Educational choice and information on labour market prospects: Evidence from a randomised field experiment*

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Abstract

We examine the impact of an information experiment conducted in 97 randomly chosen Finnish high schools. Roughly 5,000 graduating students were given information on the labor market prospects related to detailed educational degrees. Our analysis exploits a national application register that covers the entire population of the students graduating from the Finnish high schools. These data contain information about the schools the students applied to, where they were accepted and where they eventually chose to study. Similar information is available for both treatment and control schools for the year prior to the treatment. The results suggest that the intervention did lead to information updating but did not affect the application or enrollment patterns of Finnish high school students on average. However, male students from low educated backgrounds did switch to applying to programmes that they were positively surprised about.

Abstract JEL codes: I2, J24 Keywords:

1 Introduction

The level and content of ones education is perhaps the most important investment decision that a typical person makes during her lifetime. Thus it is not surprising that many policy makers, researchers and parents worry about the students ability to make the right decisions. There appears to be widespread concern that many individuals make suboptimal choices in the sense that they do not acquire the type of skills that are demanded in the labour market.

Often these suboptimal choices are blamed on lack of information about the employment and earnings prospects associated with different levels and fields of education. Because of these concerns many governments have implemented schemes to inform students about the average earnings and employment rates associated with different degrees.[1] Yet

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[1]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 at http://www.census.gov/hhes/socdemo/education/data/acs/infographics/

the mere fact that some educational choices do not appear to maximise lifetime earnings does not necessarily mean that they are based on incomplete information. Educational choices also reflect preferences. For example, certain degrees that do not offer good labour market prospects may still attract substantial amount of applications with their consumption value. Hence, whether lack of information is actually causing the alleged suboptimality of educational choice is still very much an open question.

This paper is an attempt to examine the role of information in shaping educational choice. We ask whether providing detailed information about the labour market prospects associated with alternative education degrees affects the way in which Finnish high-school students apply to further education. In order to answer this question, we conducted a field experiment that exposed roughly 5,000 graduating students in 97 randomly chosen high schools to information on the differences in incomes and employment prospects associated with different educational degrees. We evaluate the effect of this information intervention on the application behaviour by following students from the randomly selected treatment schools and the full population of remaining control schools in a national registry of higher education applications and allocations. These data contain the full population of applications to Finnish universities and polytechnics.

To the best of our knowledge, this paper is the first attempt to examine the effect of information on labour market prospects on educational choice at the post-secondary level. While previous literature has explored the effect of information on educational attainment in developing countries and on aspirations and plans in some developed countries, there is still lack of evidence on whether the choices that the students make after finishing secondary school are well informed. This applies in particular to the choice of the field of study which has been shown to be an important determinant of labour market success.

The fact that post-secondary educational choice is important for lifetime earnings is very clear from aggregate data. For example, in Finland the gap between log annual earnings between men who majored in medicine and in general education is approximately 0.659, which is nearly as large as the 0.700 difference between university and high school graduates and quite similar to the numbers reported by Altonji, Blom, and Meghir (2012) for the United States. Moreover, there is evidence that working in a job that does not match ones field of study is common and entails a significant wage penalty even after controlling for the level of education. Robst (2007) estimates this penalty to be on average 0.11 log points in the United States whereas Nordin, Persson, and Rooth (2010) show that the penalty in Sweden is as high as 0.32 log points. Hence, many individuals forgo potentially large earnings by choosing lower paid careers.

There is evidence that suggests that post-secondary educational choices are based on imperfect information. Many surveys show that earnings expectations of university students are biased in industrialised countries.[2] Misguided choices may also be an important factor behind the prevalence of late graduation in the industrialized world. For example, Finnish university students switch between fields of study very frequently. Indeed, 23 percent of all university applicants are already students in another program. Due to frequent changes and drop-outs only 49 percent of the starting university student cohort will graduate within 7 years. Not surprisingly, the Finnish university students graduate at the average age of 29, which is the third highest among all OECD countries.

