Educational Choice and Information on Labour Market Prospects: A Randomised Field Experiment*

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Abstract

We examine the impact of an information intervention offered to 97 randomly chosen high schools in Finland. Roughly 3,500 graduating students were surveyed and given information on the labour market prospects related to detailed educational degrees. Survey evidence suggests that the intervention led to information updating. However, we find no impact on the actual applications or enrollment patterns on average. Only a small subgroup of students that were most likely to update their beliefs as a result of new information applied to fields associated with higher wages. However, even for this subgroup we fail to find evidence on the effects on enrollment. These results cast doubt on the hypothesis that lack of information on labour market prospects plays an important role in shaping educational choice.

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1 Introduction

The choice of how long and what to study is among the most important investment decisions that a typical person makes during her lifetime. Thus it is not surprising that many policy makers, commentators and parents worry about the students ability to make the "right" decisions when it comes to post-compulsory education. Indeed, there appears to be widespread concern that many students lack information about the financial consequences of their educational choices and thus do not learn the type of skills for which there is demand in the labour market.

This paper presents experimental evidence suggesting that, in fact, the vast majority of high school students have realistic expectations on the labour market prospects associated with their choice of post-secondary education. We reach this conclusion by studying the effect of providing information on educational choice with the help of a field experiment, where we offered 97 randomly chosen Finnish high schools a package containing information on the distribution of earnings, employment rates and the most common occupations reported by detailed educational degrees.

In the 63 high schools that chose to participate, roughly 3,500 graduating students sat through an obligatory class given by the schools student guidance counsellor. During the class the students listened to a presentation by the student guidance counselor on the differences in earnings and employment rates between different post-secondary degrees, and completed a survey where they were asked about their preferences and expectations. Along with the survey, they were also given a leaflet reporting the distribution of earnings, employment rates and the most common occupations among the current population of 30-34 year old persons by over 60 most common educational degrees. Furthermore, the students were given the supplementary material at the end of the class, so that they could further consult it at home.

We evaluate the effect of this information intervention on the application behaviour and enrollment patterns using the survey data and, more importantly, national application registry that covers all applications to Finnish universities and polytechnics. In the register data, we can identify the students from the treatment schools and use the whole student population in the rest of the schools as a control group. The registers contain information on all applications that the students file as well as whether they are offered a slot and whether they accept the offer. Hence they allow us to study the effect of additional information seprately on both applications and final enrollments.

To the best of our knowledge, this paper is the first attempt to examine the effect of information on labor market prospects on the *actual* educational choice at the post-secondary level. Previous literature has explored the effect of information on educational attainment in developing countries and on aspirations and plans in some developed countries. Jensen (2010) finds that providing accurate information about the returns increased educational attainment by 0.20 years in the Dominican Republic. Nguyen (2008) shows that providing students with accurate statistics about the returns as well as role models of educated individuals from similar backgrounds improved attendance and test scores in Madagascar. Recent studies by Wiswall and Zafar (2011), Oreopoulos and Dunn (2013), and McGuigan, McNally, and Wyness (2012) show that providing information leads students to update beliefs in terms of the benefits of post-secondary education. Furthermore, many students are misinformed about the true costs of higher education (Hoxby & Avery, 2012) and studies suggest that providing accurate information on those costs can influence enrollment (Bettinger, Long, Oreopoulos, & Sanbonmatsu, 2009; Hoxby & Turner, 2013).[1] However, none of these papers examine the effect that information has on the actual post-secondary educational choices.

The evidence on the effect of information on choice is important because there seems to be widespread optimism about the prospects of enhancing the efficiency of educational choice simply by providing accurate information. Indeed, many governments now run schemes that aim to improve the information available to students.[2] Yet the mere fact that some choices do not appear to maximise lifetime earnings does not necessarily mean that they are based on incomplete information. Educational choices also reflect preferences and constraints. Degrees that do not offer good labour market prospects may attract a substantial amount of applications with their consumption value. On the other hand, the degrees that are strongly associated with good labour market prospects are often heavily over-subscribed. Hence, whether the lack of information causes the apparent suboptimality of educational choice remains an open question.

We argue that the Finnish context is particularly suitable for the study of the effect of information on educational choice. Unlike in many other countries, universities are not allowed to charge tuition and the Finnish government offers quite generous subsidies for students who gain entry to university. Hence, credit concerns should play a minor role in this context. Furthermore admission system is centralised and the criteria for admissions is transparent and known to all the applicants before applying. In Finland, as in most European countries, university applicants apply directly to programmes defined by major subjects which also include professional degrees such as medicine or law. The universities choose their students based on a transparent and uniform criteria which is based solely on the credits derived from the applicant's final high school exam and from the university's own entrance examination.

The final allocation of study slots is determined by a centralised application system based on the matriculation exam grades and the criteria that universities use for each programme. This centralised system also allows us to combine our experiment with the use of register data which makes it possible to overcome many problems that typically hamper large scale field experiments in education. First, it is no longer necessary to convince the control schools be a part of the experiment without receiving any of the potential benefits, as we can observe the control school students directly in the register data. Second, the ability to follow treatment school students in the register data avoids the usual attrition and selection problems in the treatment sample. Third, the ability to observe previous cohorts from the same schools the year before the intervention helps to shorten the time it takes to complete the experiment and makes the set-up more robust to any fixed differences that exist between the treatment and control schools. Finally, without the added cost of a follow-up interview round it is possible to scale up the size of the experiment and thus improve statistical power.

Our experimental results show that providing information about the labour market prospects associated with educational decrees didn't affect the likelihood of enrollment or the type of programmes where the students where enrolled on average. Furthermore, the information intervention did not lead to any detectable changes in the application

[1]Our results also add to the previous survey evidence showing that earnings expectations of university students are biased. See Betts (1996), Carvajal et al. (2000) and Dominitz and Manski (1996) for the United States and Brunello, Lucifora, and Winter-Ebmer (2004) for Europe.

[2]For example, the U.S Bureau of Census provides infographics "Pathways after a bachelors degree" that helps to compare average lifetime earnings across different careers, see http://www.census.gov/hhes/socdemo/education/data/acs/infographics./

behaviour between treatment and control schools. This despite the fact that our survey results reveal similar kind of belief updating that has been documented in the previous literature: roughly a third of the respondents in our survey declared that they were surprised about the labour market prospects associated with their most likely choice of post-secondary education. Moreover, among the students who allowed us to link their survey answers to the application register, we find that this belief updating was correlated with their later choices: those who had been negatively surprised were more likely to change the field that they actually applied to than the rest of the treatment school students.

We argue that our results call into question the hypothesis that the lack of information is a major component shaping educational choice. Even though our survey responses, and much of the earlier literature, suggest that providing information leads to belief updating, the experimental results on the effects of information on actual choice reveal that these effects are likely to be small. To support this interpretation we use the survey responses to characterize the individuals who report to be negatively surprised about their initial field of choice by our information package. By regressing the likelihood of being negatively suprised in the survey on observable characteristics of the respondents, we can predict negative suprises in the rest of the sample. Estimating the effect of our information intervention by different values of predicted negative surprises reveals that the information package did change the application portfolio of the individuals who were the most likely to be negatively surprised by the information. The treated individuals in this subgroup applied to programs that had higher mean wages than similar individuals in the control group. However, this subgroup of affected individuals is a very small fraction of the population and even for them the actual enrollment is not affected by this intervention. It thus seems that in a context where obtaining entry to popular programs requires substantial effort, simply providing information is unlikely to change the enrollment patterns.

The rest of the paper is organized as follows. In the following section we describe the institutional setting in the Finnish education system where the experiment was run. In the third section we explain how the treatment group was drawn and briefly describe the content of the information intervention. We then discuss the findings from the survey conducted among the students in our treatment schools. In the fifth section we describe the applications register data that we use to follow the students after the intervention. Section 6 presents the estimation methods and reports the results of the experiment, while section 7 concludes.

2 Institutional setting

Our intervention was timed so that it affected the information set of the students who were making their post-secondary education choices, i.e. soon to be graduating high school seniors. In Finland, these choices are made at the end of the upper secondary school, typically at the age of 18–19. In this section, we describe the main features of the Finnish educational system and the importance of post-secondary educational choice in the Finnish context.

2.1 Context: Finnish upper secondary school graduates

Figure 1 describes the main features of the Finnish education system. Compulsory schooling starts at age 7 and lasts for 9 years. After this typically above 90% of the cohort continue to the three-year non-compulsory upper secondary school which is divided into two tracks: general upper secondary schools and upper secondary vocational schools. Our intervention targeted students in the general upper secondary schools. Approximately 50% of the students who continue to upper secondary school choose the general track. This track is more academic in content and is the main channel through which students continue to post-secondary education.[3] Henceforth, we refer to the general upper secondary schools as simply "high schools".

