The effects of an information campaign beyond university enrolment: A large-scale field experiment on the choices of high school students[☆]

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Abstract

This paper presents a large-scale field experiment assessing the impact of an intervention providing evidence-based information about costs and returns to higher education. Treatment impacts are evaluated through university enrolment, choice of field of study, and performance either at university or in the labour market. Thanks to the large sample size, treatment effects can also be assessed for subgroups (by gender and parental education).

We find that treated females from high-educated families chose more economically rewarding fields of study, while treated males from low-educated families were more likely to enter the labour market. Although not necessarily in line with policy goals, choices induced by additional information were not detrimental to students' opportunities, as treated students displayed a similar academic performance and higher employment rates.

JEL Classifications: I21; I23; C93

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1. Introduction

The choice between entering the labour market and pursuing Higher Education (HE), and in the latter case the choice of a Field of Study (FoS), can be modelled as a classic instance of decision under uncertainty. The human capital model of school choice (Becker, 1964) is based on the subjective evaluation of the expected costs and benefits of each option, given student's ability.

Two stylized facts, however, are difficult to reconcile with optimal choices simply driven by heterogeneous individual preferences: (i) students with a higher socio-economic family background enroll more often in HE than their less advantaged counterparts with the same school performance (Boudon, 1974); (ii) females disproportionately choose less occupationally rewarding FoS (Charles and Bradley, 2009; Gabay-Egozi and Yaish, 2020; Zafar, 2013). To rationalize these patterns of choice in the human capital model it is necessary to identify behavioral traits that differ at the aggregate level. In principle, a possible candidate is risk aversion, which is a correlate of both family background and gender. However, the evidence shows that risk attitudes cannot account for the aforementioned stylized facts.[1] Alternative explanations of the observed patterns of HE decisions rely upon behavioural perspectives entailing group-level status maintenance concerns (Breen and Goldthorpe, 1997; Malloy, 2015), or identity and social belonging mechanisms (Akerlof and Kranton, 2000, 2002).[2]

Even though raising concerns from a perspective of equality of opportunity and efficiency, different educational choices merely based on heterogeneous preferences would still satisfy individual rationality. However, choices can be suboptimal when driven by an incor-

[1] Belzil and Leonardi (2013) show that risk aversion acts as a deterrent to HE investment, but in addition to family background. Experimental evidence suggests that females are more risk averse than males (Charness and Gneezy, 2012; Croson and Gneezy, 2009), but the magnitude of such differences is small (Filippin and Crosetto, 2016; Nelson, 2016).

[2] A literature inspired by Prospect Theory (Kahneman, 2011; Kahneman and Tversky, 1979) posits that educational choices are primarily shaped by the objective to avoid downward mobility relative to parents' occupation, which works as a reference point. High-status parents would then set a higher bar for their offspring. Similarly, as long as HE contributes to social belonging, intergenerational persistence can be rationalized by the fact that high-SES parents may encourage enrolment in HE to confirm the social and cultural identity of the family. Social stereotypes concerning gender identity, i.e. the existence of male- and female-typed FoS and related occupations, can help rationalizing persistent gender segregation in a similar vein (Croson and Gneezy, 2009; Morgan et al., 2013).

rect representation of the underlying prospect, i.e. when the potential outcomes and the corresponding probabilities are misperceived. This explanation may seem counter-intuitive at first sight because objective information concerning the consequences of educational choices is available. However, such information is difficult to collect and to process. We know from the behavioral economics literature that individuals tend to rely upon readily available information and fast and frugal heuristics in order to reduce the cost and the cognitive burden of decision-making processes. As a result, biases and sub-optimal choices can be observed.[3]

Importantly, a growing literature reviewed in the next section suggests that these information biases can be stratified along socio-economic and gender dimensions. High-educated parents are better equipped with the information-processing skills needed to navigate HE. Moreover, families rely upon their social networks when considering the costs and benefits of HE, but the quality of the available information correlates with socio-economic status (Erikson et al., 1996). Furthermore, gender stereotypes may also operate as cognitive shortcuts to reduce the cost of information acquisition, at the expenses of the choices' optimality (Barone et al., 2019; Favara, 2012). Information biases may therefore contribute to explain the persistence of intergenerational inequality and gender segregation. In this context, the provision of ready to use, reliable, evidence-based information on the costs, benefits and chances of success of different educational options may constitute an effective intervention towards levelling the playing field. This paper reports evidence from a randomised field experiment in which treated high school students were provided with information concerning the expected costs and benefits of HE, conditional on their possible career choices and on their chances of success across different FoS. The experiment involved a large, representative sample of students attending the last year of high school in four Italian provinces. All students were surveyed at the beginning of their senior high school year, when they had to choose about HE enrollment and FoS. Afterwards, schools were randomly assigned to the treatment or control condition. Students from treated schools were then provided with a five-hour outreach program, based on a face-to-face intervention at the classroom level, while control schools did not receive this type of information (usually not so easily accessi-

[3]See Kahneman (2011) and Sunstein and Thaler (2014). More specifically, Damgaard and Nielsen (2018) discuss the behavioral barriers that may affect the decision to invest in HE.

ble otherwise). Treated and control students were surveyed longitudinally three more times afterwards. In the last of these interviews, that took place at the start of their (possible) second year of university, we gathered information concerning their performance either at the university or in the labour market.

We compare the educational choices and performances of treated students with those of a control group in which decisions were taken in the usual information setting. If information biases are socially patterned, the information campaign should be more relevant to students from low-educated families. Moreover, this intervention should increase the salience of objective information relative to cognitive shortcuts and stereotypes that may magnify the influences of family background and gender.

As explained in more detail in Section 2, the scale of our intervention allows us to make significant contributions to the existing literature from different viewpoints. First, the treatment does not focus on enrollment decisions only but it also extends to the choice of FoS. Second, the statistical power of the experiment allows us to break down the effects simultaneously by family background, as measured by parental education, and gender.[4] Third and foremost, the analysis of the outcomes of the information campaign is not limited to the immediate impact on students' enrolment decisions, but also extends to their consequences for FoS choices, performance at university and labour market entry.

Our experiment indeed provides evidence of the causal impact of information barriers on HE decisions, although not always in line with theoretical expectations and policy goals. In fact, treated students displayed significantly lower university enrolment rates. On the other hand, they were also less likely to choose the FoS providing relatively low occupational returns. The magnitude of both effects is about 2-3 percentage points (pp). Splitting the sample into sub-groups defined by gender and parental education, we find that the former effect is concentrated among males coming from low-educated families, while the latter involves females coming from high-educated families, with a treatment effect of about 5 pp for both sub-groups.

These effects are persistent after enrolment and are not detrimental to students' oppor-

[4]The literature provides evidence of a stronger effect of parental education than parental occupation on the offspring's school career (Bukodi et al., 2018; Chevalier et al., 2013; Erola et al., 2016).

tunities. Indeed, students switching towards more rewarding FoS did not display negative effects on their academic performance as compared to control students. Moreover, the subgroup directly entering the labour market displayed instead a significantly higher probability of being employed one year after the end of high school, once compared to their counterparts in the control group. From a policy perspective, this experiment provides support to invest in cost-effective counseling interventions aimed at improving the efficiency of HE decisions, focused in particular on a better match between labour market demand and students' choices.[5]

The rest of the paper is organized as follows. In the next section we summarize the relevant literature and outline the contribution of our study. Section 3 provides information on the Italian educational system and illustrates the experimental design. Section 4 presents the results, while Section 5 draws some conclusions.

2. Literature Review

In the last years, an increasing number of studies have analysed the impact of information campaigns on HE enrolment decisions. While rather homogeneous in terms of research strategy (usually based on randomised controlled trials), this literature differs considerably in terms of both the treatments administered and of the outcomes investigated. Also the evidence reported is mixed in terms of measured effects and, typically, only refers to short-term outcomes. Focusing on interventions that provide information about HE's costs, some studies find a positive effect on enrolment, especially among low-income students (Avery, 2010; Bos et al., 2012; Castleman et al., 2017; Jensen, 2010; Loyalka et al., 2013; Peter et al., 2018), while others report small to null effects (Hastings et al., 2015; Rosinger, 2015). A recent literature review by Herbaut and Geven (2020) indicates that change in behavior typically occurs when procedural support is provided along with information. This result clearly emerges also in the study by Bettinger et al. (2012), in which personal assistance to complete the *Free Application for Federal Student Aid* form was manipulated across experimental condi-

[5]The reduction of direct costs has been often considered the key policy to enhance equal opportunities in HE. This policy is, however, very expensive and better suited to tackle another cause of suboptimal decisions, namely liquidity constraints. In addition, liquidity constraints are not a primary concern in the context of our experiment, because of the relatively low costs of HE in Italy (see Section 3.1 below).

tions. Positive effects on enrolment were observed only in the group that received personal assistance in addition to information.

