1.035***	1.025***	0.877***	0.651***	0.577***	1.331***	0.118*
		Collar	(0.061)	(0.072)	(0.334)	(0.062)	(0.044)	(0.010)	(0.204)	(0.106)	(0.085)	(0.097)	(0.262)	(0.066)
		Empl.	1.008***	0.949***	0.944***	0.476***	1.097***	1.033***	0.963***	0.930***	0.589***	0.521***	1.146***	0.114*
			(0.054)	(0.054)	(0.310)	(0.063)	(0.046)	(0.012)	(0.179)	(0.126)	(0.071)	(0.043)	(0.277)	(0.062)
		Self	0.961***	0.883***	0.735***	0.422***	1.117***	1.036***	0.801***	0.883***	0.550***	0.479***	0.873***	0.099*
		Empl.	(0.043)	(0.054)	(0.235)	(0.499)	(0.040)	(0.009)	(0.133)	(0.124)	(0.077)	(0.068)	(0.172)	(0.054)
		Manager	1.041***	0.988***	0.827***	0.508***	1.087***	1.031***	0.809***	0.946***	0.542***	0.492***	0.913***	0.108*
			(0.065)	(0.100)	(0.241)	(0.053)	(0.056)	(0.013)	(0.154)	(0.159)	(0.094)	(0.077)	(0.227)	(0.060)
		Entrepr.	0.954***	0.915***	0.883***	0.545***	1.061***	1.017***	0.928***	1.102***	0.799***	0.717***	1.549**	0.189*
			(0.083)	(0.105)	(0.316)	(0.545)	(0.050)	(0.013)	(0.358)	(0.231)	(0.161)	(0.144)	(0.627)	(0.110)
(8)	Motiv. Culture	Low	1.081***	1.086***	1.085**	0.568***	0.998***	1.005***	0.929**	0.929***	0.597***	0.566***	1.251*	0.127
			(0.129)	(0.189)	(0.448)	(0.121)	(0.111)	(0.025)	(0.403)	(0.196)	(0.208)	(0.202)	(0.722)	(0.088)
		High	0.978***	0.907***	0.842***	0.452***	1.112***	1.035***	0.895***	0.926***	0.592***	0.519***	1.067***	0.112*
			(0.040)	(0.062)	(0.252)	(0.043)	(0.036)	(0.008)	(0.139)	(0.113)	(0.058)	(0.048)	(0.186)	(0.060)
(9)	Moti. Jobs	Low	0.987***	0.922***	0.891***	0.551***	1.116***	1.035***	0.952***	1.143***	0.528***	0.461***	1.006***	0.123
			(0.063)	(0.095)	(0.266)	(0.123)	(0.079)	(0.020)	(0.403)	(0.286)	(0.117)	(0.108)	(0.293)	(0.076)
		High	0.981***	0.912***	0.843***	0.447***	1.109***	1.034***	0.892***	0.915***	0.594***	0.521***	1.072***	0.112*
			(0.043)	(0.064)	(0.258)	(0.044)	(0.036)	(0.008)	(0.139)	(0.107)	(0.058)	(0.049)	(0.189)	(0.060)
(10)	Fert.	Low	0.995***	0.939***	0.917***	0.470***	1.090***	1.028***	0.937***	0.917***	0.631***	0.567***	1.231***	0.124*
			(0.042)	(0.069)	(0.266)	(0.046)	(0.034)	(0.009)	(0.158)	(0.147)	(0.052)	(0.064)	(0.187)	(0.071)
		Interm.	0.979***	0.908***	0.841***	0.456***	1.111***	1.035***	0.893***	0.925***	0.587***	0.516***	1.064***	0.114*
			(0.041)	(0.064)	(0.245)	(0.043)	(0.034)	(0.009)	(0.140)	(0.113)	(0.057)	(0.045)	(0.187)	(0.061)
		High	0.969***	0.891***	0.796***	0.448***	1.125***	1.039***	0.866***	0.930***	0.562***	0.489***	0.970***	0.107*
			(0.045)	(0.068)	(0.241)	(0.049)	(0.037)	(0.009)	(0.144)	(0.099)	(0.065)	(0.042)	(0.201)	(0.056)
(11)	Empl.	Low	1.003***	0.967***	0.772***	0.459***	1.036***	1.012***	0.724***	0.837***	0.731***	0.683***	1.171***	0.141*
			(0.047)	(0.071)	(0.233)	(0.052)	(0.041)	(0.009)	(0.122)	(0.105)	(0.094)	(0.078)	(0.222)	(0.073)
		Interm.	0.964***	0.866***	0.886***	0.455***	1.150***	1.047***	0.959***	0.956***	0.554***	0.480***	1.048***	0.109*
			(0.042)	(0.064)	(0.261)	(0.045)	(0.034)	(0.010)	(0.154)	(0.122)	(0.054)	(0.044)	(0.190)	(0.059)
		High	0.959***	0.848***	0.909***	0.454***	1.177***	1.055***	1.013***	0.986***	0.525***	0.450***	1.025***	0.103*
			(0.044)	(0.066)	(0.270)	(0.048)	(0.039)	(0.012)	(0.166)	(0.138)	(0.054)	(0.045)	(0.192)	(0.056)