However, the previous literature has not been able to establish whether these allegedly suboptimal patterns in educational choice are actually caused by lack of information. There are some examples of experiments where information about real returns to edu-

[2]See Betts (1996); Carvajal et al. (2000); as well as Dominitz and Manski (1996) for the United States and Brunello, Lucifora, and Winter-Ebmer (2004) for Europe

cation is provided to high school students but these studies have mostly taken place in developing countries where the most pressing problem is the low level of attainment rather than the type of education chosen at the tertiary level. 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. The long-run effects of providing information about the returns to education in a developing country context have been studied by Jensen (2010) who ran an experiment in Dominican schools and found that providing accurate information about the returns increased educational attainment by 0.20 years.

So far we know very little about the effects of information on actual choices of students in developed countries. 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 about future earnings. Furthermore, there is evidence that suggests that many students are misinformed about the true costs of higher education (C. M. Hoxby and Avery (2012)) and that providing correct information on those costs can influence enrollment (Bettinger, Long, Oreopoulos, and Sanbonmatsu (2009); C. Hoxby and Turner (2013)). However, none of these papers examine the effect of information about the returns to education on the actual post-secondary educational choices.

In this paper we exploit data from a field experiment in which the students in our treatment schools completed a survey and sat through an obligatory 45 minutes class given by the schools student guidance counselors. These classes are the most important channel through which the Finnish educational system informs students about issues related to educational choice and transition to the labour market. During the intervention the students listened to a short presentation by the counselor on the differences in incomes between different post-secondary degrees which was prepared by our team of researchers. In the survey the students were asked about their preferences, expectations, and personality traits. Importantly, the survey also included information about the distribution of earnings, employment rates and the most common occupations among the population of 30-34 year old persons by over 60 educational degrees. Furthermore, the students were given the supplementary material at the end of the class, so that they could consult it later.

We can use the responses to our survey to study whether providing information leads to similar belief updating as has been observed in previous studies. However, in order to examine the effect of this information intervention on actual post-secondary educational choice we exploit the national registers of applications where all the applications to the tertiary level institutions in the country are registered. In these data, we can identify the students from our treatment schools and the whole population of the rest of the schools as a control group. The registers contain information on all the applications that the students file as well as the entrance examination that they participate in. In the Finnish system the students can apply up 11 programs at a time and can accept a slot in only one programme. The registers record all the programs that the students are accepted to and their final choice of field of study.

The responses to our survey suggest that providing information on the labour market prospects does lead to information updating among Finnish high school students. Approximately third of the respondents declare that they are surprised about the actual expected earnings and employment levels. This belief updating is also correlated with choice behaviour since the students who report to be positively biased in their expectations are more likely to change the field that they apply to from the one that they report in our survey than the rest of the treatment school students.

However, the comparison of students from our treatment and control schools reveals that, on average, the information intervention does not lead to any detectable changes in the application behaviour between treatment and control schools. Also enrollment is on average not affected. The only group that shows any response to the intervention are boys from low-educated backgrounds, approximated by the average educational attainment in the immediate neighbourhood of the student. This subgroup applied more to fields where they reported to be positively surprised about the actual level of expected earnings. Also the expected average income of their application portfolio increased as a result of the information intervention. However, these changes in the applications patterns did not lead to any changes in actual enrollment.

We argue that these results call in question the role information in shaping the observed 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. While the information may affect the application behaviour of certain sensitive subgroups, the actual enrollment is not affected by this intervention. In a context where obtaining entry to popular programmes 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 that was 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 used in our analysis and reports the results of the experiment and 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. 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]

[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.