The evidence of this strand of literature, however, is concentrated in countries where enrolment in HE imposes a considerable financial burden and, at the same time, financial aid measures are widespread (e.g. UK, US). Little is known about other countries where both the tuition fees and the chance of receiving financial support are lower, so that opportunity costs – rather than direct costs – take the lion's share. Our study contributes to the literature providing evidence in this respect.

Focusing on interventions that provide information on returns to HE, there is little evidence of their effectiveness. Several contributions consistently showed that information significantly increased the *intention* to enroll (e.g. Baker et al., 2018; Bleemer and Zafar, 2018; McGuigan et al., 2016; Oreopoulos and Dunn, 2013; Peter and Zambre, 2017). However, the change in student intentions did not automatically translate into actual enrolment *decisions*. Some programs effectively increased enrolment (Avitabile and De Hoyos, 2018; Peter et al., 2018), but many others proved to be ineffective regardless of whether information on costs was included or not (Bonilla et al., 2017; Pekkala Kerr et al., 2020). A possible explanation for this seeming ineffectiveness is that interventions were usually rather short, lasting from 20 minutes to one hour. In such a limited time spell, information on expected returns cannot be detailed enough to take into account individual heterogeneity and the different possible career choices.

Our experiment makes an original contribution in three respects. First, we provide evidence about the effect of an information campaign on FoS choice. While many studies investigated the effect of information campaigns on enrolment decisions, little is known about their effects on the horizontal stratification of HE. A few studies so far approached this issue: Wiswall and Zafar (2015), Baker et al. (2018), Pekkala Kerr et al. (2020) and Conlon (2021). With a slightly different design, Pistolesi (2017) looks at the impact of information provided to college applicants on their subsequent field choice. All of them found that information on FoS returns affects the probability of Major choice, but the evidence is confined to bachelor students, already enrolled in HE. To our knowledge, our study is the first to investigate the effect of informative campaigns on both the vertical and the horizontal stratification of the educational system. FoS entail different expected economic returns, and their composition is heterogeneous in terms of both gender (OECD, 2016) and family background (Kim et al., 2015; OECD, 2019b; Webber, 2014). Our design is equipped to test whether information is effective both in shaping university enrolment decisions and in reallocating students among FoS.

Second, our experiment investigates the effects of information campaigns beyond enrolment. With the exception of Hastings et al. (2015), who link survey data with administrative records for university careers, and Peter et al. (2018), who assessed treatment effects on enrolment decisions one year after the intervention, there is no evidence about the persistence of the effects of information campaigns. Assessing them beyond enrolment decisions is instead of paramount importance from an efficiency perspective. While increasing enrolments in HE and rebalancing the composition of students across FoS may constitute desirable policy goals, it is crucial to assess that these effects do not backfire in terms of students' later negative academic outcomes. Convincing students to undertake HE, or to choose a more rewarding but possibly also more difficult FoS may not be a good idea if the marginal student affected by the information campaign is doomed to fail. To fill this gap in the literature, our study investigates both academic and labour market outcomes, observing the participants almost two years after the intervention.

Third, our experiment is the first one characterized by a sufficient statistical power to investigate possibly heterogeneous effects of the information campaign among treated students. Thanks to the large sample size we can break down the sample jointly by gender and family background (as measured by parental education).

3. Intervention and experimental design

3.1. Why in Italy

The educational system in Italy is an ideal test case to assess the effectiveness of information campaigns. Before explaining why this is the case, a short description is in order (more details in Ballarino, 2015, among others). Primary and lower secondary education in Italy are comprehensive and last until the age of 14, when students must choose between three main upper secondary tracks: general, technical and vocational. All tracks take five years to complete and grant access to HE in any field, although they display a remarkably different academic orientation.

HE in Italy virtually coincides with university education. Post-secondary vocational training is marginal and highly fragmented, as it is organized and delivered by local institutions. The university system is centralized, with degree programs structured uniformly at the national level (3-year bachelor's that can be followed by 2-year master's programs). Nevertheless, universities display high levels of autonomy and they can set different selective entry examinations.[6]

The Italian education system is an ideal test case to assess the effectiveness of information campaigns for three reasons. First, the distribution of graduates among FoS is poorly aligned with labour market demands. Some fields, particularly the humanities and the social sciences, display a strong surplus of graduates and thus grant poor economic returns. The opposite occurs in other fields, notably engineering, ICT and medicine.[7]

In an international comparison, Italy ranks indeed among the rich countries with the severest skills mismatch (Montt, 2017). As a consequence, high rates of youth unemployment and overeducation paradoxically coexist with shortages in the supply of highly qualified workers (Adda et al., 2017). These mismatches entail also important consequences for gender inequalities, since women graduate less in the more rewarding fields of study (Piazzalunga, 2018).

Second, according to OECD statistics, Italy displays extremely high university dropout rates in comparison with other European countries (OECD, 2008). These two problems raise strong efficiency issues related to one of the key missions of HE, namely training skilled human capital matching labour market demands. They also imply a waste of resources for families as well as for the society as a whole, considering that Italian HE is mostly publicly funded.

Third, Italy displays large socio-economic gaps in HE choices. On average, students from lower-status families are less likely to enroll in HE, choose less rewarding FoS, and

[6] Italy does not display a well-recognised hierarchy of prestige among public universities, therefore this dimension of HE choices is not considered in this work.

[7] The shortage of medical doctors, however, is mainly due to a *numerus clausus* threshold fixed yearly by the Ministry of Education, University and Research.

are at greater risk of dropping out (Aina, 2013; Ballarino et al., 2011). Consequently, a remarkably lower graduation rate in tertiary education is observed among lower-status families (Cingano et al., 2007). While not being an Italian peculiarity, the importance of family background for HE attainment is stronger and more resilient in Italy than in other Western countries (Braga et al., 2013; Breen et al., 2009; Hertz et al., 2008).

Among the several characteristics of the Italian education system that contribute to this state of affairs, the lack of effective school and university counseling is surprisingly under-investigated. High school students receive no systematic information on university costs, waivers, and grants. When available, information on costs and returns is widespread through occasional initiatives carried out at a local level. Information provided by universities tends to over-emphasize the positive prospects and downplay the remarkable differences between FoS (Ballarino, 2015). In a similar vein, students receive no information on their dropout risks across FoS. Furthermore, the issue of early dropout, despite the high percentage of students involved, is generally ignored in counseling activities as well as by the media.

In the absence of recognized providers of information concerning HE prospects, the amount of data to collect and to tailor at the individual level is out of reach for most of the families, particularly those with low-educated parents. Such a context constitutes therefore a suitable environment to assess the importance of reducing information barriers in HE choices.

3.2. The structure of the intervention

Our intervention provided students with detailed information concerning the costs, the academic selectivity, and the occupational prospects of university programs. The information concerned universities and FoS most commonly chosen in each of the four provinces involved in the experiment. Data on costs were collected by the research team using administrative sources. Information on opportunity costs, returns to education and academic selectivity relied upon detailed and updated data from the National Statistical Office (ISTAT).[8] The information on returns to HE had been disaggregated between bachelor's and

[8]We used regression models to control for selection into different educational programs and to compute the predicted values conditional on several individual characteristics. Occupational outcomes were regressed on FoS, controlling for geographical area of the country, gender, parents' nationality, occupation and education, age

master's programs and across FoS.

We selected, trained and briefed a team of 18 senior instructors, with experience of educational activities for high school students. They met each class of senior high school students separately on three occasions in treated schools. Each meeting lasted about two hours, making the information intervention quite intense. Instructors relied upon presentations and information materials prepared by the experimenters and illustrated in a reharsal meeting in order to ensure treatment uniformity. The meetings occurred during school hours to foster student participation.[9]

In our study we categorize FoS according to a well-established pattern in the literature that is robust across outcome indicators (AlmaLaurea, 2015; Ballarino and Bratti, 2009; Reimer and Jacob, 2011). *Weak fields* are defined as those yielding relatively low returns with respect to every indicator considered, both at the undergraduate and graduate level (Humanities and Social Sciences, including Sociology, Anthropology, Psychology, Communication Studies, Criminology and Political Science). Returns to *intermediate fields* are moderate at the undergraduate level, but they are large with a master's degree (Economics, Law, Math and Natural Sciences). Finally, *strong fields* are highly rewarding even at the undergraduate level (Engineering, ICT, Medicine and other health-related fields).