The three-year high school concludes with a compulsory matriculation examination which provides the general eligibility for university studies. It consists of four compulsory exams: mother tongue (either Finnish or Swedish), the second national language (Finnish or Swedish), one foreign language, and either mathematics or science and humanities exam. In addition students can take as many voluntary exams as they wish. The examination is national and graded externally by a centralized examination board. The results are standardized to be comparable across years. The exams are held each spring and autumn during a two-week period.

2.2 Applying to post-secondary education

After the matriculation exam, the graduating students can file applications to post-secondary education. Typically around 75% of students apply the year they graduate from high school. The Finnish tertiary education system consists of two kinds of institutions: universities and polytechnics. Universities focus on scientific research and education and have the right to award advanced degrees. Polytechnics, on the other hand, concentrate on advanced vocational education. The prospective students apply directly to the specific degree program they are interested in, and it is not generally easy to switch programs after entering (other than by re-applying and completing the entry exam). Students typically obtain their terminal degree (BA or MA) from these programs, and these degree programs include medical school, law school and other professional degrees.

The admission system is centralised but, unlike in most other European countries, admission is not based solely on grades in high school certificates. Instead, Finnish universities and polytechincs can affect the student admission by using entrance examinations that they are free to design. Indeed, the vast majority of the institutions use a combination of entrance examinations and points awarded based on the standardized grades in the matriculation examination as the criteria for admissions. Entrance examinations are programme-specific and not typically based on material that is taught in high schools. Unlike the American universities and colleges, Finnish universities do not use personal essays, sports performance or extra-curricular activities to determine who is accepted to the degree programs.

The applicant is allowed to apply up to 11 post-secondary programs (7 university programs and 4 polytechnic programs) which are defined by major subjects. However,

[3] Graduates with tertiary vocational degrees can also apply to universities. However, only 5% of the university students actually have only vocational degrees. Students with only general upper secondary school degrees make up 83% of the Finnish university students.

the need to prepare for entrance examination limits the number of applications in practice. In the data, the average number of applications per individual was 4.5. The number of available slots per program is determined in the joint negotiations between the universities and the Ministry of Education on annual basis. Since the applications are usually very unevenly distributed across university programs, the average acceptance rate is low. In year 2011, only 19% of the high school graduates of that year were accepted to a university and 18% to polytechnics which means that approximately two thirds of the high school graduates did not gain admission in the first year that they tried.[4] However, most high school graduates succeed in being admitted few years after graduating.

Admission to a university programme typically gives a right to study until the master's degree. This also includes professional degrees like law and medicine. Universities are not allowed to charge tuition and the main source of funding is the state budget through the Ministry of Education. The state funding is allocated on the basis of the number of targeted and completed master's and advanced degrees. This creates an incentive for the universities to attract the best available students. Students are provided generous study grants, highly subsidized accommodation and access to government guaranteed student loans. Thus credit constraints should not be a major concern.

2.3 Post-secondary degrees in Finland

The choice of post-secondary program is an important one in the Finnish context. Programs differ in the kind of labor market prospects that they provide and in the kind of applicants that they attract. Table 1 documents the applications patterns in 2011–2013 using data discussed in detail in section 5.1. It describes various characteristics associated with the most popular fields in Finland: share of applicants, fraction female, the share of applicants taking the optional advanced mathematics exam in the matriculation exam, the share of applicants accepted to a program, and the average grade in the matriculation exam and its standard deviation among the applicants.[5] Moreover, the table provides summary statistics on annual earnings for the full time employed and employment rates among 30-34 year old men and women by their field of education, drawn from the information package that was given to students in the treatment schools (and based on the data from Statistics Finland).

As shown in table 1, nursing degrees from the polytechnics attract most applications followed by university level natural sciences which also seem to attract, along with engineering and medicine, the most mathematically orientated applicants. The applicants to natural sciences also have the highest average grades in the matriculation exam, whereas the applicants to polytechnic engineering degrees have the lowest grades.

Importantly, annual earnings vary considerably across degrees. Graduates from university level engineering degrees, medicine and business tend to earn, on average, almost twice as much as the graduates from the popular fields of nursing and education.[6] Employment prospects are also, if anything, positively correlated with average earnings.

[4]There is considerable variation across fields, with sciences accepting 34% whereas small fields such as theatre and arts accept only 3% of the applicants.

[5]The average grade was calculated based on four compulsory subjects in the high school matriculation examination: Mother tongue, and the best three grades out of a) mathematics (long or short curriculum), b) foreign language, c) the second domestic language (Swedish), and d) the best grade in the battery of tests in humanities and sciences.

[6]These differences are similar in relative terms to the ones reported by Altonji, Blom, and Meghir (2012) for the United States.

Employment rates at age 30–34 in engineering and medicine are well above 90 percent.

Figure 2 suggests that the link between degrees and earnings is not solely driven by differences in students' academic achievement. It plots the average earnings of the 30–34 old individuals currently holding the degrees on the average matriculation exam scores of the students who enrolled in these programs in 2011–2013. The figure shows a clear positive association between matriculation exam scores and degrees' average earnings. However, it also shows that conditional on matriculation exam scores, large differences in expected earnings remain. For example, students enrolled in university level engineering and humanities programs have similar average matriculation exam scores despite the almost 20,000 euros or x% differences in the expected annual earnings. Hence, the information that was given to students (in a more detailed format) strongly suggested that the choice of major in post-secondary education has major implications for ones' labor market prospects.

3 Intervention

In this section, we describe the design and implementation of the information experiment. We start by describing how the treatment schools were selected and document their pre-treatment characteristics. We then describe the content of the information package in detail.

3.1 Treatment group

The treatment group was derived by randomized block design. The initial list of all 442 Finnish high schools was compared with the information on recent school closings, openings and mergers that we received from the Statistics Finland. These changes reduced the number of schools by 11. We also dropped evening and adult high schools, and other speciality schools such as religious institutes, resulting in a reduction by a total of 32 schools. We further excluded the only high school in the autonomous Åland archipelago and another school operating in Spain for Finnish students located there, as well as any Swedish language high schools, or schools specializing in another language (e.g. French, German or Russian). Our target group is the 2011 list of operating Finnish language schools which includes 363 high schools in the continental Finland.

The schools were stratified by province and their ranking in the average matriculation examination grades during 2008-2010. In each of the 18 provinces in Finland, the schools were ranked based on the average grade and these rankings were divided into bins of four schools. When the number of schools was not divisible by four, the location of the incomplete bin in the ranking distribution was randomly selected. For the treatment group, we randomly drew one school from each bin.

The bins of treatment and control schools can be plotted against the average grades to visually inspect the drawing of the treatment group within each province. This is done in figure 3 for eight provinces for purposes of illustration. These graphs also give an idea of the distribution of schools by grades in each province. Our treatment group consists of schools from the top and bottom of the ranking, in some cases including the very best or worst school in the province. The final treatment group consisted of 97 high schools.

Table 2 examines the average characteristics of the treatment and control schools in 2011. There are no significant differences in average matriculation grades of the treatment and control schools. To further assure that the randomization was implemented successfully, we obtained information on the background characteristics of the students using Statistics Finland's geocode data that reports average demographics by 250m x 250m squares in Finland.[7] This geocode information was linked to student addresses to obtain regional background characteristics for each school. In table 2, we report the average share of high school and university graduates in the population of 15-65 year olds in the geographic location of each high school in the treatment and control groups. Furthermore, we report the average household income in euros as well as the share of unemployed individuals in the labor force. As is clear from table 2, none of these background variables differ significantly between treatment and control schools, with the borderline exception of regional unemployment. To us, these results indicate that the randomization worked as intended.

For each treatment school, we visited the school website to obtain the contact details of the student guidance counselors. In cases where the school had multiple counselors we obtained the contact details of all of them. This list was then used to contact the student guidance counselors and invite their schools to participate in the study. Of the 97 schools contacted, 40 responded positively and none negatively to the invitation. The 57 schools that did not respond were once further contacted by email. After the second email round, 23 additional schools were recruited for the study, and one refused to participate due to the absence of student guidance counselors. 33 schools never responded to our invitation. The participating sample included a total of 63 schools with altogether 5,323 students. Complete survey responses were received from 60 schools by the end of 2011.

3.2 Student guidance counseling in Finland

Our information intervention was implemented at the student guidance counselors class which is a mandatory part of the high school curriculum. In total, students at Finnish high schools have to take one mandatory course (38 lessons usually spread out over 3 years) in counseling. These classes are the most natural channel through which to distribute information about the labour market prospects related to different post-secondary degrees. Indeed, informing students about career choices is one of the main tasks of a guidance counselor.

Finnish student guidance counselors are highly qualified by international standards. Counselors are teachers who have specialized in guidance counseling training at the University of Jyväskylä, Finland. This is additional training for teachers and consists of approximately one year of full-time study and the pre-requisite for this training is a Master's degree, and a teacher qualification from a university.