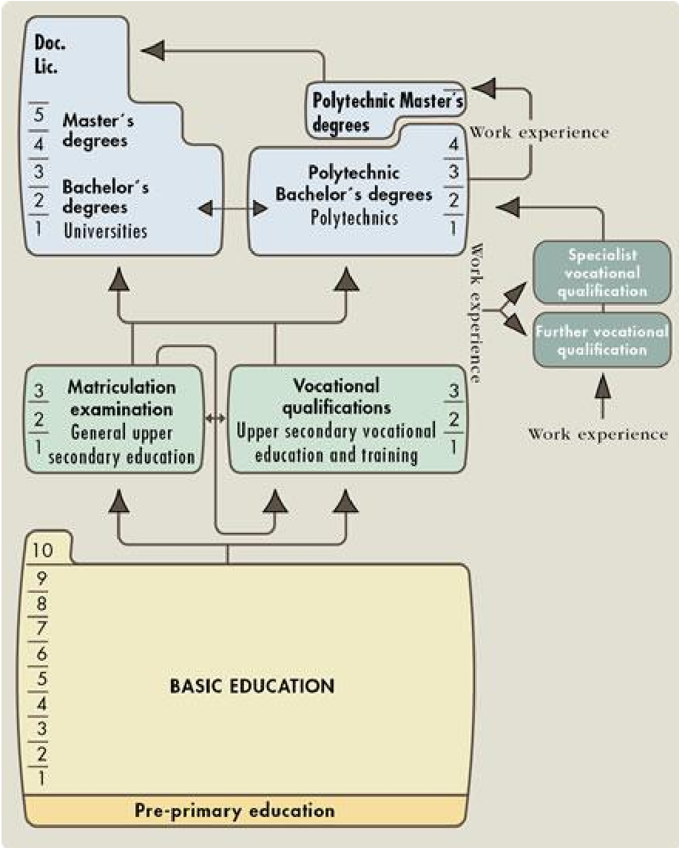

Figure 1: Finnish educational system

The three-year general upper secondary 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, one foreign language, and either mathematics or science and humanities exam. 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 approximately 75% of the students apply the year they graduate from upper secondary school. The Finnish tertiary education system consists of two kinds of tertiary 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 admission system is highly decentralized and, unlike in other European countries, is not based solely on grades in school certificates. Instead, the Finnish institutions are free to set their own admission criteria and almost all institutions use entrance examinations or a combination of entrance examinations and points awarded based on the standardized grades in the matriculation examination. Entrance examinations are designed by the universities and are typically based on material that is not taught in upper secondary schools.

The applicant can apply up to 11 post-secondary programmes (7 university programmes and 4 polytechnic programmes). However, 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 slots per programme is determined in the joint negotations between the universities and the ministry of education on annual basis. Since the applications are usually very unevenly distributed across university programmes, the average acceptance rate is low. In year 2009, only 17% of the applicants were accepted on average. However, there is considerable variation across fields with sciences accepting 34% whereas small fields such as theatre and arts accepting only 3% of the applicants.

Admission to universities typically gives a right to study until the masters degree. 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 masters and advanced degrees. This creates the incentive for the universities to attract the best available students.

2.3 Post-secondary degrees in Finland

The choice of post-secondary programme is an important one in the Finnish context. Programmes differ in the kind of labour market prospects that they provide and in the kind of applicants that they attract. Table 1 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 matricualtion exam, the average grade in the matricualation exam and its standard deviation. Moreover, the table provides summary statistics on wages and employment rates among 30-34 year olds across fields drawn from the same information package that was given to the students in the treatment schools.

As can be seen from table 1, nursing degrees provided by the polytechnics attract most applications followed by natural sciences which also seem to attract, along with engineering and medicine, the most mathematically orientated applicants. The applicants to natuaral sciences also have the highest average grades in the matricuation exam whereas the applicants to polytechnic engineering degrees have the lowest grades.

Importantly, wages vary considerably across degrees. Graduates from university level engineering degress and medicine tend to earn on average twice as much as the graduates from the popular fields of health and welfare and education. Employment prospects are also, if anything, positively correlated with average wages. Employment rates at age 30-34 in engineering and medicine are well above 90 percent. Hence, based on this information that was given to students in a more detailed format, the choice of major in post-secondary education should have major implications for ones labour market prospects.

3 Intervention

In this section, we describe the way in which the experiment was designed. In particular, we focus on the draw of the treatment schools. In addition, we 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 upper secondary schools was evaluated against Statistics Finland information on recent school closings, openings and merges. These changes reduced the number of schools by 11. We also dropped evening- and adult upper secondary schools, and other speciality schools such as religious institutes, resulting in a reduction by a total of 32 schools. We further excluded the only upper secondary school in the autonomous Åland archipelago and another school operating in Spain for Finnish students located there, as well as any Swedish language upper secondary 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 upper secondary schools in the continental Finland.