During the first hour of the first meeting (October 2013) all students, including the controls, filled out a questionnaire concerning their family background and previous school career, as well as their beliefs and plans about HE.[10] Then, the intervention started only for students in treated schools. Instructors provided students with detailed information concerning costs and opportunities for financial aid, including procedures to apply for university grants. The instructors provided statistics illustrating the indirect costs (foregone earnings), and how both direct and indirect costs depend on the time to graduation. Stu-

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and age squared of the graduates, high-school track and several indicators of school performance. Predictions were computed separately for each geographical area. For each occupational indicator, results were displayed across 14 FoS.

[9]Indeed, 99.8% of students attended at least one meeting and 94.4% at least two meetings. Given that the main messages of the information campaign were reiterated at each meeting, we consider as treated all the students assigned to the treatment group.

[10]We proxy family background using parental education. Besides for reliability issues, we did not collect information on parents' income because a one-shot and possibly inaccurate measure would not be a good proxy for the parental lifetime income on which educational choices mostly depend (Cameron and Heckman, 2001).

dents were invited to examine data about costs of tertiary education regardless of their prior intention to enrol or not to university. Hence, information about costs was delivered to all treated students, underlying the most relevant factors in the economic investment in tertiary education. The general information could be adjusted to the individual situation taking into account a restricted set of parameters including family income, preferred FoS, and province of residence. Each student had the chance to estimate his/her university cost in terms of fees, transportation, meals, study materials and accommodation (when relevant).

In the second meeting (February 2014) students received information on economic returns to university degrees, compared with the prospects of high school degrees in the same track and province as theirs. Four outcomes were considered during the presentations: i) duration of first job search, ii) net monthly salary four years after graduation from high school, bachelor's and master's programs,[11] iii) risks of over-education and iv) risks of horizontal mismatch between job and degree. By means of detailed figures, the instructors showed how these returns vary across undergraduate and graduate programs and across FoS, allowing students to figure out their earning according to different university choices.

The third and final meeting (March 2014) first delivered numeric estimates of the risks of university dropout and delayed graduation. Also in this case, information was disaggregated across FoS and conditioned on four individual characteristics (gender, parental education, school track, and previous academic performance) representing the major predictors of failure in university education. Moreover, students received information concerning vocational HE and post-secondary non academic training, in terms of available study opportunities and related occupational prospects.[12] The instructors then reiterated the main messages of the previous two meetings stressing the financial accessibility of university education and the different labour market prospects across FoS. At the end of each meeting, students were

[11] Data on returns were calculated for workers with the same seniority, although not necessarily of the same age. This choice was forced by the use of ISTAT data, the only source providing both detailed information on students' proficiency and a sufficient granularity of high school track and FoS required by the treatment. This limitation, clarified to the students, is not of first order importance, since growth curves for returns to education are notoriously flat in Italy especially for high school and bachelor graduates (Barone et al., 2011).

[12] As mentioned above, the vocational sector is marginal in the Italian HE system and therefore we do not consider this outcome in this paper. The interested reader is referred to Abbiati et al. (2018), who present evidence concerning the impact of the treatment on vocational training.

invited to bring home their notes and to share them with their parents.[13]

3.3. Experimental design

The experiment entailed a multi-site clustered randomised controlled trial involving senior high school students. Schools had been sampled in four Italian provinces, located in three geographical areas (North-West: province of Milan; North-East: provinces of Vicenza and Bologna; South: province of Salerno) in order to enhance the external validity of the experiment.

3.3.1. Sample

We drew a random sample of 62 schools from the official list of schools operating in the three selected areas. The sample, representative of high school students in the selected areas, resulted in 24 valid strata defined by the three areas and the 10 high-school tracks.[14] The number of strata is 24 instead of 30 due to some tracks not being present in a given area, as well as to the need of having an even number of schools within each stratum in order to randomise the assignment to the treatment (see below). We then invited the principals of the selected schools to join in the project: 58 of them accepted, while the remaining four were replaced with schools drawn from the same stratum and not already in the sample.

3.3.2. Randomisation and equivalence

Once the final list of participating schools was defined, within each stratum we randomly assigned half of the schools to the treatment and the other half to the control group. To incentivize the participation in the experiment we relied on a delayed-treatment strategy. Schools were promised to receive the same treatment for the subsequent cohort of students in case they ended up in the control group. Hence, students of the control group contributed only the survey in the first meeting but did not receive any information treatment.

[13] The order of the topics was chosen having in mind the sequence of choices to be made by the students, i.e.: i) whether or not to enroll to university; ii) which course to choose; iii) managing to get the degree. The timing of the meetings was also thought to be compatible with some early admission tests that typically take place in late spring.

[14] The complete list of tracks reads as follows: general, humanities (comprising classical, foreign languages, social sciences and arts curricula); general, scientific; technical, business and administration; technical, industrial; vocational, business and administration; vocational, industrial; comprehensive with prevalence of technical and vocational tracks; comprehensive with prevalence of general tracks. For the sake of comparability, the schools in North East were constrained to belong to the same province (either Vicenza or Bologna) in each stratum.

Randomisation was implemented at school level in order to minimise the risks of treatment contamination. In this way, contamination could have occurred only among students from different schools and can reasonably be excluded.[15] The absence of treatment substitution have been also verified interviewing each schools' outreach cohordinator. Both treatment and control schools put in place during the treatment only standard outreach activities (i.e. meetings with former students, participation to University Open Days, etc.).

The comparison of the two treatment groups shows that the randomisation procedure was successful. Using a large number of individual predictors of university choice we could never reject the null hypothesis that the two groups come from the same population, even when considering subgroups (see Table A.6 to Table A.11 in the Appendix).[16]

3.3.3. Data collection

The treatment was nested in a longitudinal survey. The first wave of data collection (October 2013, pre-intervention) was fielded administering PAPI questionnaires in the classroom. We collected ex ante information on students' social background and school career, as well as on their beliefs and plans regarding HE. Data collection took place in 62 schools and 475 classes, involving 9.045 students. The response rate was 99% both at class and at individual level.[17]

The evolution of students' beliefs was elicited in Wave 2 (May 2014), i.e. after the completion of the treatment but before the opening of university applications. The response rate in this wave was 100% at school/class level and 82.8% at individual level, well balanced between treatment and control group.[18] Questionnaires of this wave, as well as of the following two, were administered via CATI by interviewers blind to the treatment/control status of respondents.

[15] In fact, control students were asked in wave 2 whether they heard about the intervention and only 3 percent gave a positive answer.

[16] The equivalence between the two groups was tested by regressing student characteristics on a dummy for the experimental status (treated/control). We used regressions rather than simple tests across groups because we needed to control also for the specific curriculum within school and for the geographical area.

[17] Unfortunately, the questionnaires of one treated class got lost during field operations.

[18] In this paper we do not focus on the evolution of beliefs and we refer the interested reader to Barone et al. (2017). The main results are that: i) students of both groups initially overestimated both costs and returns to university degrees; ii) significant belief updating about costs and benefits was detected only among treated students iii) the intention to enroll in weak FoS decreased in the treatment group.

The third wave (November 2014) recorded students' decisions about HE. The response rate was 100% at school/class level and 79.6% at the individual level, again balanced across experimental conditions.

The fourth and final wave was conducted one year later (November 2015) collecting information on students' outcomes: delayed enrolment, change of FoS, drop-out after the first year, academic performance for students enrolled in HE; occupational condition for those who did not enrol in HE. The response rate was 100% at the school/class level and 70.3% at the individual level, again remarkably similar between the two groups (70.5% vs 69.7%).[19]

4. Results

In this section we first present results concerning the impact of the information campaign on enrolment decision and choice of FoS. We then concentrate on the implications in terms of efficiency of effects found, analyzing the university performance for the students in HE, and the labour market outcomes for the others, almost two years after the intervention.

4.1. Impact on enrolment and FoS

Enrolment status was measured twice, at the beginning of the academic year after the diploma (Wave 3) and one year later (Wave 4). Both outcomes are considered, separately, in the following analyses.