Note: Multinomial logit estimates. The dependent variable is a categorical capturing whether a student graduates in Economics, Business, Finance, STEM, or Humanities. The GPI is the ratio of the probability of females to the probability of males to graduate in any field and equals 1 when the probabilities are equal. All models include enrollment year and region of residence fixed effects, Female, High School Math, High School Grade, Parents, Motivations, Macro Indicators, and Bachelor Field. The number of observations is 187,622. Robust standard errors clustered at the university level in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A10 continued: Gender parity in all fields - Master level - Interactions

			GPI							
			STEM				Business			
			Economics Bachelor	Business Bachelor	STEM Bachelor	Humanities Bachelor	Economics Bachelor	Business Bachelor	STEM Bachelor	Humanities Bachelor
(1)	Female Interacted With Bachelor		0.853***	0.858***	0.997***	0.515***	1.119***	1.247***	1.780***	1.016***
			(0.145)	(0.159)	(0.000)	(0.076)	(0.192)	(0.152)	(0.233)	(0.004)
Female and Bachelor Interacted With:										
(2)	High School Math	No	0.867***	0.874***	0.995***	0.543***	1.061***	1.183***	1.664***	1.010***
			(0.184)	(0.202)	(0.002)	(0.107)	(0.180)	(0.156)	(0.241)	(0.004)
		Yes	0.852***	0.857***	0.997***	0.506***	1.134***	1.262***	1.815***	1.021***
			(0.146)	(0.159)	(0.001)	(0.074)	(0.199)	(0.159)	(0.261)	(0.004)
(3)	High School Grade	Low	0.970***	0.991***	0.997***	0.565***	1.141***	1.296***	1.601***	1.014***
			(0.186)	(0.227)	(0.002)	(0.101)	(0.208)	(0.212)	(0.279)	(0.004)
		Intermediate	0.874***	0.878***	0.997***	0.520***	1.120***	1.250***	1.744***	1.015***
			(0.149)	(0.166)	(0.001)	(0.078)	(0.192)	(0.155)	(0.239)	(0.003)
		High	0.789***	0.779***	0.997***	0.478***	1.102***	1.209***	1.900***	1.017***
			(0.146)	(0.142)	(0.001)	(0.073)	(0.200)	(0.143)	(0.254)	(0.004)
(4)	Mother Education	Low	0.753***	0.765***	0.995***	0.426***	1.197***	1.339***	2.127***	1.020***
			(0.156)	(0.159)	(0.001)	(0.065)	(0.230)	(0.182)	(0.286)	(0.004)
		Intermediate	0.856***	0.849***	0.997***	0.523***	1.106***	1.207***	1.745***	1.015***
			(0.143)	(0.154)	(0.001)	(0.081)	(0.186)	(0.154)	(0.237)	(0.004)
		High	1.002***	1.053***	0.999***	0.625***	1.075***	1.251***	1.468***	1.014***
			(0.192)	(0.230)	(0.001)	(0.108)	(0.205)	(0.176)	(0.245)	(0.004)
(5)	Father Education	Low	0.863***	0.880***	0.997***	0.504***	1.185***	1.322***	1.808***	1.018***
			(0.165)	(0.172)	(0.001)	(0.077)	(0.215)	(0.166)	(0.264)	(0.004)
		Intermediate	0.859***	0.868***	0.997***	0.515***	1.117***	1.249***	1.771***	1.016***
			(0.150)	(0.175)	(0.001)	(0.078)	(0.197)	(0.168)	(0.251)	(0.004)
		High	0.842***	0.832***	0.997***	0.524***	1.066***	1.173***	1.751***	1.014***
			(0.163)	(0.162)	(0.001)	(0.095)	(0.194)	(0.154)	(0.256)	(0.004)
(6)	Mother Work	Homemaker	0.829***	0.856***	0.995***	0.447***	1.243***	1.418***	2.007***	1.021***
			(0.149)	(0.151)	(0.002)	(0.063)	(0.212)	(0.205)	(0.317)	(0.003)
		Blue Collar	0.696***	0.721***	0.996***	0.472***	0.987***	1.130***	1.909***	1.013***