The schools were stratified by province and their ranking in the average matriculation examination grades during 2008-2010. The average grade was calculated based on four 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. Student level data from years 2008-2010 was used in calculating this average.

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 2 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.

To confirm that the treatment and control groups did not differ significantly in terms of their average matriculation exam grades, simple t-tests were run. The results of these tests are reported in the first row of table 2 and they confirm that no significant differences existed nationally. We also ran this test in each province separately without finding significant differences in matriculation grades in any single province.

To further assure that the randomisation worked well we obtained information on the background characteristics of the students using Statistics Finlands geocode data that reports average demographics by 250m x 250m squares in Finland. 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 labour force. As is clear from table 2, none of these background variables differ significantly between treatment and control regions, with the borderline exception of regional unemployment. To us, these results indicate that the randomisation 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 in the study, and one refused to participate due to the absence of student guidance counselors. 33 schools never responded to our invitation.

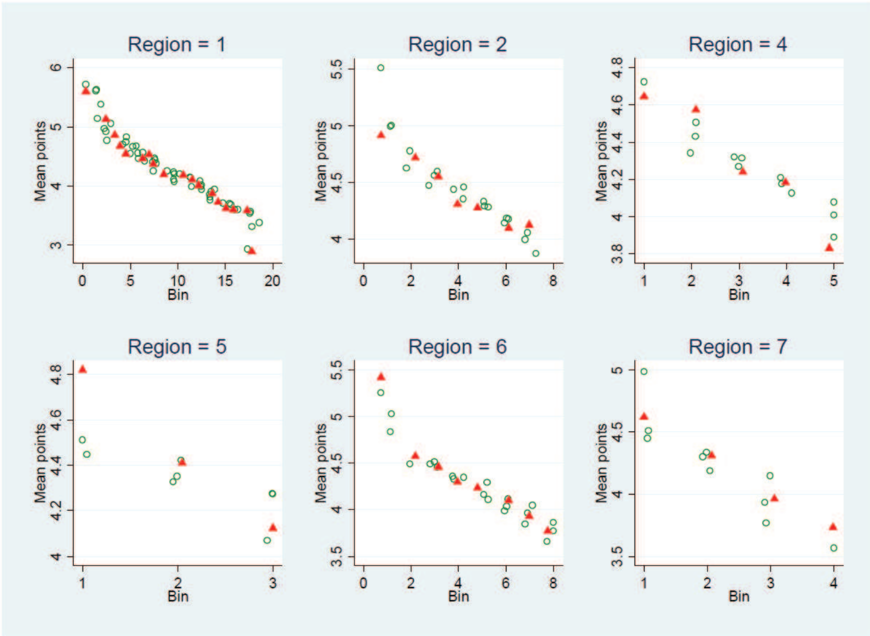

Figure 2: Illustration of the randomised block design

The participating sample included a total of 63 schools with altogether 5,323 students. Complete 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 general upper secondary school curriculum. In total, students at Finnish secondary schools have to take one mandatory course (38 lessons typically spread out over 3 years) in counseling. Typically these classes would be the most natural channel through which to distribute information about the labour market prospects offered by different post-secondary degrees. Informing students about career choices is one of the most important tasks of a guidance counselor in the Finnish educational system.

Finnish student guidance conselors are well trained by international standards. Counselors are teachers who have taken the guidance counselors training at the University of Jyväskylä, Finland. This is extra training for teachers and consists of approximately one year of full-time study and the prequisite for this training is a Master's degree and a teacher qualification from a university.

3.3 The intervention

During the fall of 2011 we communicated with 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 a weekly basis 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 would therefore expect the information package to affect the application behaviour in

2012.

The information experiment was implemented by doing a survey during class for high school seniors about their post-secondary education plans and factors affecting their choices, including economic considerations as well as personality and other non-economic factors.[4] The survey provides information on students beliefs about average earnings in the fields that they are interested in. More importantly, however, we can evaluate how the information provided in the course of this study affects the students decisions to apply to various programs. Students were handed information regarding the earnings and employment of recent graduates from various programs based on the most current register data from Statistics Finland. In addition, student guidance counselors delivered a short presentation on the value of educational degrees in the labor market prepared by our team of researchers.