FoS choice is jointly made with the decision to enroll. Therefore, we built a variable with four categories: (i) no university enrolment; enrolment in a (ii) "weak", (iii) "intermediate", and (iv) "strong" FoS, as described in the previous section to mirror the message conveyed to students. Treatment effects are then estimated via multinomial logistic regression models, with error terms clustered at the school level. Table 1 shows the results, presented as marginal effects.[20]

[19] The third and fourth waves did not include the negligible minority (0.3%, equally distributed between treated and controls) who did not manage to graduate from upper secondary school. We report in the Appendix (Figure A.1) a flow diagram summarizing sample sizes of treatment and control groups for all waves of data collection, in accordance with the CONSORT guidelines (see http://www.consort-statement.org/, ac-

Table 1: Treatment effect on college choice (frequencies)

2014	M1	M2	M3	2015	M1	M2	M3
Not enrolled to college				**Not enrolled to college**			
Controls	*0,372*			Controls	*0,344*		
Treated	0,028	0,020	0,019	Treated	0,029*	0,020*	0,021*
SE	0,018	0,013	0,012	SE	0,016	0,012	0,011
P-val	0,117	0,137	0,111	P-val	0,064	0,080	0,062
Enrolled, weak fields				**Enrolled, weak fields**			
Controls	*0,167*			Controls	*0,174*		
Treated	-0,022	-0,018**	-0,017*	Treated	-0,018	-0,018**	-0,019**
SE	0,014	0,009	0,009	SE	0,012	0,009	0,009
P-val	0,116	0,048	0,051	P-val	0,137	0,042	0,038
Enrolled, intermediate fields				**Enrolled, intermediate fields**			
Controls	*0,317*			Controls	*0,325*		
Treated	-0,011	-0,004	-0,004	Treated	-0,007	0,003	0,002
SE	0,017	0,014	0,013	SE	0,017	0,013	0,012
P-val	0,547	0,778	0,766	P-val	0,689	0,827	0,857
Enrolled, strong fields				**Enrolled, strong fields**			
Controls	*0,144*			Controls	*0,156*		
Treated	0,004	0,002	0,003	Treated	-0,005	-0,006	-0,004
SE	0,012	0,010	0,010	SE	0,012	0,009	0,009
P-val	0,733	0,823	0,796	P-val	0,664	0,504	0,511
N	*7277*	*7277*	*7277*	*N*	*6338*	*6338*	*6338*

Notes: *: p<.10; **: p<.05; ***: p<.01. Coefficients represent marginal effects from multinomial logit models. Standard errors clustered at the school level.
M1 controls: stratification vars.; M2: M1 + pre-treatment intentions; M3: M2 + final upper secondary mark.

Models 1 (M1) estimates treatment effects controlling only for the two stratification variables (school track and area). Models 2 (M2) also controls for the ex-ante intention to enroll and Model 3 (M3) adds the final mark at high school as an additional predictor. The additional explanatory variables in M2 and M3 are orthogonal to the treatment status and help only to control for individual heterogeneity, gaining statistical power.[21]

Table 1 shows a decrease of enrolment in weak FoS of about 2pp, consistent across spec-

cessed 12/15/2020).

[20] The left panel refers to Wave 3, the right panel to Wave 4. The fact that attrition increased from 20.4% in wave 3 to 29.7% in wave 4 imposes some caution when comparing the treatment effect across waves. However, results are robust to restricting the models for Wave 3 to Wave 4 respondents.

[21] In principle, the final upper secondary mark may raise some endogeneity issues. This variable, however, is balanced across experimental conditions. In what follows, estimates from models without this control variable hold essentially unchanged (results available upon request).

ifications. The point estimates are stable, reaching conventional levels of statistical significance in M2 and M3, where the estimator is more precise, thanks to the inclusion of pre-treatment predictors. Considering that 16.7% of control students selected a weak FoS, a magnitude of the treatment effect of about 2pp is remarkable. Importantly, the effects for initial enrolment (left panel) and after one year (right panel) are of similar magnitude and, if anything, they are generally stronger for the final wave, thus pointing to the stability of the treatment impact.

The coefficient of the treatment dummy is very close to zero for intermediate and strong FoS, purportedly suggesting that treated students who avoided weak FoS mainly chose not to enroll. However, this result may hide a more complex pattern that we further investigate breaking down the sample across gender and family background. We assign to 'high-status' (HS) families the students with both parents holding at least a high school degree, and to 'low-status' (LS) families those with at least one parent without a high school degree.[22]

Table 2 replicates M3 with the disaggregated sample. Results show that what displayed in Table 1 is a composition of different treatment effects that mainly characterize two subgroups, namely low-status males (LSM) and high-status females (HSF). The negative impact on university enrolment is concentrated among treated LSM, whose probability not to enroll in university was about 5 pp higher than their counterparts in the control group. Conversely, the lower propensity to enroll in weak FoS was concentrated among HSF: treated students in this subgroup display a shift towards intermediate FoS of about 5-6 pp as compared to their counterparts in the control group.

Splitting the sample clarifies how intermediate FoS are indeed those mostly affected by the information campaign. The null coefficient in Table 1 results from a combination of i) a significant decrease (of about 4 pp) of LSM students, who in the end display a net outflow from HE; ii) a significant increase of treated HSF, who show an aggregate shift upwards in the choice of FoS. These two effects are stable over time, as confirmed by the estimates using Wave 4. A further impact emerges only in Wave 3, in which LSF also experience an upward

[22]We use high school as a threshold because the percentage of tertiary educated Italians for older cohorts is low (OECD 2020). Moreover, we prefer parental education to parental occupation as a proxy of family background for two reasons. First, our analysis focuses on educational choices. Second, liquidity constraints are not a key issue because of the low tuition fees in Italy. Results (available upon request) are qualitatively similar but slightly weaker when using parental occupation.

Table 2: Treatment effect on college choice, by sub-group (frequencies)

	2014				2015			
	LSM	**LSF**	**HSM**	**HSF**	**LSM**	**LSF**	**HSM**	**HSF**
Not enrolled to college					**Not enrolled to college**			
Controls	*0,563*	*0,429*	*0,283*	*0,166*	*0,551*	*0,391*	*0,252*	*0,140*
Treated	0,053***	0,021	-0,017	0,008	0,055***	0,014	0,020	-0,007
SE	0,019	0,023	0,021	0,015	0,021	0,021	0,020	0,013
P-val	0,005	0,368	0,413	0,604	0,008	0,517	0,319	0,588
Enrolled, weak fields					**Enrolled, weak fields**			
Controls	*0,076*	*0,19*	*0,095*	*0,292*	*0,089*	*0,193*	*0,122*	*0,287*
Treated	-0,007	0,001	0,014	-0,063***	-0,016	-0,012	-0,008	-0,046**
SE	0,011	0,015	0,013	0,020	0,117	0,016	0,017	0,023
P-val	0,549	0,959	0,278	0,002	0,159	0,478	0,650	0,049
Enrolled, intermediate fields					**Enrolled, intermediate fields**			
Controls	*0,201*	*0,312*	*0,358*	*0,412*	*0,222*	*0,327*	*0,354*	*0,409*
Treated	-0,038**	-0,038*	0,010	0,053***	-0,0484**	-0,002	-0,002	0,071***
SE	0,019	0,021	0,026	0,020	0,021	0,017	0,023	0,026
P-val	0,040	0,064	0,711	0,008	0,020	0,904	0,917	0,007
Enrolled, strong fields					**Enrolled, strong fields**			
Controls	*0,160*	*0,069*	*0,265*	*0,130*	*0,137*	*0,089*	*0,272*	*0,165*
Treated	-0,009	0,017*	-0,007	0,003	0,010	0,000	-0,015	-0,018
SE	0,017	0,009	0,021	0,016	0,016	0,008	0,018	0,020
P-val	0,618	0,053	0,752	0,847	0,538	0,974	0,412	0,362
	1783	*2067*	*1542*	*1693*	*1596*	*1735*	*1388*	*1468*

Notes: *: p<.10; **: p<.05; ***: p<.01. Coefficients represent marginal effects from multinomial logit models.
Standard errors clustered at the school level.
All models control for stratification variables, pre-treatment intentions and final upper secondary mark.
LSM: low status males; LSF: low status females; HSM: high status males; HSF: high status females.

shift in the choice of FoS. This effect, however, is less significant and not stable over time.[23] The treatment instead appears to have hardly affected the aggregate choices of high-status male students.