			(0.193)	(0.157)	(0.002)	(0.122)	(0.191)	(0.210)	(0.306)	(0.008)
		Employee	0.895***	0.897***	0.997***	0.552***	1.080***	1.195***	1.657***	1.014***
			(0.160)	(0.189)	(0.001)	(0.088)	(0.196)	(0.147)	(0.233)	(0.003)
		Self-Employed	0.825***	0.783***	0.996***	0.493***	1.126***	1.185***	1.858***	1.015***
			(0.160)	(0.242)	(0.002)	(0.116)	(0.258)	(0.187)	(0.187)	(0.005)
		Manager	1.071***	1.129***	0.999***	0.610***	1.167***	1.387***	1.513***	1.017***
			(0.372)	(0.378)	(0.003)	(0.191)	(0.304)	(0.289)	(0.501)	(0.008)
		Entrepreneur	0.861*	0.889*	0.998***	0.639**	0.896***	1.022***	1.426**	1.006***
			(0.490)	(0.502)	(0.006)	(0.295)	(0.279)	(0.363)	(0.654)	(0.013)
(7)	Father Work	Homemaker	0.561	0.418	0.986***	0.417*	0.934*	0.766*	2.180*	1.005***
			(0.396)	(0.292)	(0.010)	(0.243)	(0.490)	(0.412)	(1.245)	(0.014)
		Blue Collar	0.750***	0.755***	0.995***	0.430***	1.212***	1.351***	2.178***	1.021***
			(0.167)	(0.121)	(0.002)	(0.082)	(0.231)	(0.196)	(0.365)	(0.004)
		Employee	0.792***	0.806***	0.996***	0.489***	1.099***	1.237***	1.888***	1.015***
			(0.142)	(0.150)	(0.001)	(0.081)	(0.193)	(0.191)	(0.262)	(0.004)
		Self-Employed	0.969***	0.958***	0.997***	0.560***	1.186***	1.308***	1.671***	1.017***
			(0.171)	(0.197)	(0.001)	(0.088)	(0.224)	(0.157)	(0.259)	(0.004)
		Manager	0.946***	0.963***	0.998***	0.600***	1.065***	1.208***	1.561***	1.013***
			(0.196)	(0.239)	(0.001)	(0.118)	(0.206)	(0.179)	(0.271)	(0.005)
		Entrepreneur	0.804**	0.832**	0.997***	0.599***	0.901***	1.024***	1.531***	1.008***
			(0.336)	(0.394)	(0.004)	(0.215)	(0.216)	(0.194)	(0.576)	(0.009)
(8)	Motivations Culture	Low	0.732***	0.797**	0.996***	0.502**	0.937***	1.121***	1.771**	1.015***
			(0.278)	(0.354)	(0.003)	(0.208)	(0.190)	(0.231)	(0.732)	(0.008)
		High	0.857***	0.860***	0.997***	0.515***	1.126***	1.253***	1.779***	1.016***
			(0.147)	(0.157)	(0.001)	(0.076)	(0.195)	(0.153)	(0.225)	(0.003)
(9)	Motivations Jobs	Low	0.803***	0.805***	0.994***	0.592***	0.925***	1.019***	1.550***	1.004***
			(0.197)	(0.211)	(0.002)	(0.136)	(0.202)	(0.202)	(0.215)	(0.003)
		High	0.857***	0.862***	0.997***	0.507***	1.161***	1.290***	1.847***	1.019***
			(0.148)	(0.160)	(0.001)	(0.076)	(0.206)	(0.160)	(0.290)	(0.004)
(10)	Fertility	Low	0.807***	0.818***	0.996***	0.488***	1.109***	1.249***	1.865***	1.016***
			(0.118)	(0.154)	(0.001)	(0.087)	(0.202)	(0.155)	(0.282)	(0.005)
		Intermediate	0.861***	0.865***	0.997***	0.516***	1.122***	1.246***	1.762***	1.016***
			(0.147)	(0.162)	(0.001)	(0.077)	(0.193)	(0.156)	(0.224)	(0.003)
		High	0.898***	0.895***	0.997***	0.536***	1.130***	1.244***	1.700***	1.016***
			(0.176)	(0.179)	(0.001)	(0.077)	(0.197)	(0.173)	(0.219)	(0.003)
(11)	Employment	Low	0.940***	0.978***	0.997***	0.567***	1.141***	1.318***	1.625***	1.019***
			(0.155)	(0.178)	(0.001)	(0.082)	(0.195)	(0.178)	(0.206)	(0.004)
		Intermediate	0.790***	0.765***	0.997***	0.490***	1.103***	1.189***	1.874***	1.015***
			(0.134)	(0.133)	(0.001)	(0.080)	(0.207)	(0.157)	(0.274)	(0.004)
		High	0.765***	0.730***	0.996***	0.474***	1.099***	1.167***	1.926***	1.014***
			(0.133)	(0.150)	(0.001)	(0.083)	(0.217)	(0.164)	(0.304)	(0.004)