English language version of the information packages is included in the appendix of this paper. As can be seen from the appendix, the package uses both graphical and numerical presentation of the income distribution. Furthermore, the package also lists the most typical professions associated with the educational degrees.

4 Survey evidence

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 labour market prospects associated with different educational choices, and on which sources they relied for such information. Altogether 3,418 students participated in the survey. This represents 64% of the last year students in the schools that complied with the information experiment. Out of these 3,418 students 2,301 (67%) gave us the permission to link their survey answers with register information on their actual application decisions in the applications registers. We were able to link 1,169 survey respondents to their actual application data.

In this section, we present some results based on our analysis of the survey responses. In particular, the survey enables us to examine differences in the aspirations and the amount of information that the students had by gender and social background. Furthermore, we study whether our information intervention was associated with similar kind of belief updating as has been observed in previous studies (e.g. Wiswall and Zafar (2011); McGuigan et al. (2012); Oreopoulos and Dunn (2013)). Finally, the possibility of linking a subgroup of respondents to information on the actual choices made in the application process enables us to examine whether belief updating in correlated with changes in the application behaviour.

4.1 Aspirations

The general upper secondary 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 have not such plans the rest stating that they are unsure. Furthermore, 60% state they plan to apply directly after finishing with the

[4] The framework was tested in a pilot high-school, and lessons learned in the pilot were incorporated in the final set-up. The pilot results confirmed the relevance of labour market information for graduating high-school students.

matriculation examination. Hence, practically none of the students in our treatment group have no intentions of continuing their studies after finishing high school.

However, the kind of institutions that students plan to apply to differ clearly by gender and parental background. 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%). There are even more striking differences in the level of aspirations by parental background. These differences are revealed in figure 3 where we plot the level of aspirations by gender and parental background. Figure 3 shows that while university is the most popular destination among all students, the students from highly educated families are much more likely to state that they are going to apply to a university (66%) than students from low educated families (46%). This difference in the popularity of the university option by family background is equally large among boys and girls.

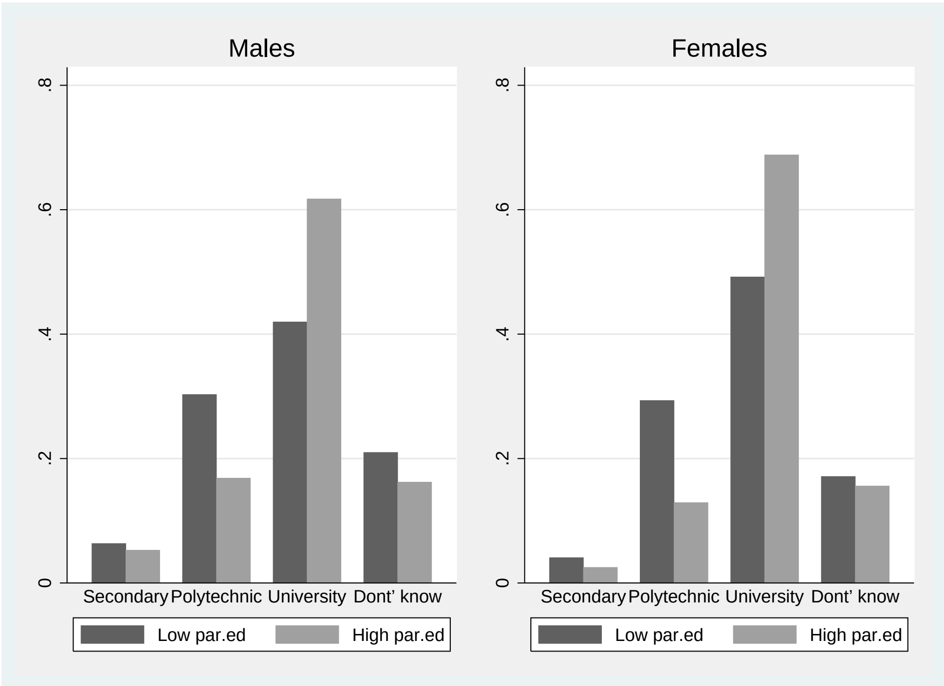

Figure 3: Shares of survey respondents by where they plan to apply after high school by gender and parental background

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

As our goal was to inform the students about the labour 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. In the survey, we asked about how well informed the students thought they were. Approximatley 60% of the students reported that they felt that they were well informed. Again, the level of information differed by gender, with girls less (56%) likely to be well informed than boys (66%), and by parental background, with those from low educated families being less likely to state that they are well informed (59%) than the students from high educated families (63%). Interestingly, this difference in the level of information by family background was only detected among boys whereas among girls the family background was not correlated with the level of information.