The estimates in Table 2 are informative of the difference between treated and control individuals within each subgroup, but not of whether the impact is different across subgroups. We formally test that this is also the case by means of a battery of Chow tests, contrasting every significant parameter with those of the other three subgroups taken separately. Table

[23] We can exclude that this result is driven by selection issues (see Table A.11 in Appendix). The instability of this treatment effect can be rationalized observing that LSF controls are more likely to change course (see Table A.12 in Appendix).

A.13 in the Appendix shows the p-values associated to each test. The null hypothesis (no difference) is always rejected concerning the shift of LSF towards intermediate FoS. The effect on LSM not enrolling is significant when compared to high status students, while more caution is needed when comparing them with LSF students. The Chow tests confirm that the shift of LSF toward strong FoS detected in Wave 3 is not robust. One could then wonder about the mechanisms underlying the treatment effect found. A natural candidate is the change in beliefs concerning costs and returns of college choice, and the probability to get the degree. While beliefs did indeed react to the treatment to some extent (Barone et al., 2017), we did not find any evidence of an impact of belief updating on the actual choices (see Table A.16 in Appendix) in line with Conlon (2021).

In the next two sub-sections we investigate whether the effect of the information campaign were detrimental to students' outcomes, finding that this is not the case. In particular, the choice of more selective and more rewarding FoS occurred without any academic displacement of treated HSF. The net outflow of LSM from HE, although not aligned with the policy goal of increasing enrollments in HE, is mirrored by a significantly better performance in the labour market.

4.2. Impact on university performance

Our data allows us to assess the impact of the treatment on university performance during the freshman year. Students' performance was measured using four outcomes, namely: (i) the total number of university credits; (ii) having obtained at least one credit, meaning that at least one exam was passed; (iii) having obtained at least forty credits, i.e. 2/3 of what is expected in a regular academic year; (iv) regular class attendance. We do not use data on drop-out directly collected by our survey because actual drop-outs in Italy cannot be reliably assessed in the first year.[24] The number of university credits attained in the first year is instead the most reliable predictor of drop-outs (ANVUR, 2018).

In order to estimate the effect of information on academic performance, it is necessary to take into account that the treatment also affected the enrolment decision. To avoid this

[24] We only observe 3% of drop-outs in Wave 4, but this figure likely underestimates the actual number. Tuition fees are relatively low and students do not have to fulfil any requirement to enroll to the second year. Hence, students tend to delay their formal drop-out even when already pursuing other activities (e.g. a full-time job).

selection bias, we estimate unconditional models on the whole sample assigning values of the outcome variables also to students who did not enroll in HE. For instance, when using university credits attained as a dependent variable, we input them zero credits.

We estimate OLS regression models for the total number of credits, and logit models for the other three outcomes, with error terms clustered at the school level. The model specification is as follows: M1 controls only for treatment status and the two stratification variables (school track and area); M2 adds the upper-secondary school final mark; M3 also controls for the FoS chosen in 2014. M3 is our preferred specification because it also controls for differences in academic performance driven by shifts across FoS characterized by different selectivity, possibly induced by the treatment.

Table 3 reports the (marginal) effects of the treatment on the four outcome variables described above. No effect is apparent for any outcome, with point estimates of the treatment coefficients fairly close to zero across all specifications.

To check whether a null average effect conceals again significant heterogeneity across sub-groups, we estimate M3 breaking down our sample along gender and family background. Table 4 shows also in this case no evidence of a different impact. It is worth stressing that this null result constitutes an encouraging message: the shift towards more rewarding FoS detected for HSF did not backfire them in terms of academic proficiency.[25] Hence, the treatment induced a net gain in terms of efficiency through the choice of more selective (and rewarding) FoS by HSF, reducing gender inequalities without enhancing the risks of academic failure.

4.3. Impact on labour market outcomes

In this section we analyse the impact of the intervention on the employment condition of the students who did not enroll at university.[26] Labour market outcomes are particularly interesting because the treatment induced a net outflow from HE. It is therefore important to assess whether more informed choices simply contradict the policy goal of increasing university enrollment, or whether they ended up in better returns in the labour market.

[25] As regards LSF we can observe a positive (though admittedly weak) impact consistent with the instability of the treatment effect displayed in Table 2 (see Appendix, Table A.12 and Footnote 23 above).

[26] As in the analysis of university performance, models were estimated on the whole sample to avoid selection bias.

Table 3: Treatment effect on college proficiency

	M1	M2	M3
Number of credits			
Controls	*21,3*		
Treated	-0,09	-0,11	-0,03
SE	0,08	0,09	0,09
P-val	0,30	0,19	0,74
At least one credit (frequency)			
Controls	*0,472*		
Treated	-0,017	-0,020	-0,003
SE	0,017	0,011	0,011
P-val	0,302	0,215	0,800
At least two thirds of credits (frequency)			
Controls	*0,324*		
Treated	-0,001	-0,004	0,006
SE	0,018	0,016	0,011
P-val	0,972	0,787	0,600
N	*6414*	*6352*	*6352*
Lecture attendance (frequency)			
Controls	*0,424*		
Treated	0,002	0,000	0,015
SE	0,013	0,012	0,011
P-val	0,900	0,995	0,178
N	*7325*	*7325*	*7325*

Notes: Coefficients represent marginal effects from logit models, except the first row (N. of Credits).
Standard errors clustered at the school level.
M1 controls: stratification vars.; M2: M1 + final upper secondary school mark; M3: M2 + FoS chosen in 2014.

Table 5 shows that this is indeed the case. In 2015, i.e. when enrolled students entered their university sophomore year, treated students had a probability to be employed about 3.6 pp higher than the controls, and significantly so. The effect is even stronger when focusing on full-time jobs. Interestingly, the difference is concentrated on students coming from a low-educated family background, and on males in particular.

This finding indicates that the choice of not going to university, induced by the treatment, yielded positive returns in the labour market, at least in the short term. Additional evidence corroborates this interpretation. By including an interaction term of the treatment with geographical area, we see that both the negative effect on enrollment and the positive effect on employment are concentrated in the Northern provinces (Milan, Bologna and Vi-

Table 4: Treatment effect on college proficiency, by sub-group

	LSM	LSF	HSM	HSF
Number of credits				
Controls	*14,9*	*18,4*	*23,9*	*29,7*
Coeff	-0,849	0,854	0,871	-1,330
SE	0,839	0,844	1,120	1,240
P-val	0,316	0,316	0,441	0,285
At least one credit (frequency)				
Controls	*0,34*	*0,41*	*0,53*	*0,64*
Coeff	-0,016	0,019	0,020	-0,033
SE	0,017	0,017	0,019	0,024
P-val	0,361	0,256	0,292	0,167
At least two thirds of credits (frequency)				
Controls	*0,22*	*0,27*	*0,36*	*0,46*
Coeff	-0,009	0,031*	0,010	-0,012
SE	0,016	0,018	0,025	0,023
P-val	0,563	0,079	0,696	0,602
N	*1602*	*1738*	*1391*	*1470*
Lecture attendance (frequency)				
Controls	*0,3*	*0,38*	*0,48*	*0,57*
Coeff	0,002	0,025	0,015	0,030
SE	0,018	0,018	0,018	0,020
P-val	0,903	0,162	0,402	0,137
N	*1796*	*2079*	*1554*	*1703*

Notes: *: p<.10.
Coefficients represent marginal effects from logit models, except the first row (Number of Credits).
Standard errors clustered at the school level.
All models control for stratification variables, final upper secondary mark and FoS chosen in 2014.
LSM: low status males; LSF: low status females; HSM: high status males; HSF: high status females.

cenza), where the labour market offers better opportunities to high school graduates (see Table A.14 and A.15 in Appendix).