Note: Multinomial logit estimates. The dependent variable is a categorical capturing whether a student graduates in Economics, Business, Finance, STEM, or Humanities. The GPI is the ratio of the probability of females to the probability of males to graduate in any field and equals 1 when the probabilities are equal. All models include enrollment year and region of residence fixed effects, Female, High School Math, High School Grade, Parents, Motivations, Macro Indicators, and Bachelor Field. The number of observations is 187,622. Robust standard errors clustered at the university level in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A11: Gelbach decomposition - Master level

	(1)	(2)	(3)	(4)	(5)
	Economics	Business	Finance	STEM	Humanities
Δ Female coefficient	-0.004*	-0.030***	-0.002**	-0.253***	0.289***
	(0.002)	(0.010)	(0.001)	(0.021)	(0.014)
Field Bachelor	-0.004*	-0.026***	-0.002***	-0.252***	0.284***
	(0.002)	(0.010)	(0.000)	(0.021)	(0.014)
High School Math	0.000	-0.002***	0.000	-0.001***	0.004***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
High School Grade	0.000	-0.000*	0.000**	0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mother Education	0.000	0.000	0.000	-0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Father Education	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Mother Work	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Father Work	-0.000**	0.000*	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Motivations Culture	-0.000*	0.000	0.000*	0.000	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Motivations Jobs	0.000	-0.001***	-0.000***	-0.000***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Fertility	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Employment	0.000*	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Note: OLS estimates. The dependent variables are binary variables that take value one if a student graduates in each specific field, and zero otherwise. All models include enrollment year and region of residence fixed effects. The number of observations in all models is 187,682. Robust standard errors clustered at the university level in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A12: Oaxaca-Blinder decomposition - Master Level