3.3 The intervention

During the fall semester of 2011 we contacted the treatment school student guidance counselors who were also responsible for the actual implementation of the information and survey sessions. The research team communicated with the student guidance counselors on daily basis to offer instructions and to respond to any questions that arose during the experiment. After the schools implemented the information sessions during 2011 fall semester, the survey forms were returned to the research team, and the students retained the information packages. We therefore expect the information provided to affect the application behavior from the spring of 2012 onwards.

[7] This corresponds to about 0.05 square miles or 30 acres.

The 45 minute long information session was structured as follows. First, the student guidance counselors were instructed to present to the students some general information on the value of education in the labor market. The Powerpoint presentation included 19 information slides, along with talking points and the general message to convey for each slide as a separate document. The slides included information on earnings distributions by education level and broad field, the lowest and highest earning degrees by field, the cost and funding of studies, and the overall entry probabilities and completion times for various degrees. The slide deck and talking points are shown in the appendix of this paper. Second, the teachers were asked to hand the information packages and questionnaire forms to the students, and allow 15-20 minutes to fill in the questionnaires. Finally, we instructed the teachers to collect the questionnaires but let the students retain the information materials.

The earnings and employment information was given by level of education as follows: secondary education (41 degrees), lower level tertiary education (19 degrees), and upper level tertiary education (44 degrees). To keep the package at a reasonable length the information was mostly given at the 3-digit level of the education classification, and at the 4-digit level only where the specific degrees differed noticeably from the 3-digit level averages. For example, most of the university level engineering degrees are well-described by the 3-digit level M.Sc. in Technology, whereas graduates from the Industrial Management program earn significantly more and graduates from the Process Technology program significantly less than the average engineering graduate. The graphs in our information package show clearly how both the means and distributions of earnings vary significantly across degree programs. An English language version of the information packages is included in the appendix of this paper.

As described, the package uses both graphical and numerical presentation of the earnings distribution. Furthermore, the package also lists the most typical professions associated with the educational degrees. While most students have a general idea of low- and hig-earning occupation they do not have easy access to information on earnings and employment at the level of detail and accuracy provided in our information package. In addition, information on earnings distributions by degree are not readily available anywhere.

Before implementing the intervention in the treatment schools we piloted the entire experiment in a single high-school during spring 2011. Most students (89%) in the pilot school thought the information on the labour market prospects related to education should be made available in all schools. Likewise, students in our treatment schools indicated that the information was novel and useful, and the guidance councellors communicated their enthusiasm about the materials. Based on the responses from the participating schools and the overall tone in the open-ended comments from students we expect the intervention to have been successful in communicating the message on labor market prospects to students.

4 Survey

As was explained above, we conducted a survey among the treatment school students as a part of the intervention. The purpose of this survey was to acquire information on the students' aspirations, the level of information they had about the labor market prospects associated with different educational choices, and on which sources they relied for such information. Altogether 3,418 students returned the survey. This represents 64% of the last year students in the schools that complied with the information experiment.

4.1 Aspirations

High school is typically the track through which most of the students attempt to proceed to tertiary education. Therefore it is not surprising that in our survey 94% of the students answer that they are planning to apply to post-secondary education while only 0.4% say that they do not have such plans, with the rest stating that they are unsure. Furthermore, 60% state that they plan to apply directly after finishing with the matriculation examination. Hence, practically all of the students in our treatment group have intentions of continuing their studies after finishing high school.

However, the kind of institutions that students plan to apply to differ clearly by gender. These differences are clear in figure 4. While on average 53% of the respondents say that they plan to apply to universities, this percentage is clearly higher among girls (55%) than among boys (48%).

4.2 The level and sources of information about the labor market prospects

As our goal was to inform the students about the labor markets prospects associated with different degrees, it is useful to get a sense of how well informed the students in our treatment group were before the intervention. Approximately 60% of the students considered themselves well informed. Again, the level of information differed by gender, with girls less (56%) likely to answer that they were well informed than boys (66%).

In the survey the students were also asked to state the sources that the students use to obtain useful information about further study options. The alternative sources included parents, peers, guidance counselors, study guides, the internet, and the residual other category. The students were allowed to choose multiple alternatives. Figure 5 plots the use of information sources by student gender. This figure reveals that both male and female students rely on student guidance counselors for information on the labour market prospects. Therefore, we would expect the information given by the counselors to be generally effective.

4.3 Belief updating

Previous information experiments examining educational choice in developed countries have mainly focused on belief updating. Using our survey we can replicate some of the findings in the previous literature. Specifically, we asked the students to list up to five programs they were planning to apply to in preference rank order. Later in the survey, we asked them to check the average earnings and employment rates of their preferred degree from the supplementary material that was given to the students as a part of our experiment. Figure 6 plots the distributions of average monthly earnings of the students' first ranked programs by gender and family background. As can be seen from 6, the average monthly earnings of the programs where the students are planning to apply to vary considerably by gender with girls planning to apply to programs that are associated with lower paid jobs.

We then asked the students whether they were surprised about the actual level of average earnings in the field that they ranked as their first choice. Approximately third of the respondents replied that they were. Negatively and positively surprised respondents were almost evenly distributed with shares 19% and 18%, respectively. Table 3 presents the surprises by field of study. The average updating is calculated by assigning value -1 for negative, 1 for positive, and 0 for no surprises. Table 3 reveals that among reasonably large university fields business, medicine, and engineering were associated with most positive belief updating whereas education and psychology were associated with negative surprises. [8]

It is also informative to examine the characteristics of the individuals who update their beliefs according to our survey. In table 4 we report the distribution of surprises by various background characteristics. First thing to note from table 4 is that women are clearly more likely to be negatively surprised by the actual level of wages in their preferred field. Survey responses also seem fairly consistent. Those respondents who report not to be well informed and for whom wage is an important factor in determining choice are more surprised by the information they received in the package. In addition, suprises are correlated with several measures of academic achivement. Respondents who have studied advanced mathematics in high school are less likely to be surprised than students who did not study this subject. This is important since the failure to take advanced mathematics in the matriculation examination makes it impossible to apply to some of the more technical fields in post-seondary education. Surprises are also correlated with the quality of the school that the students attend. Students from schools whose average matriculation grades are lower than the median are clearly more likely to be surprised by the nformation that we provide. However, the average matriculation examination scores of the students do not seem to be correlated with being surprised.

5 Results

The availability of register data on the applications and final enrollment decisions allows us to follow all the students graduating from the treatment and control schools. This is a major strength of this study. In this section, we present the effects of our information intervention on the application behavior of Finnish high school students, as well as on the final allocation of study slots. We end the section with a discussion of the results.

5.1 Application register

The estimation of the effects of our information intervention is based on the comparison of changes in the application behavior and enrolment outcomes of the treatment and control school students. This is made possible by the detailed register data available in Finland. Educational applications, acceptances and final study choices are recorded in centralised data bases (HAREK- and AMKOREK-registers), allowing us to observe post-experiment outcomes without having to reach the students for a second round survey. This avoids the problem of attrition that often plagues experimental designs and allows us to keep track of those students who initially failed to obtain a place to study in 2012.

[8] The measurement of surprises by field is based on students who listed a program in that field as their number one choice at the time of survey. We assume that other students (i.e. those not listing a program in that field as their first choice, but simply reviewing the information at home) would be, on average, equally surprised about the salary information.

Most other countries do not have information on failed applications or the possibility to follow students over time, thus making the Finnish data particularly valuable.

The register data identify for each graduating high school student the set of university programs and polytechnic programs they applied to, which ones they were accepted into and which one they eventually chose to enter. For polytechnic schools the students also report the preference order of programs, and for all programs we know whether the student chose to queue for an entry place. In addition, the data contain the students' matriculation exam grades and the high school from which they graduated. Acceptance criteria into educational programs vary greatly by university and subject. All programs give points according to the matriculation examination grades, although with varying weights. In addition, most university programs require attending an entry examination and heavily weigh the points obtained in the exam. Some programs also use psychological tests. Our data reveal whether the student attended the entry examination, but the points obtained in the exam are not recorded as that is a university and program specific measure for evaluating students.

5.2 Impact on the distribution of applications

The fact that we can observe all the applications - both the failed and the successful ones- for each applicant makes its possile to study the effect of information on the application behaviour. We can therefore potentially provide more detailed answers on the question of correct information about the distribution of earnings across degrees affects students' aspirations. We are interested in how the information intervention affected the whole application protfolio of the students.