5. Conclusion

The information campaign delivered in our field experiment produced two effects. The first is a decrease in university enrolment that mainly concerns male students coming from relatively low family background. This effect can be considered an unexpected result at first glance, at least against the background of positive or null effects reported in the literature. Our interpretation has to do with the different structure of the Italian labour market as

Table 5: Treatment effect on employment (frequencies)

	Whole sample	**LSM**	**LSF**	**HSM**	**HSF**
Works in 2014					
Controls	*0,184*	*0,299*	*0,204*	*0,144*	*0,065*
Coeff	0,001	0,033*	-0,003	-0,049**	0,013
SE	0,009	0,019	0,020	0,019	0,012
P-val	0,911	0,075	0,870	0,010	0,288
N	*7300*	*1787*	*2073*	*1315*	*1688*
Works in 2015					
Controls	*0,217*	*0,383*	*0,239*	*0,152*	*0,069*
Coeff	0,027**	0,044	0,042**	0,01	0,004
SE	0,012	0,027	0,02	0,017	0,009
P-val	0,024	0,103	0,031	0,554	0,658
N	*6352*	*1575*	*1738*	*1391*	*1460*
Works in 2015 $>$20 weekly hours					
Controls	*0,184*	*0,339*	*0,191*	*0,130*	*0,056*
Coeff	0,028**	0,053**	0,039**	0,014	0,007
SE	0,012	0,027	0,018	0,016	0,01
P-val	0,014	0,05	0,032	0,379	0,512
N	*6291*	*1575*	*1719*	*1385*	*1454*

Notes: **: p<.5; *: p<.10. Coefficients represent marginal effects from logit models.
Standard errors clustered at the school level.
All models control for stratification variables, final upper secondary mark and pre-treatment intentions to enroll.
LSM: low status males; LSF: low status females; HSM: high status males; HSF: high status females.

compared to that of Anglo-Saxon countries, where most of the previous studies have been conducted. The labour market in Italy is characterized by small firms in the manufacturing and other low value-added sectors (OECD, 2019a), granting comparatively low returns to HE. Data from the first wave of our study indicate that, differently from previous research, students overestimated the monetary returns to HE before the intervention (Abbiati and Barone, 2017). Costs were also overestimated, in this case in line with the literature. In terms of lifetime earnings returns have a much larger impact than costs. Hence, in contexts where the investment in HE is poorly rewarding, information campaigns providing transparent information on these low returns can determine a negative impact on enrolment. Interestingly, the bulk of the decrease of the enrolment rate is observed in the provinces where the opportunity cost of HE is higher. In light of these considerations, the behavior of a student not enrolling in HE after having received this information could be regarded as rational, particularly for agents with a relatively high discount rate. Indeed, we also find that the counterpart of a lower enrollment rate among treated students is a significantly higher probability of employment one year after high school.

The second effect of the information campaign is a shift towards fields of study that are occupationally more rewarding, in line with previous studies that take this dimension into consideration (Hastings et al., 2015; Pekkala Kerr et al., 2020; Pistolesi, 2017). The effect in this case is observed mainly among females coming from a family with more educated parents. When provided with detailed and reliable information on labour market returns to university degrees, these students moved out from the humanities and social sciences, opting instead for fields providing better occupational opportunities (such as Economics or Law). This effect does not extend with the same strength to occupationally stronger fields (Medicine and other health fields, Engineering and ICT), possibly due to higher selectivity and, in case of Medicine, also to *numerus clausus* rule and longer duration.

It is worth repeating that these results concern decisions rather than intentions and that our study looks at persistence in university education, while most of the previous studies focus on enrolment choices only. This is an important contribution because short-term treatment effects on enrolment may fade out or cause later unintended consequences in terms of poor academic performance, increased drop-out rates or delay at graduation. We considered multiple indicators of academic proficiency at the beginning of sophomore year, all pointing to similar academic performance of treated and control peers. Pursuing more rewarding careers occurred without negative consequences, on average. Overall, the treatment had an efficiency-enhancing impact by reducing the overcrowding of weak FoS. To the best of our knowledge, this is the first large scale information experiment documenting significant treatment impacts on reducing enrolments in less rewarding FoS.

Another distinguishing feature of our study is that, thanks to the high statistical power, we could analyse the interplay between family background and gender as mediators of treatment effects. In order to interpret the diverging impacts emerged, it is useful to remind that treated students learnt that intermediate FoS are more rewarding than weak FoS only with a master degree. A master degree requires a longer investment than a bachelor's, entailing significantly higher direct and indirect costs. Females from high-educated families, who are more likely to be able to afford this higher investment, reacted by switching on average from weak to intermediate fields, but this was not the case for their counterparts from low-educated family background. Conversely, male students from low-educated families opted out of higher education more often.

It should be noted that the initial information biases concerning the costs and benefits of university investments did not differ by gender nor by family background, and that these two characteristics did not affect information updating during the last year of high school (Barone et al., 2017). The information conveyed to the students likely interacted with (gender- and status-specific) preferences, related for instance to identity (Akerlof and Kranton, 2002) or to avoidance of status demotion (Breen and Goldthorpe, 1997).

Overall, our field experiment shows that the provision of evidence-based information may have persistent effects on the choices of a significant subset of high school students. These effects are of moderate magnitude once the heterogeneity for different sub-groups is taken into account. However, the potential to reduce social inequalities in HE participation appears limited to the choice of FoS by gender, while it does not extend to family background and enrolment decisions.

A general comment is in order concerning the policy issues to which this work relates. Expanding college participation has evident and positive effects from a social point of view. However, projecting general policy implications onto optimal choices at the individual level may backfire. Enrolling to college should not be seen as the best choice for each and every individual. Our study shows that individuals reacted to the information provided based on idiosyncratic characteristics that are ex ante unknown to the researchers or to the policy makers. We also find that these impacts are not detrimental to their opportunities, although not necessarily in line with the policy goal of expanding college participation. Consistently with previous evidence (see for instance Pekkala Kerr et al., 2020), we argue that these choices are to a good extent rational.

It is also worth noting that the recent Italian National Recovery and Resilience plan acknowledges the low rate of tertiary education, but attributes its persistence to the scarcity of post-secondary vocational programs and to the lack of adequate counseling in the transition from school to university. The plan allocates substantial investments for outreach activities.

Moreover, it pursue the goal of enhancing tertiary *professional* education system.[27] The goal is no longer expanding tertiary education in general, but rather to reduce the mismatch between demand and supply of technical skills in the labor market. Both the narrower target and the outreach activities go in the direction of a fine tuning of the policy to individual characteristics and are therefore in line with our results.

[27] See https://italiadomani.gov.it/en/Interventi/investimenti/Sviluppo-del-sistema-di-formazione-professionale-terziaria.html, accessed on July 15, 2022.

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Appendix A.

Table A.6: Equivalence, whole sample (frequencies, when not specified differently)

Stratification variables	**Controls**	**Treated**	**P-val**
School track			
General, classical humanistic	0.08	0.14	0.413
General, other humanistic	0.18	0.07	0.129
General, scientific	0.26	0.28	0.889
Technical, business	0.21	0.20	0.936
Technical, industrial	0.09	0.13	0.523
Vocational, business	0.09	0.10	0.920
Vocational, industrial	0.08	0.09	0.898
Area			
North-West	0.30	0.31	0.965
North-East	0.45	0.42	0.789
South	0.25	0.28	0.791
School characteristics			
Number of students enrolled in 4th grade	196.5	179.1	0.141
Number of buildings	1.57	1.49	0.693
School location			
Province capital, city centre	0.19	0.18	0.902
Province capital, outskirts	0.18	0.27	0.456
Other towns	0.63	0.55	0.570
Individual characteristics			
Female	0.43	0.46	0.542
Both parents with a diploma	0.56	0.48	0.267
Low Sstatus Males	0.24	0.28	0.733
High Status Males	0.20	0.24	0.305
Low Status Females	0.32	0.26	0.294
High Status Females	0.24	0.22	0.913
Final mark : Language ($mean \in [0, 10]$)	6.68	6.67	0.749
Final mark : Maths ($mean \in [0, 10]$)	6.93	6.87	0.308
Plans - Intention to enroll to university			
Probably or surely yes	0.69	0.65	0.128
Does not know	0.09	0.09	0.627
Probably or surely no	0.22	0.24	0.275
Plans - Preferred field of study			
Weak FoS	0.30	0.33	0.546
Intermediate FoS	0.46	0.44	0.241
Strong FoS	0.19	0.18	0.305
Does not know	0.05	0.05	0.562
N	*4768*	*4277*	

Notes: P-values refer to the treatment coefficient retrieved from logit models variable by variable.
Models on individual and school characteristics control for stratification variables.
Standard errors clustered at the school level.