	(1)	(2)	(3)	(4)	(5)
	Economics	Business	Finance	STEM	Humanities
Difference	-0.009**	-0.023***	-0.008***	-0.257***	0.295***
	(0.003)	(0.005)	(0.002)	(0.002)	(0.003)
Explained	-0.005*	-0.028***	-0.002***	-0.254***	0.286***
	(0.003)	(0.004)	(0.001)	(0.002)	(0.004)
Field Bachelor	-0.005*	-0.037***	-0.002***	-0.236***	0.264***
	(0.003)	(0.008)	(0.001)	(0.003)	(0.004)
High School Math	0.000	0.006*	0.000	-0.017***	0.018***
	(0.000)	(0.003)	(0.000)	(0.003)	(0.002)
High School Grade	0.000	0.001	0.000**	0.002***	-0.002**
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)
Mother Education	0.000	0.000	0.000	-0.001**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Father Education	0.000	0.000	0.000	-0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
Mother Work	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Father Work	0.000	0.000	0.000	-0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Motivations Culture	0.000	0.000	0.000	0.000	0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Motivations Jobs	0.000	0.002*	-0.000**	-0.002***	0.004***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Fertility	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Employment	0.000	0.001	0.000	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Unexplained	-0.004**	0.006***	-0.005***	-0.003***	0.009***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
Field Bachelor	-0.001**	0.037	-0.001	-0.001*	0.002**
	(0.003)	(0.203)	(0.001)	(0.000)	(0.001)
High School Math	-0.001	-0.018	0.001	0.000	0.001
	(0.001)	(0.101)	(0.001)	(0.001)	(0.001)
High School Grade	-0.001	-0.209	-0.001	-0.003	0.001
	(0.002)	(1.217)	(0.002)	(0.002)	(0.006)
Mother Education	-0.000*	-0.010	0.000	0.000	0.000
	(0.000)	(0.058)	(0.000)	(0.000)	(0.000)
Father Education	0.000	0.004	0.000	0.000	0.000
	(0.000)	(0.026)	(0.000)	(0.000)	(0.000)
Mother Work	-0.001	-0.012	0.000	0.000	0.001
	(0.001)	(0.072)	(0.000)	(0.000)	(0.000)
Father Work	0.001*	0.052	0.000	0.000	0.001
	(0.001)	(0.306)	(0.000)	(0.000)	(0.000)
Motivations Culture	-0.002	-0.052	-0.001	0.000	0.001
	(0.002)	(0.319)	(0.002)	(0.003)	(0.000)
Motivations Jobs	0.001	-0.047	0.001	0.000	0.003
	(0.001)	(0.280)	(0.001)	(0.001)	(0.000)
Fertility	-0.001	-0.038	0.000	0.001	-0.001
	(0.001)	(0.229)	(0.001)	(0.000)	(0.000)
Employment	-0.001	-0.369	-0.007***	-0.004*	-0.002
	(0.002)	(2.146)	(0.003)	(0.002)	(0.000)
Intercept	0.017**	1.273	0.012	0.007	-0.010
	(0.008)	(7.391)	(0.009)	(0.012)	(0.017)

Note: Logit estimates. The dependent variables are binary variables that take value one if a student graduates in each specific field, and zero otherwise. All models include enrollment year and region of residence fixed effects. The number of observations in all models 187,682. Robust standard errors clustered at the university level in parentheses: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A13: The treatment effect of the high school reform on the treated in Economics - OLS coefficients

	(1)	(2)	(3)	(4)
	Baseline	Trend	Trend + Region	Full
Treat	-0.020***	-0.020***	-0.020***	-0.018***
	(0.004)	(0.004)	(0.003)	(0.003)
Post	0.012**	0.004	0.004	0.003
	(0.005)	(0.003)	(0.004)	(0.003)
Gender	-0.009***	-0.009***	-0.009***	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)
Treat*Post	0.010**	0.010**	0.010**	0.010**
	(0.004)	(0.004)	(0.004)	(0.004)
Treat*Female	-0.003*	-0.003*	-0.003**	-0.003**
	(0.002)	(0.004)	(0.002)	(0.002)
Post*Female	-0.006**	-0.006**	-0.006**	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
Treat*Post*Female	-0.013***	-0.013***	-0.013***	-0.014***
	(0.002)	(0.004)	(0.004)	(0.004)
Constant	0.044***	-2.748**	-2.831***	0.049***
	(0.005)	(1.150)	(1.054)	(0.014)
Time Trend		√	√	√
Region Fixed Effects			√	√
Covariates				√
Observations	1,488,972	1,488,972	1,488,972	1,235,467

Note: OLS estimates. The dependent variable is a binary that takes value one if a student graduates in Economics, and zero if a student graduates in another field. Model 1 is the DDD baseline estimator. Model 2 adds a linear enrollment year trend. Model 3 further adds region of residence fixed effects. Model 4 further adds High School Grade, Parents, Motivations, and Macro Indicators. Robust standard errors clustered at the university level in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

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