There were also interesting differences by family background in the sources that the students used to obtain information. In the survey the students were asked to state from which sources they have obtained 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.

Largest differences arose in the use of parents as a source of information. Whereas approximately half (51%) of the students from highly educated families stated that they relied on their parents for information about post-secondary education, among the students from low-educated families this share was only 28%. Figure 4 plots the use of information sources by student gender and family background. This figure also reveals that the students from low-educated families rely more on student guidance counselors than the students from high educated families. Therefore, we would expect the information given by the counselors to be more effective among students from low-educated backgrounds.

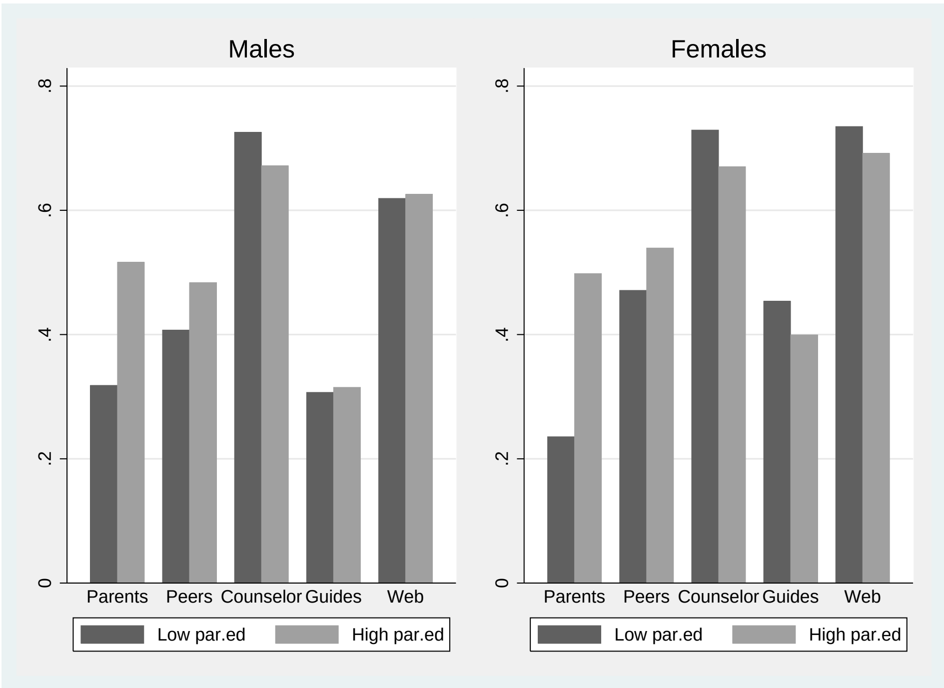

Figure 4: Sources of information by gender and parental background

4.3 Belief updating and choice

Previous information experiments on educational choice have mainly focused on belief updating. Using our survey we can try to replicate some of the findings in the previous literature. More specifically, we asked the students to name the programmes they were planning to apply to in preference order and check the average earnings and employement rates of that degree from the supplementary material that was given to the students as a part of our experiment. Figure 5 plots the distributions of average monthly earnings of the first ranked programmes by gender and family background. As can be seen from 5, the average monthly earnings of the programmes where the students are planning to apply to vary considerably by gender and family background. More precisely, girls and students from low educated families are planning to apply to lower paid careers.