Table A.7: Equivalence, Low Status Males (frequencies, when not specified differently)

Stratification variables	**Controls**	**Treated**	**P-val**
School track			
General, classical humanistic	0.03	0.02	0.742
General, other humanistic	0.05	0.02	0.313
General, scientific	0.18	0.17	0.889
Technical, business	0.25	0.22	0.770
Technical, industrial	0.23	0.30	0.610
Vocational, business	0.10	0.13	0.716
Vocational, industrial	0.16	0.13	0.788
Area			
North-West	0.36	0.32	0.803
North-East	0.37	0.45	0.553
South	0.27	0.22	0.693
School characteristics			
Number of students enrolled in 4th grade	179.3	168.03	0.489
Number of buildings	1.59	1.60	0.964
School location			
Province capital, city centre	0.13	0.04	0.177
Province capital, outskirts	0.11	0.30	0.113
Other towns	0.76	0.65	0.426
Individual characteristics			
Final mark : Language ($mean \in [0,10]$)	6.68	6.67	0.749
Final mark : Maths ($mean \in [0,10]$)	6.93	6.87	0.308
Plans - Intention to enroll to university			
Probably or surely yes	0.48	0.43	0.357
Does not know	0.12	0.12	0.678
Probably or surely no	0.40	0.43	0.422
Plans - Preferred field of study			
Weak FoS	0.34	0.43	0.025
Intermediate FoS	0.47	0.39	0.053
Strong FoS	0.11	0.12	0.267
Does not know	0.08	0.07	0.648
N	*1131*	*1158*	

Notes: P-values refer to the treatment coefficient retrieved from logit models variable by variable.
Models on individual and school characteristics control for stratification variables.
Standard errors clustered at the school level.

Table A.8: Equivalence, Low Status Females (frequencies, when not specified differently)

Stratification variables	**Controls**	**Treated**	**P-val**
School track			
General, classical humanistic	0.06	0.06	0.945
General, other humanistic	0.27	0.13	0.233
General, scientific	0.17	0.18	0.944
Technical, business	0.26	0.35	0.483
Technical, industrial	0.04	0.03	0.725
Vocational, business	0.14	0.14	0.976
Vocational, industrial	0.07	0.11	0.558
Area			
North-West	0.31	0.33	0.855
North-East	0.43	0.40	0.802
South	0.26	0.27	0.939
School characteristics			
Number of students enrolled in 4th grade	200.0	172.50	0.069
Number of buildings	1.53	1.68	0.446
School location			
Province capital, city centre	0,19	0,11	0.455
Province capital, outskirts	0,13	0,31	0.132
Other towns	0,68	0,58	0.473
Individual characteristics			
Final mark : Language (*mean* $\in [0,10]$)	6.68	6.67	0.749
Final mark : Maths (*mean* $\in [0,10]$)	6.93	6.87	0.308
Plans - Intention to enroll to university			
Probably or surely yes	0.69	0.62	0.240
Does not know	0.10	0.12	0.750
Probably or surely no	0.20	0.26	0.370
Plans - Preferred field of study			
Weak FoS	0.21	0.19	0.278
Intermediate FoS	0.50	0.49	0.532
Strong FoS	0.26	0.27	0.304
Does not know	0.04	0.05	0.324
N	*1492*	*1099*	

Notes: P-values refer to the treatment coefficient retrieved from logit models variable by variable.
Models on individual and school characteristics control for stratification variables.
Standard errors clustered at the school level.

Table A.9: Equivalence, High Status Males (frequencies, when not specified differently)

Stratification variables	**Controls**	**Treated**	**P-val**
School track			
General, classical humanistic	0.10	0.18	0.348
General, other humanistic	0.07	0.03	0.255
General, scientific	0.47	0.45	0.890
Technical, business	0.17	0.09	0.198
Technical, industrial	0.10	0.17	0.385
Vocational, business	0.05	0.05	0.960
Vocational, industrial	0.06	0.04	0.646
Area			
North-West	0.27	0.28	0.971
North-East	0.52	0.44	0.622
South	0.21	0.28	0.588
School characteristics			
Number of students enrolled in 4th grade	194.5	177.3	0.298
Number of buildings	1.64	1.33	0.090
School location			
Province capital, city centre	0.19	0.22	0.840
Province capital, outskirts	0.25	0.26	0.930
Other towns	0.56	0.52	0.804
Individual characteristics			
Final mark : Language (*mean* $\in [0, 10]$)	6.68	6.67	0.749
Final mark : Maths (*mean* $\in [0, 10]$)	6.93	6.87	0.308
Plans - Intention to enroll to university			
Probably or surely yes	0.76	0.75	0.243
Does not know	0.07	0.07	0.352
Probably or surely no	0.17	0.17	0.862
Plans - Preferred field of study			
Weak FoS	0.39	0.40	0.639
Intermediate FoS	0.44	0.43	0.656
Strong FoS	0.12	0.12	0.372
Does not know	0.05	0.04	0.296
N	*909*	*980*	

Notes: P-values refer to the treatment coefficient retrieved from logit models variable by variable.
Models on individual and school characteristics control for stratification variables.
Standard errors clustered at the school level.

Table A.10: Equivalence, High Status Females (frequencies, when not specified differently)

Stratification variables	**Controls**	**Treated**	**P-val**
School track			
General, classical humanistic	0.17	0.34	0.144
General, other humanistic	0.31	0.10	0.034
General, scientific	0.30	0.35	0.658
Technical, business	0.13	0.11	0.806
Technical, industrial	0.02	0.01	0.347
Vocational, business	0.04	0.05	0.904
Vocational, industrial	0.03	0.05	0.602
Area			
North-West	0.27	0.29	0.915
North-East	0.51	0.37	0.404
South	0.22	0.34	0.417
School characteristics			
Number of students enrolled in 4th grade	214.1	179.8	0.114
Number of buildings	1.53	1.30	0.175
School location			
Province capital, city centre	0.24	0.39	0.337
Province capital, outskirts	0.26	0.19	0.658
Other towns	0.50	0.41	0.606
Individual characteristics			
Final mark : Language (*mean* $\in [0,10]$)	6.68	6.67	0.749
Final mark : Maths (*mean* $\in [0,10]$)	6.93	6.87	0.308
Plans - Intention to enroll to university			
Probably or surely yes	0.88	0.88	0.552
Does not know	0.05	0.04	0.556
Probably or surely no	0.07	0.06	0.783
Plans - Preferred field of study			
Weak FoS	0.29	0.32	0.509
Intermediate FoS	0.44	0.45	0.914
Strong FoS	0.25	0.21	0.713
Does not know	0.02	0.02	0.801
N	*1086*	*922*	

Notes: P-values refer to the treatment coefficient retrieved from logit models variable by variable.
Models on individual and school characteristics control for stratification variables.
Standard errors clustered at the school level.

Table A.11: Variable distribution by treatment status and wave (frequencies, when not specified differently)

	Wave 1		**Wave 3**		**Wave 4**	
	C	T	C	T	C	T
Stratification variables						
School track						
General, classical humanistic	0.18	0.07	0.18	0.07	0.18	0.07
General, other humanistic	0.08	0.14	0.09	0.14	0.09	0.14
General, scientific	0.26	0.28	0.27	0.28	0.28	0.29
Technical, business	0.21	0.20	0.21	0.20	0.21	0.20
Technical, industrial	0.09	0.13	0.10	0.14	0.10	0.14
Vocational, business	0.09	0.10	0.08	0.09	0.07	0.09
Vocational, industrial	0.08	0.09	0.07	0.08	0.07	0.07
Area						
North-West	0.30	0.31	0.31	0.31	0.30	0.31
North-East	0.45	0.42	0.46	0.43	0.47	0.44
South	0.25	0.28	0.24	0.26	0.23	0.25
School variables						
Number of buildings	196.5	179.1	198.2	174.3	197.9	174.6
Number of students enrolled in 4th grade	1.57	1.49	1.55	1.48	1.55	1.46
School location						
Province capital, city centre	0.19	0.18	0.18	0.17	0.17	0.17
Province capital, outskirts	0.18	0.27	0.19	0.28	0.19	0.27
Other towns	0.63	0.55	0.64	0.55	0.63	0.55
Background						
Female	0.43	0.46	0.44	0.47	0.44	0.48
Both parents with a diploma	0.56	0.48	0.56	0.48	0.55	0.47
Low Status Males	0.24	0.28	0.24	0.27	0.25	0.27
High Status Males	0.20	0.24	0.20	0.24	0.20	0.25
Low Status Females	0.32	0.26	0.32	0.26	0.31	0.25
High Status Females	0.24	0.22	0.24	0.23	0.24	0.23
Mark at the end of 11th grade						
Language (*mean* $\in [0, 10]$)	6.68	6.66	6.73	6.70	6.74	6.73
Maths (*mean* $\in [0, 10]$)	6.94	6.87	6.97	6.88	6.98	6.90
Intention to enroll to university						
Probably or surely yes	0.69	0.65	0.72	0.67	0.73	0.68
Does not know	0.09	0.09	0.08	0.08	0.08	0.08
Probably or surely no	0.22	0.24	0.20	0.23	0.19	0.22
Plans - Preferred field of study						
Weak FoS	0.30	0.33	0.31	0.35	0.31	0.35
Intermediate FoS	0.46	0.44	0.47	0.43	0.47	0.44
Strong FoS	0.19	0.18	0.19	0.18	0.18	0.18
Does not know	0.05	0.05	0.04	0.04	0.03	0.04

Notes: C: Controls; T: Treated.