However, to examine how the information intervention affects the application portfolio is not straightforward. It is not a priori clear how the information should change the portfolio in a complex setting such as the Finnish one where the high school graduates can apply up to 11 programmes out of 658.[9] This abundance of choice also makes it each possible combination of applications separately not feasible.[10]

One way to analyze the effect of the information intervention on application behaviour is to examine the differences in the distribution of applications across programs between the treatment and control groups. In table 5, we have listed the shares of applicants aggregated by field of study in both universities and polytechnics by treatment/control group and year. In column 6 of table 5, we present odds ratios of how shares of applications changed in control and treatment groups between 2011 and 2012. If the odds ratios are larger than one, treatment group members became more likely to apply to that field than the control group members after our information intervention was implemented. Hence, these odds ratios can be interpreted as differences-in-differences tests for significant changes in applications behavior. Column 7 of table 5 reports the standard p-values of these odds ratios and column 8 reports the p-values that are corrected for within school clustering by randomization inference where the odd ratios of changes in treatment and control groups are compared to to the distribution of placebo odd ratios using 500 random divisions of schools.

[9]Some theoretical work examining problems of this level of complexity exist, but they provide little guidance that would allow us to characterise the optimal strategy in our context. Chade and Smith (2006) analyse the general problem and Chade, Lewis, and Smith (in press) analyse and characterise the optimal strategies in a simplified case with only two schools.

[10]This would results in $\binom{658}{11} + \binom{658}{10} + ... + \binom{658}{1} = 2.35 \times 10^{23}$ possible application combinations.

As can be seen from table 5, randomization inference reveals that only one of the odds ratios is different from one at the conventional levels of significance. Furthermore, the test for homogeneous association, i.e. that the odds ratios are equal, cannot be rejected when accounting for within school clustering.

5.3 Impact on the application behaviour and enrollment at the individual level

The tests based on table 5 are very general and impose practically no structure on the data. While this approach analyzes the distributions of applications at the program level, we can also analyze the effect of intervention on behavior at the individual level. Here we present results on the effect of information on both application behaviour and enrollment patterns.

We use two measures to characterize the earnings implications of the portfolio choice to measure changes in application behaviour. The most obvious one is the log mean wages of the fields that the applicants include in their portfolio. However, this measure does not take into account the likelihood of being accpeted to these fields. In order to weight the fields in the application portfolio with the probability of being accpeted we construct following measues of the expected income associated with the applications of each individual as

$$V_i = p_{i1}E_1 + \sum_{j=2}^{J_i} \left[\prod_{n=1}^{j-1} (1 - p_{in}) \right] p_{ij}E_j \tag{1}$$

where p_{ij} is the probability that person i is admitted to her j^{th} choice, and E_j is the expected earnings associated with her j^{th} choice. The logic of this measure is the following. If a person applies to only one program, she can either be admitted and receive E_1 or be rejected and get her outside option (normalized as zero). The probability that she is admitted is p_{i1} and thus her expected income is $p_{i1}E_1$. If instead she applies to two programs, she can be admitted to her first choice and receive E_1, be rejected from the first choice but admitted to the second and get E_2, or be rejected from both and get nothing. Thus her expected income is $p_{i1}E_1 + (1 - p_{i1})\, p_{i2}E_2$. Equation (1) generalizes this idea for a person applying to J_i programs.

A useful feature of this measure is that the ps are person specific and thus applying to a high paying program increases expected income only to the extent that the person has a chance of being admitted.[11] However, it also has three obvious limitations. First, it may be sensitive to the ranking of applications which we do not observe in the actual data. We deal with this potential sensitivity by experimenting with different rankings such as using average earnings (in the order from the largest to the smallest), likelihood of being accepted (from smallest to the largest) and a random ranking as for ranking the applications of an individual student. Second, this measure only approximates expected income, while the students supposedly maximize their utility. The approximation of the expected income is also very rough as it is based on the average earnings at age 30-34 for each degree and therefore does not take into account any within-degree heterogeneity.

[11] We estimate the ps using 2011 application register data. For each program, we take all applicants and regress an indicator for being accepted on matriculation exam degrees using a flexible specification (dummies for each possible grade in the four subjects of the matriculation exam and interacting math grades with a dummy for long curriculum). Using estimates from these regressions, we then construct the probabilities of being admitted for each application.

We also lack any valuation for the outside option of the applicants which should lead us to systematically underestimate the value of the portfolios. Third, the calculation of the expected income of the portfolio is based on the assumption that the elements of vector p_i are independent of each other. This assumption is violated, for example, in the realistic situation where the study material tested in the entry exams of several degrees partly overlap. While these limitations are real, they should affect the measurement of the application portfolios of the treatment and the control groups in a similar way. Thus we consider the issues primarily as measurement error.

Whereas characterising the application portfolios is complictad analysing the effect of information on enrollment is relatively straightforward. In what follows, we simply estimate the effect of the intervention on the probability of being enrolled in post-secondary education after the application process is finished and on the log mean wage of the field in which the accepted applicants are enrolled.

For each individual level outcome, our empirical specification is a simple differences-in-differences regression

$$y_{its} = \alpha + \beta D_s + \gamma D_t + \delta D_s D_t + \epsilon_i \tag{2}$$

where y_{its} is the outcome of interest (expected value or the "surprise content" of the application portfolio), D_s is an indicator variable for the student i having graduated from school s that was offered the treatment and D_t is an indicator variable for year 2012.

This specification provides a parsimonious way to summarize our entire data. The coefficient β measures the extent to which the treatment and control groups differed already in 2011 (prior to the intervention). Coefficient γ measure the changes in the outcome over calendar year. Most importantly, coefficient δ measures the treatment effect at the year of graduation.

In table 6 we report the differences in differences estimates of the effect of information on enrollment and applications outcomes. The table reports the estimates of δ coefficients in the equation (2) and school clustered standard errors in parentheses and p-values that are based on similar randomisation routine as was conducted in table 5. As is clear from table 6, the information intervention clearly didn't have any effects on these outcomes on average. All our estimates are fairly precisely estimated zeros and this also holds when estimating the effects separately by gender. Based on these results it seems clear that this kind of information does affect average applicants in our data.

5.4 Belief updating and choice

The fact that our survey result suggest that belief updating took place at the time of the intervention in combination with our failure to find any average treatment effects of the intervention on application or enrollment patterns suggests that the information provided could have been forgotten at the time when the treatment school students were making their actual choices. We can study whether this is true by exploiting the fact that a subgroup of the survey respondents gave us the permission to link their responses to their later choice data in the applications registers. For these students we can check whether they really applied to the program that they listed as their first choice in the survey. In other words, we can examine whether their plans changed between the time of the intervention (in November 2011) and the application deadline (in April 2012).

In table 7 we tabulate the fraction of students who applied to at least one program in the same field that they listed as their first choice in the survey against whether they reported to be surprised about the average earnings of recent graduates in that field or not. We also tabulate the fraction of students that were serious applicants in the sense that they participated in the entrance exam of a program in the chosen field, the fraction who were offered a place and the fraction accepting the offer.

According to table 7, three quarters of the students actually applied to the program that they listed as their first choice in the survey. This suggests that a large fraction of the students in our treatment group had already made up their mind at the time of the survey. More than half of the respondents took an entrance exam in the field that they reported as their first choice and a fifth of the respondents were eventually accepted to the program.

Interestingly, however, the students who were negatively surprised were much more likely to revise their plans between the survey and the time they had to file in the application. The difference is even larger for serious applicants taking the entrance exam, and persists in the fraction accepted and eventually enrolling in their survey-time first choice program. Furthermore, there are no significant differences between the students that found graduate earnings larger than they expected and students who were not surprised to see the data on wages of their first choice program.

The evidence in table 7 is clearly based on a selected sample. Intentions and beliefs data was only collected from the treatment group. However, these correlations suggest that a subgroup of students reacted to the new information on wages. If we were able to find a comparable control group for this subgroup of treatment group applicants we could potentially find significant effects of the intervention.

In figure 7 we graphically present the differences-iin-differences estimates by different values of predicted values of suprises. These predicted values are derived by estimating a linear probability model with the survey data where the probability of being negatively surprised by our information package, in the sense that the respondents report the average wages in the field that they were thinking of applying to be less than they expected, is regressed on their matriculation exam grades, on a full set of dummies for the optional subjects that they choose in the matriculation exam, for the shares of students that applied and were admitted to each field in year 2011 before the intervention took place. This model allows us to predict the probability of being negatively surprised by the information package in the whole register data since the same information that is used as regressors in our survey regressions is available for the rest of the data.

Figure 7 reports the treatment effects for 10 groups where the support of the distribution of predicted surprises is split groups based on the values of the preductions. As the figure 7 show the treatment effects are zero for all outcomes for most values of the predicted surprises. However, for the group the highest probability of being negatively surprised by information we actually observe significant or borderline significant effects on the log mean wage and log expected value of the application portfolio. It seems that the individuals who are most likely to update their beliefs do change their application behaviour. However, this is only a small fraction of the population. Moreover, these changes in the application behaviour do not lead to any changes in the enrollment patterns even for this group.

6 Conclusions

The apparent suboptimality of educational choice is a widely shared concern among many commentators, politicians, and parents who appear to feel that students are not making the kind of choices that would prepare them for a successful entry into the labor market. Often the suboptimality of educational choice is blamed on the lack of information about actual labor market prospects associated with alternative choices. However, since educational choice is also shaped by preferences and constraints, the role of information in explaining the alleged suboptimal choices is an empirical question.

We examine the effect of providing accurate and detailed information about the average earnings and employment prospects associated with different degrees on post-secondary educational choice. We ran a randomized field experiment where students in the treatment schools were given a presentation and a detailed information package on the labor market prospects related to secondary and post-secondary degrees. We follow the application behavior of both treatment and control group students by using the Finnish higher education application register data.

Our results confirm the findings from previous literature that these kinds of information interventions do lead to belief updating. Roughly a third of the students surveyed in our treatment schools stated that they were surprised about the actual level of average earnings in the field that they were planning to apply to. Moreover, these surprises were correlated with the actual application behavior. In particular, students who were negatively surprised about the labor market prospects associated with the field that they had ranked as their first choice in the survey were less likely to apply to that field than students who were not surprised or who were positively surprised.

However, our experimental results on the actual application behavior, and particularly on enrollment, should make one skeptical on that this kind of belief updating would lead to large changes in educational choice. We detect no changes in the application behavior on average. The only subgroup whose application behavior seems to robustly respond to our information intervention are the applicants that are most likely to update their beiliefs as a result of new information. However, this group represents a small fraction of the population and we still fail to find any effect on enrollment even for this sensitive subgroup.

These results can be contrasted with the important studies on information interventions in developing countries, particularly with Jensen (2010) who finds that information on labor market prospects decreases the probability of dropping out of high school in the Dominican Republic. The main difference between our setting and the one he studies, apart from the obvious developing/developed country difference, is that students in our study face a choice that is much more severely constrained. Students participating in the experiment of Jensen (2010) are free to choose whether they continue their high school studies or drop out. In our case, students have to engage in a costly and risky application procedure, where they compete for a fixed number of slots available in the Finnish post-secondary system. Clearly, understanding the role of information in both contexts is valuable.

An important question for future research concerns the extent to which our results can be generalized to other context and other variants of information interventions. We chose to implement our experiment through the standard curriculum that graduating high school students have to complete. The motivation for this approach was to use the expertise of the student career counselors and to examine an intervention that could be easily scaled up within the Finnish high school system. The survey results and the finding that those applicants who were most likely to update their beliefs responded to the treatment suggests that the intervention also managed to convey information to the students.

However, a potential reason for why we find no effect on enrollment is that our intervention took place too late. The set of feasible post-secondary programs for graduating high school students may be already restricted by their past choices of subjects and their achievement. Therefore, earlier interventions, or indeed a student guidance system that continuously reminds the students about the potential labor market implications of their choices, could be more effective in shaping application behavior and enrollment. Of course, learning whether this is the case will require another experiment. Given the small cost of providing information to students and the large impacts documented in other context, we hope that such experiments will be carried out in the future.

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Figure 1: Finnish educational system