Table A.12: Probability of changing field from the freshman to the sophomore year

	Whole sample			**Heterogeneity**			
	M0	**M1**	**M2**	**LSM**	**LSF**	**HSM**	**HSF**
Treated	-0,01*	-0,01*	-0,01*	0,01	-0,03***	-0,02	0,00
SE	0,01	0,01	0,01	0,01	0,01	0,01	0,02
P-val	0,088	0,085	0,087	0,536	0,009	0,291	0,907
N	*6352*	*6352*	*6352*	*1429*	*1728*	*1330*	*1451*

*: p<.10; **: p<.05; ***: p<.01.
Coefficients represent marginal effects from logit models.
Standard errors clustered at the school level.
M1 controls: stratification vars.; M2: M1 + pre-treatment intentions; M3: M2 + final upper secondary mark.
M2 model used to estimate the effects in the analysis by sub-group.
LSM: low status males; LSF: low status females; HSM: high status males; HSF: high status females.

Table A.13: Chow tests on effects on enrollment status by sub-group - Only effects pval: <.10

	Effect calculated in wave 3			
	vs LSM	**vs LSF**	**vs HSM**	**vs HSF**
LSM not enrolling	/	0,303	*0,005*	*0,037*
HSF exiting weak FoS	*0,026*	*0,004*	*0,000*	/
HSF entering intermediate FoS	*0,000*	*0,000*	*0,089*	/
LSM exiting intermediate FoS	/	0,998	0,13	*0,000*
LSF exiting intermediate FoS	0,998	/	0,13	*0,000*
LSF entering strong FoS	0,352	/	0,433	0,46
	Effect calculated in wave 4			
LSM not enrolling	/	0,234	*0,099*	*0,031*
HSF exiting weak FoS	0,313	0,161	0,139	/
HSF entering intermediate FoS	*0,000*	*0,022*	*0,044*	/
LSM exiting intermediate FoS	/	*0,066*	*0,064*	*0,000*

P-values lower than 0.10 in italics.
Chow tests calculated from model coefficients reported in Table 2.
Standard errors clustered at the school level.
LSM: low status males; LSF: low status females; HSM: high status males; HSF: high status females.

Table A.14: Treatment effect on enrollment, by geographical area

	Whole sample	**LSM**	**LSF**	**HSM**	**HSF**
Treated	-0,025*	-0,055**	-0,029	0,001	-0,009
SE	0,014	0,023	0,028	0,021	0,017
P-val	0,070	0,016	0,296	0,969	0,619
South	-0,084***	-0,078***	-0,099***	-0,094***	-0,013
SE	0,012	0,026	0,022	0,024	0,026
P-val	0,000	0,003	0,000	0,000	0,612
Treated*South	0,031*	0,027	0,019	0,088**	-0,007
SE	0,017	0,037	0,035	0,042	0,030
P-val	0,064	0,467	0,581	0,034	0,815
N	7300	1787	1546	2073	1702

Notes: *: p<.10; **: p<.05; ***: p<.01.
Coefficients represent marginal effects from logit models.
Standard errors clustered at the school level.
All models control for stratification variables, final upper secondary mark and pre-treatment intentions to enroll.
LSM: low status males; LSF: low status females; HSM: high status males; HSF: high status females.

Table A.15: Treatment effect on the probability of having a job> 20 weekly hours, by geographical area

	ALL	**LSM**	**LSF**	**HSM**	**HSF**
Treated	0,042***	0,068**	0,053**	0,027	0,0082
SE	0,016	0,034	0,022	0,021	0,0113
P-val	0,006	0,044	0,014	0,190	0,47
South	0,018	0,017	0,030	0,013	-0,084*
SE	0,018	0,035	0,035	0,032	0,0499
P-val	0,300	0,630	0,390	0,680	0,094
Treated*South	-0,044	-0,064	-0,064	-0,048	0,027
SE	0,030	0,064	0,048	0,043	0,0556
P-val	0,150	0,320	0,180	0,260	0,63
N	6291	1575	1719	1385	1464

Notes: *: p<.10; **: p<.05; ***: p<.01.
Coefficients represent marginal effects from logit models.
Standard errors clustered at the school level.
All models control for stratification variables, final upper secondary mark and pre-treatment intentions to enroll.
LSM: low status males; LSF: low status females; HSM: high status males; HSF: high status females.

Table A.16: Treatment effects (Eff.) and treatment effects mediated by the difference in beliefs about costs, returns and probability of success induced by the treatment (Med.)

	LSM		**LSF**		**HSM**		**HSF**	
	Eff.	**Med.**	**Eff.**	**Med.**	**Eff.**	**Med.**	**Eff.**	**Med.**
2014								
Not enrolled								
Treated	0.051**	0.054**	0.022	0.022	-0.019	-0.021	0.010	0.010
SE	0.022	0.021	0.026	0.025	0.021	0.021		0.016
P-val	0.0188	0.0114	0.386	0.390	0.367	0.323		0.544
Weak fields								
Treated	-0.005	-0.007	-0.001	-0.003	0.003	0.005	-0.074	-0.072***
SE	0.013	0.013	0.016	0.017	0.014	0.014		0.022
P-val	0.721	0.584	0.952	0.859	0.828	0.714		0.00118
Intermediate								
Treated	-0.041**	-0.036*	-0.041*	-0.039*	0.028	0.026	0.068	0.071***
SE	0.019	0.019	0.021	0.021	0.028	0.028		0.024
P-val	0.0354	0.0555	0.0567	0.0640	0.315	0.347		0.003
Strong fields								
Treated	-0.007	-0.010	0.020**	0.020**	-0.013	-0.011	-0.003	-0.009
SE	0.020	0.020	0.009	0.010	0.024	0.024		0.018
P-val	0.754	0.605	0.0376	0.0326	0.600	0.658		0.614
N	1483		1726		1316		1425	
2015								
Not enrolled								
Treated	0.043*	0.044*	0.008	0.007	0.018	0.017	-0.002	-0.003
SE	0.026	0.025	0.022	0.021	0.019	0.019	0.014	0.014
P-val	0.096	0.077	0.719	0.746	0.342	0.360	0.887	0.831
Weak fields								
Treated	-0.018	-0.019	-0.008	-0.012	-0.016	-0.014	-0.058**	-0.056**
SE	0.014	0.014	0.018	0.018	0.018	0.018	0.025	0.025
P-val	0.178	0.166	0.663	0.512	0.358	0.417	0.020	0.026
Intermediate								
Treated	-0.038*	-0.038*	0.003	0.006	0.020	0.020	0.089***	0.095***
SE	0.022	0.022	0.017	0.017	0.026	0.025	0.029	0.029
P-val	0.084	0.089	0.884	0.714	0.445	0.516	0.002	0.001
Strong fields								
Treated	0.014	0.013	-0.005	-0.001	-0.021	-0.019	-0.029	-0.036
SE	0.021	0.021	0.009	0.009	0.018	0.018	0.022	0.022
P-val	0.502	0.546	0.775	0.904	0.252	0.278	0.188	0.109
N	1335		1493		1203		1248	

Notes: *: p<.10; **: p<.05; ***: p<.01. Coefficients represent marginal effects from multinomial logit models.
Standard errors clustered at the school level. Standard errors for the main effect of HSM in 2014 could not be calculated.
Main effect models control for stratification variables, final upper secondary mark and pre-treatment intentions to enroll.
Med. effect models also control for the difference in beliefs across waves on costs, returns and probability of success in HE.
Main effects are estimated on the same sample on which mediated effects estimated (wave 2 respondents).
LSM: low status males; LSF: low status females; HSM: high status males; HSF: high status females.

Figure A.1: Consort 2010 Flow diagram