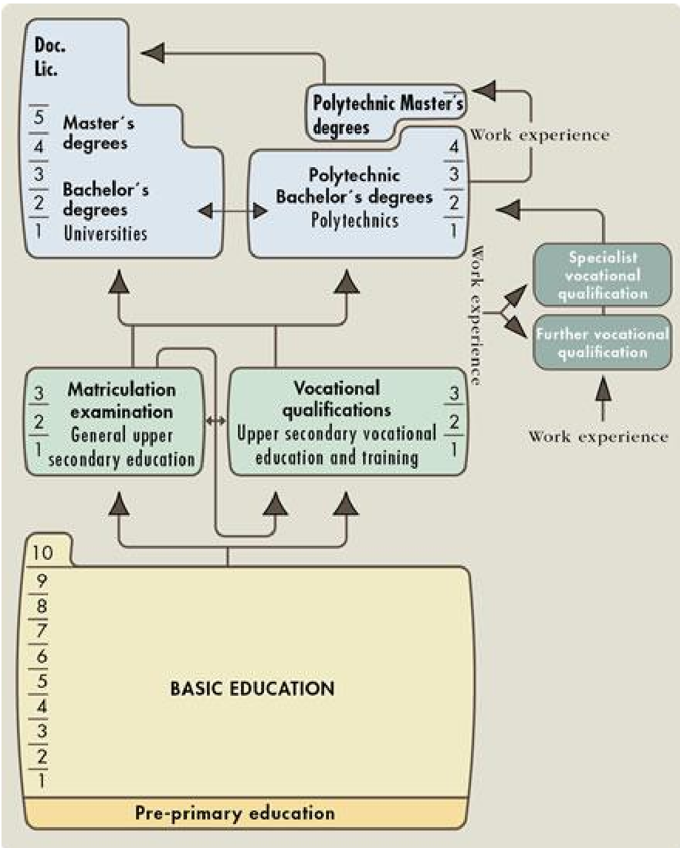

Figure 2: Average earnings and matriculation exam scores among enrolled students

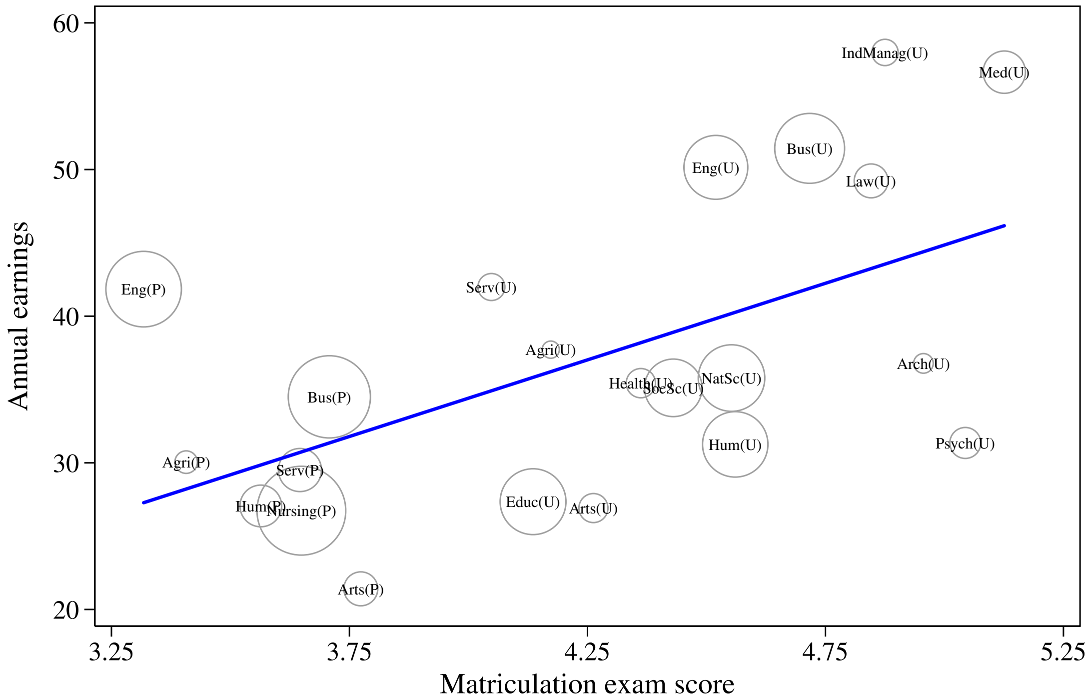

Figure 3: Illustration of the randomized block design

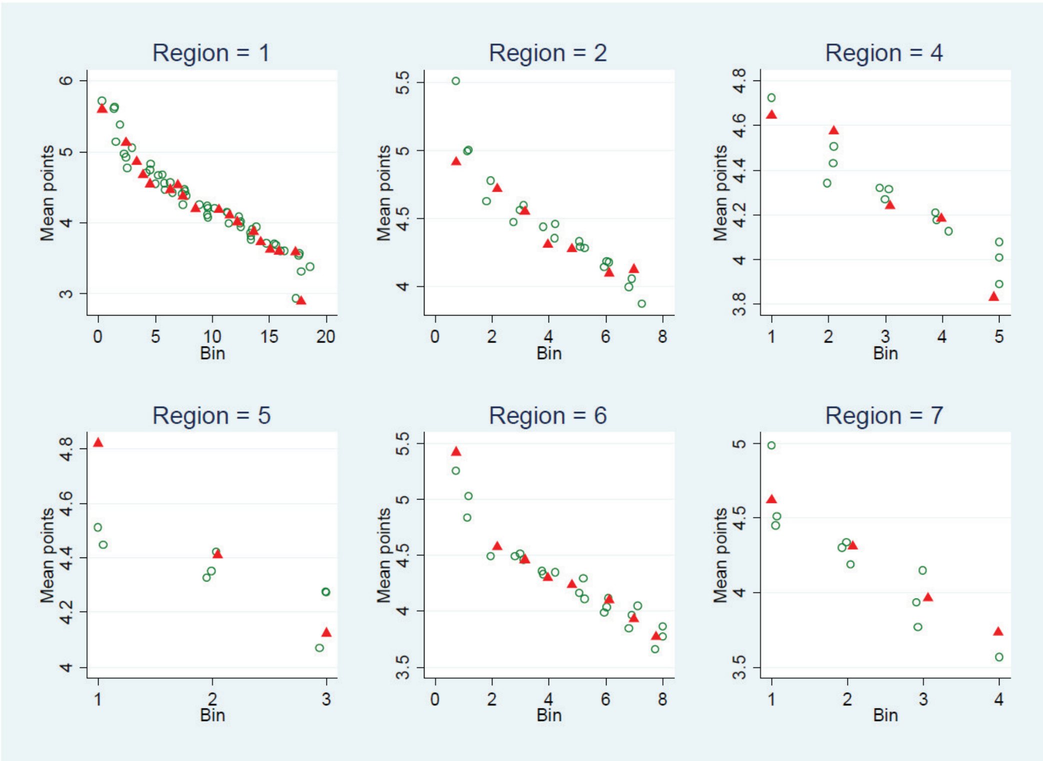

Figure 4: Shares of survey respondents by the highest educational degree they expect to obtain

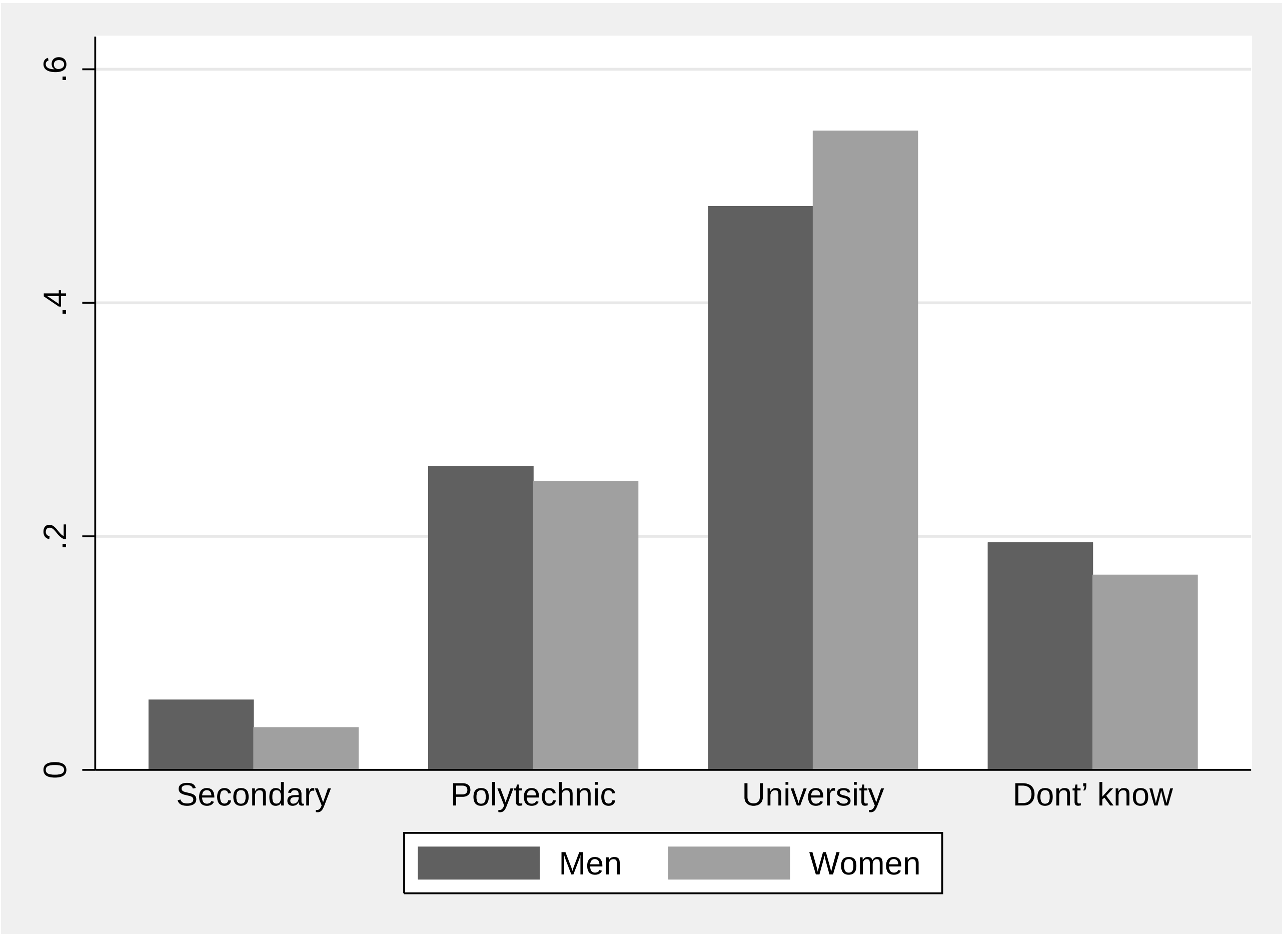

Figure 5: Sources of information among survey respondents

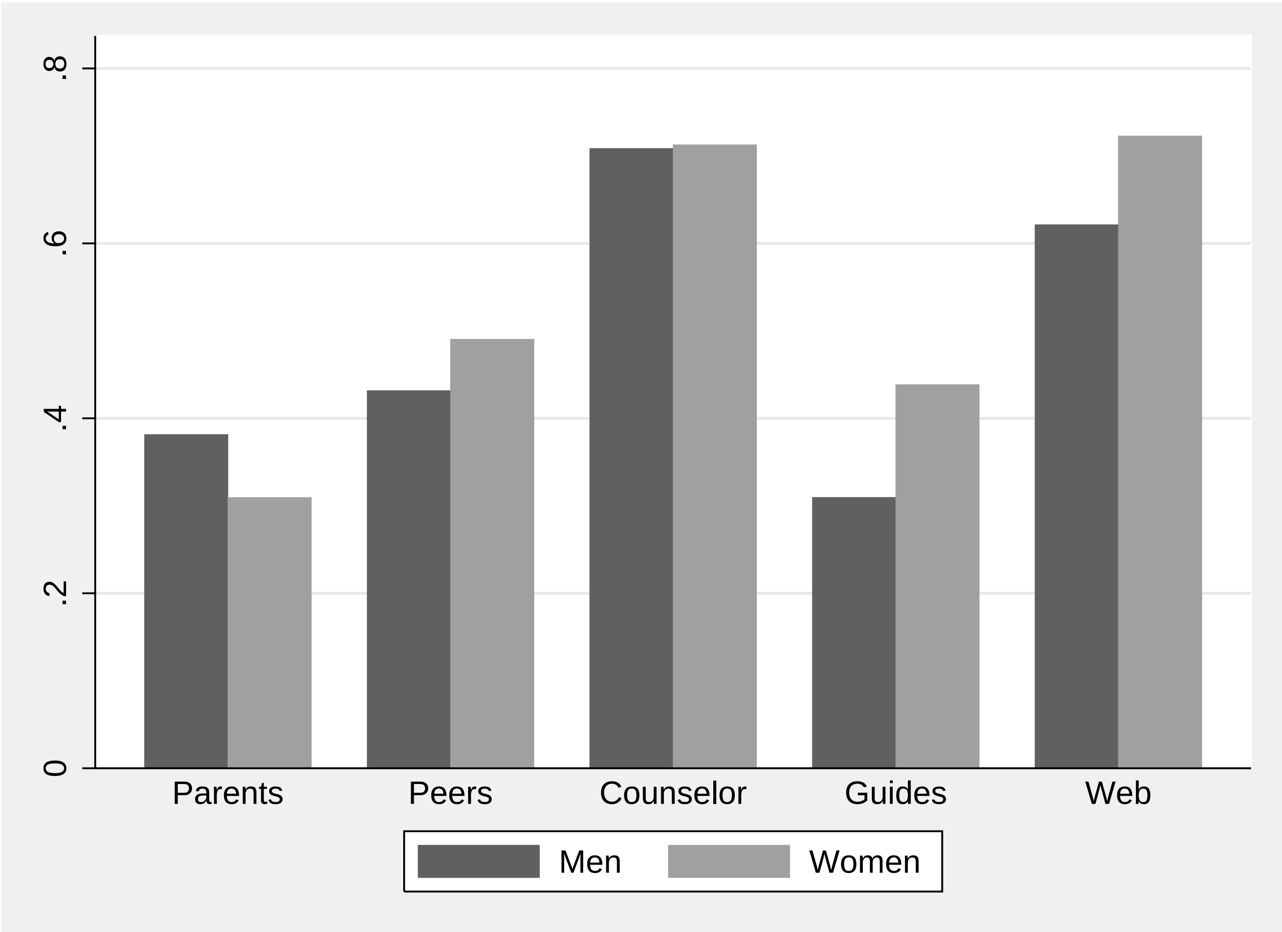

Figure 6: Average annual earnings (in thousands of euros) of graduates from the students' preferred program among survey respondents

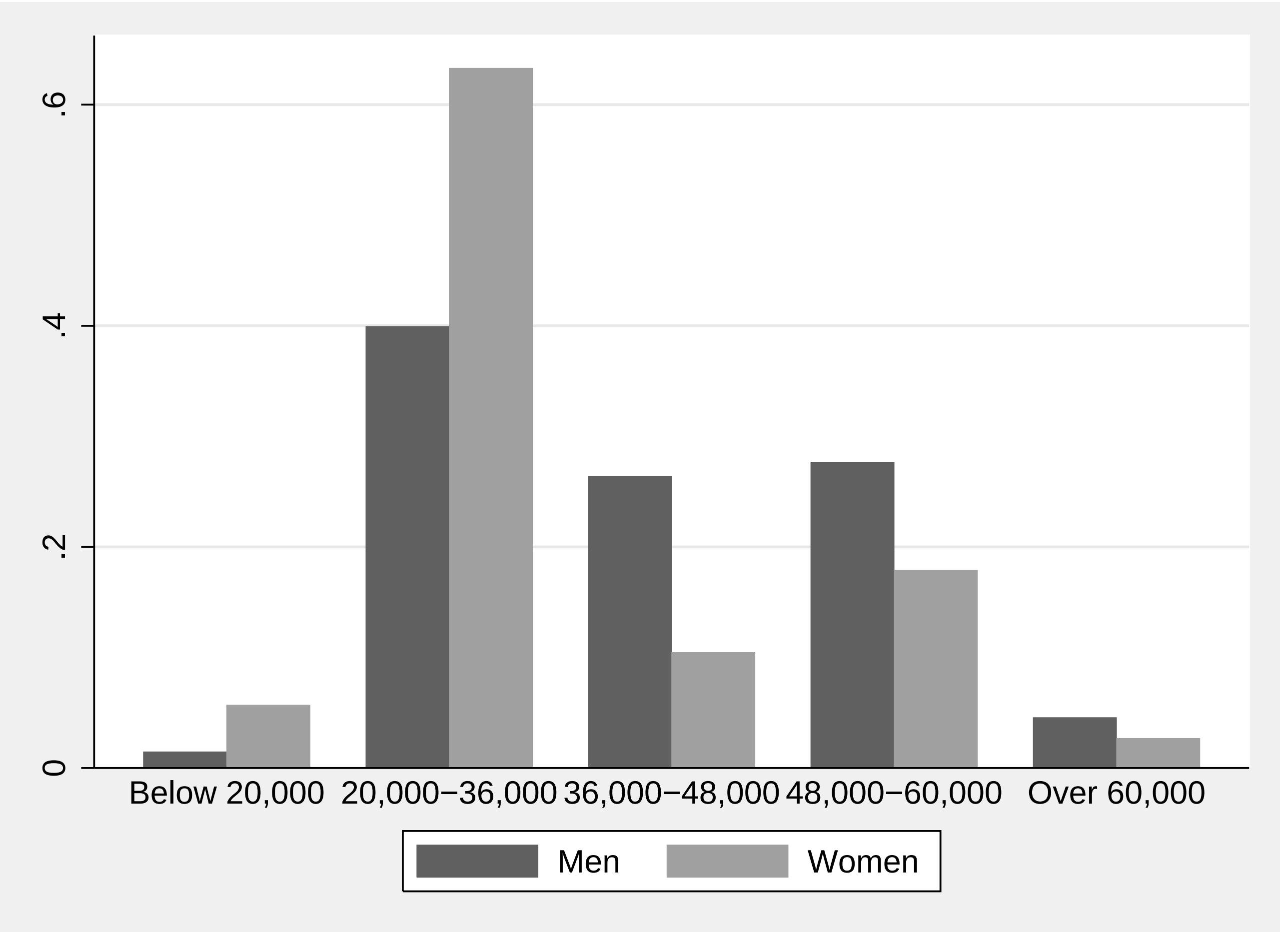

Figure 7: Effect of the intervention by predicted surprises

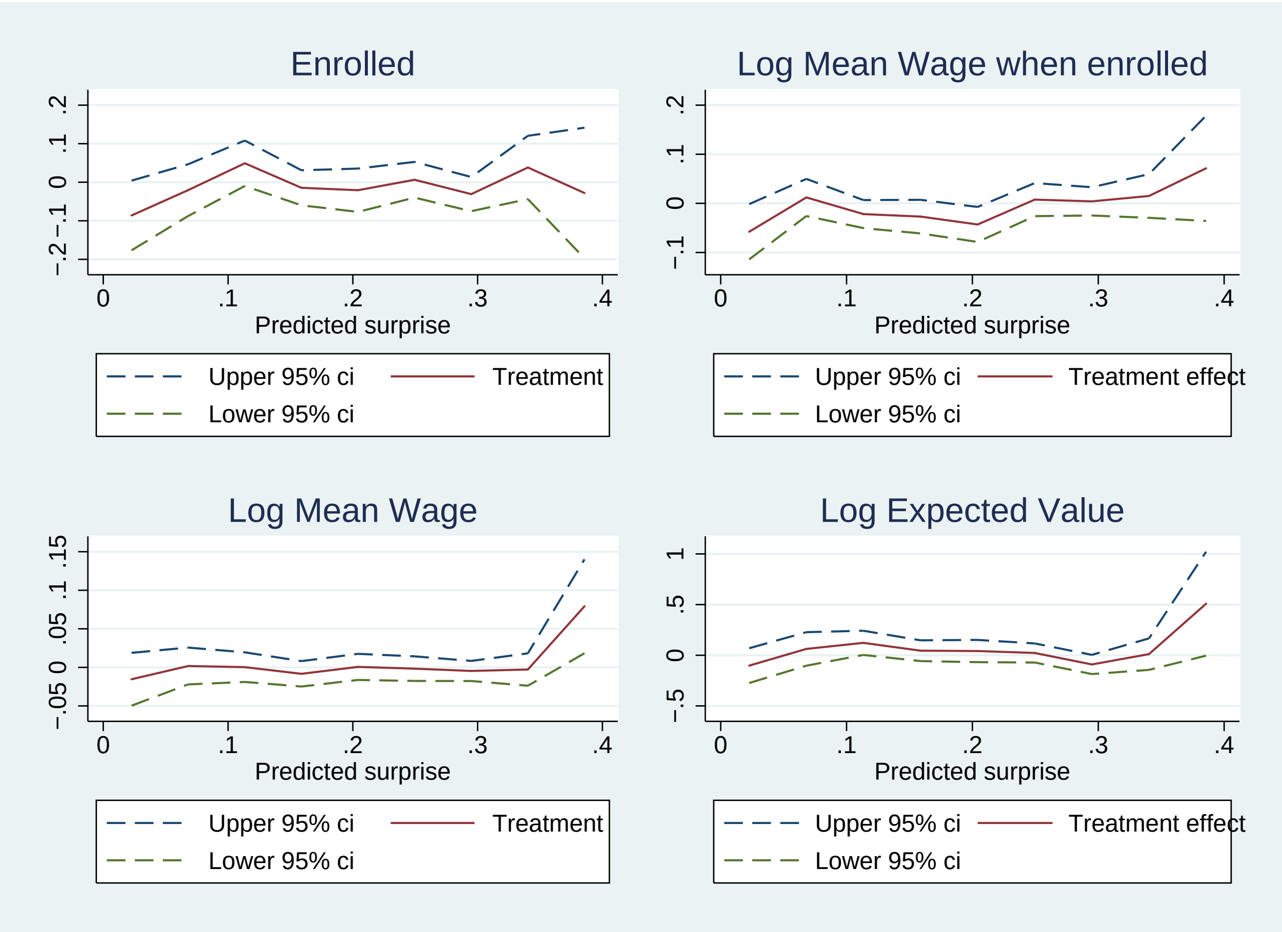

Table 1: Post-secondary degree characteristics

					Matriculation Exam Score		Employment	Annual earnings		
	Applications (1)	Female (2)	Adv. Math (3)	Accepted (4)	Average (5)	Std. dev. (6)	Rate (7)	Mean (8)	p10 (9)	p90 (10)
A: Polytechnics										
Humanities	0.04	0.64	0.17	0.11	3.43	0.97	0.80	27,060	10,860	40,740
Arts	0.03	0.76	0.20	0.12	3.57	1.00	0.55	21,408	7,740	34,680
Business	0.12	0.54	0.22	0.15	3.43	0.96	0.90	34,500	15,696	53,856
Engineering	0.08	0.19	0.42	0.22	3.24	0.88	0.94	41,844	28,392	56,568
Agriculture	0.01	0.49	0.32	0.31	3.39	0.96	0.88	30,048	17,544	42,576
Nursing	0.17	0.82	0.20	0.09	3.36	0.96	0.89	26,736	11,232	36,960
Services	0.04	0.73	0.15	0.13	3.42	0.95	0.87	29,508	12,912	46,404
B: University										
Education	0.09	0.81	0.25	0.08	3.68	0.98	0.75	27,351	11,370	38,220
Arts	0.02	0.69	0.24	0.07	3.83	1.06	0.77	26,914	9,377	43,270
Humanities	0.08	0.68	0.25	0.12	4.09	1.03	0.83	31,258	13,571	44,631
Business	0.06	0.43	0.45	0.08	4.04	1.06	0.92	51,444	20,904	80,280
Social sciences	0.06	0.61	0.31	0.10	3.95	1.06	0.86	35,112	14,964	52,272
Psychology	0.02	0.77	0.34	0.04	4.19	1.07	0.88	31,356	12,036	41,712
Law	0.01	0.58	0.35	0.14	4.10	1.12	0.93	49,224	23,100	76,164
Natural sciences	0.07	0.52	0.69	0.28	4.27	1.09	0.83	35,779	18,826	52,330
Engineering	0.05	0.24	0.89	0.17	4.16	1.07	0.95	50,148	30,912	70,044
Ind. management	0.01	0.24	0.85	0.13	4.23	1.11	0.95	57,984	32,640	85,344
Architecture	0.01	0.65	0.66	0.07	4.15	1.07	0.91	36,780	21,924	49,248
Agriculture	0.00	0.59	0.46	0.24	3.89	1.05	0.86	37,716	16,116	55,812
Medicine	0.02	0.57	0.76	0.13	4.43	1.09	0.93	56,641	25,511	82,153
Other health care	0.01	0.80	0.52	0.14	3.90	1.08	0.89	35,433	16,067	51,071
Services	0.01	0.43	0.38	0.08	3.67	0.98	0.95	41,988	27,252	55,344
All	913,566	0.60	0.35	0.13	3.71	1.07	0.86	34,414	16,436	50,108

Note: Charateristics of the applications and degrees. Columns (1) to (6) use the universe of applications into polytechnics and universities in 2011–2013. Columns (7) to (10) use data on the e

Table 2: Average background variables in treatment and control schools

	Treatment schools		Control schools		Difference		
	Mean	sd.	Mean	sd.	Diff.	se.	p-value
Average matriculation grade 2011	3.769	0.359	3.799	0.392	-0.030	0.044	0.496
Share holding Bachelor/Masters degree in the neighborhood	0.191	0.099	0.195	0.086	-0.004	0.011	0.708
Share holding Masters degree in the neighborhood	0.103	0.081	0.104	0.069	-0.001	0.009	0.906
Average household income in the neighborhood	30,314	18,653	32,469	17,266	-2,155	2,171	0.322
Regional unemployment rate	0.098	0.044	0.089	0.043	0.010	0.005	0.065
Number of high schools	97		266				

Table 3: Updating Beliefs about Average Wages by Field

	% updating					
	↓	0	↑	na.	Mean	Obs.
			A: Polytechnics			
Humanities	0.18	0.55	0.15	0.11	-0.03	123
Arts	0.25	0.25	0.13	0.38	-0.20	8
Business	0.16	0.68	0.12	0.04	-0.05	135
Engineering	0.09	0.64	0.21	0.05	0.13	118
Agriculture	0.26	0.57	0.13	0.04	-0.14	23
Nursing	0.19	0.69	0.08	0.05	-0.12	278
Services	0.24	0.62	0.05	0.10	-0.21	156
			B: Universities			
Education	0.37	0.55	0.05	0.02	-0.33	167
Arts	0.21	0.49	0.23	0.07	0.02	61
Humanities	0.19	0.64	0.13	0.04	-0.06	189
Business	0.04	0.62	0.31	0.03	0.28	271
Social sciences	0.25	0.61	0.08	0.07	-0.19	104
Psychology	0.57	0.35	0.05	0.04	-0.54	109
Law	0.08	0.78	0.13	0.01	0.04	159
Natural sciences	0.24	0.56	0.11	0.09	-0.14	117
Engineering	0.08	0.62	0.27	0.03	0.20	128
Ind. management	0.00	0.50	0.40	0.10	0.44	10
Architecture	0.26	0.55	0.11	0.08	-0.17	38
Agriculture	0.00	0.56	0.44	0.00	0.44	9
Medicine	0.04	0.68	0.25	0.02	0.22	221
Other health care	0.34	0.52	0.09	0.05	-0.27	93
Services	0.25	0.60	0.11	0.04	-0.14	81
Total	0.19	0.62	0.15	0.05	2,598	

Note: XXX

Table 4: Belief updating by background characteristics

	Wage less than expected	Wage equal to expectations	Wage larger than expected
Men	14.1	63.8	22.2
Women	23.1	61.8	15.7
Not enough info	27.6	54.4	18
Enough info	15	66.9	18.1
Wage doesn't matter	15	63.2	21.5
Wage matters	20.7	62.4	16.9
No advanced math	22.4	61.4	16.2
Advanced math	15.1	64.3	20.6
Below median test score	19.7	62	18.3
Above median test score	19.1	63.2	17.7
Below median school	22.8	60.4	16.8
Above median school	17.9	63.6	18.5
All	19.4	62.6	18

Table 5: Applications by Field, Year and Treatment Group

	2011		2012		2012 vs. 2011		
					Odds	p-values	
	Control	Treated	Control	Treated	Ratio	stand.	rand.
	(1)	(2)	(3)	(4)	(7)	(8)	(9)
B: Universities							
Education	0.067	0.067	0.092	0.086	0.931	0.040	0.269
Arts	0.016	0.014	0.015	0.013	1.023	0.777	0.803
Humanities	0.091	0.087	0.085	0.083	1.017	0.607	0.740
Business	0.056	0.053	0.061	0.061	1.047	0.244	0.452
Social sciences	0.049	0.055	0.046	0.050	0.953	0.241	0.488
Psychology	0.019	0.019	0.019	0.018	0.969	0.640	0.754
Law	0.012	0.014	0.013	0.013	0.896	0.178	0.208
Natural sciences	0.101	0.104	0.088	0.088	0.971	0.333	0.563
Engineering	0.076	0.078	0.066	0.063	0.938	0.069	0.316
Ind. management	0.010	0.011	0.009	0.009	0.923	0.397	0.455
Architecture	0.008	0.004	0.007	0.005	1.319	0.033	0.070
Agriculture	0.004	0.005	0.004	0.004	1.003	0.984	0.986
Medicine	0.015	0.015	0.017	0.018	1.032	0.672	0.627
Other health care	0.010	0.012	0.011	0.012	0.898	0.208	0.278
Services	0.008	0.009	0.010	0.010	0.935	0.497	0.587
Test of homogeneity of odds-ratios						0.009	0.512

Note: Columns 1 to 6 report the distribution of applications from the treatment and control high-schools in 2011 (pre-treatment) and 2012–2013 (post-treatment). Column 7 reports odds ratios for the change between years 2011 and 2012 by treatment status and column 10 between years 2012 and 2013. Columns 8 and 11 report p-values for the odds ratios using the standard methods. Columns 9 and 12 reports p-values from randomization inference.

Table 6: The effect of the information on application behaviour and enrollment: Differences-in-differences estimates

	All	Men	Women
Enrolled	-0.007	-0.014	0.011
	(0.009)	(0.018)	(0.014)
	[0.544]	[0.536]	[0.392]
log Mean Wages	-0.011	-0.008	-0.007
in the program	(0.007)	(0.008)	(0.008)
where enrolled	[0.088]	[0.364]	[0.480]
log Mean Wages	-0.003	-0.004	-0.000
of the application	(0.004)	(0.006)	(0.004)
portfolio			
Log Expected value	0.023	0.052	0.001
of the application	(0.025)	(0.040)	(0.004)
Portfolio	[0.448]	[0.216]	[0.848]

Note: ITT estimates, robust standard errors (in parantheses) and randomization inference p-values [in brackets] using 250 replications.

Table 7: Belief updating and application behavior

	Wage less than expected	Wage equal to expectations	Wage larger than expected	Total	χ^2-test p-value
Applied to first choice program	67.67	76.17	75.83	74.42	0.031
Took entrance exam	43.97	57.44	52.13	53.81	0.001
Accepted to program	16.81	22.18	25.59	21.73	0.073
Enrolled	14.22	20.39	20.39	19.85	0.027
N	232	726	211	1,169	