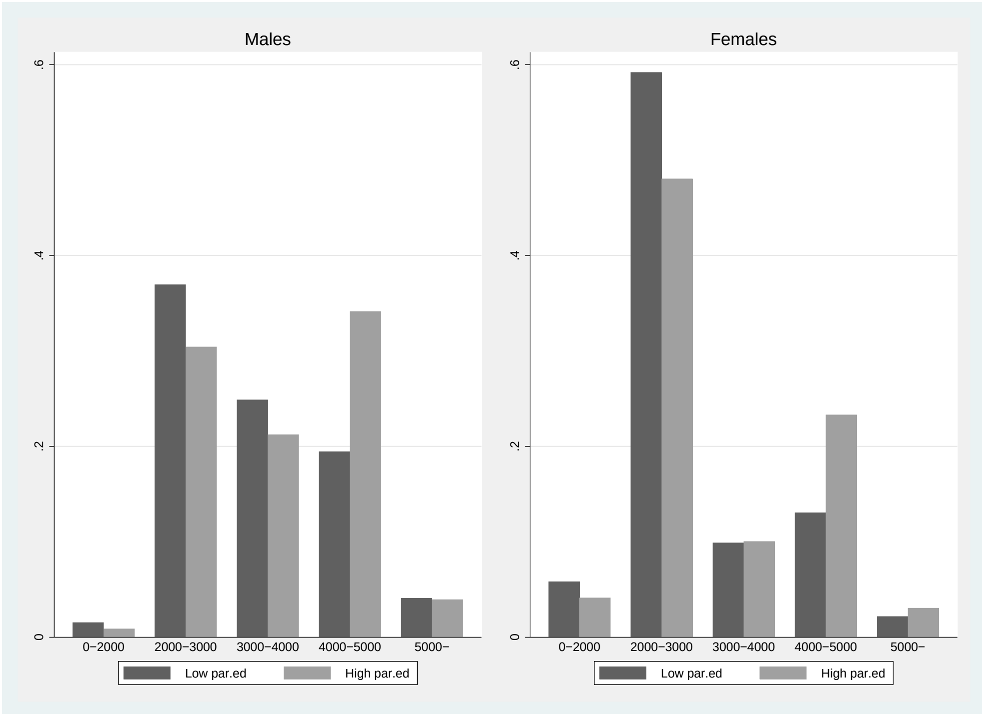

Figure 5: Average monthly earnings of the preferred programmes by gender and parental background

We then asked the students whether they were surprised about the actual level of average earnings among the graduates from the programme that they ranked as their first choice. 35% of the respondents replied that they were surprised. Negatively and positively surprised respondents were almost evenly distributed with shares 16% and 19%, respectively. However, among boys the share of negatively surprised students was slightly larger (19%) than the share of positively surprised students (14%) where as for women these differences went the opposite way with only 14% stating that they were negatively surprised and 22% stating thah they were positively surprised.

As was explained at the beginning of this section, a subgroup of the respondents gave us the permission to link their survey 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 survey (in November 2011) and the application deadline (in April 2012).

In table 3 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 3, 74.5% 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. Fraction taking the entrance exam in the field that they reported as their first choice was 53.8%

and the fraction eventually accepted was 21.7%. Fraction accepting the offer was only slightly lower 19.9%.

Interestingly, however, the students who were negatively surprised about the average wage level of the graduates from the program that they were planning to apply to at the time of the survey 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 persits in the fraction accepted and eventually enrolling in their November 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 3 is naturally based on a selected sample. Intentions and beliefs data was only collected from the treatment group. Also the sample gets selected in several stages. First, the student counselor that we contacted had to agree to implement our survey. Second, the student had to be in class and respond to the survey questions. Third, she had to allow us a permission to link her responses to register data and provide proper name information that makes linking possible. Finally, the student had to apply to university-level education so that we could find her applications from the register. Hence the data in table 3 cannot be viewed as a representative sample from a population of high school students. Still there is no obvious reason why the numbers would be severely biased to any particular direction. We therefore consider the numbers in table 3 as at least suggestive evidence that students react to new information on wages. Those who are surprised of low earnings are more likely to revise their plans. Possibly the reaction is larger in the group that responded to the survey, and who therefore had probably at least read through the information, than in general student population.

5 Data

The estimation of the effects of our information intervention is based on the comparison of the application behaviour of the treatment and control school students. This is made possible by the detailed register data available to researchers. Educational applications and final study choices are recorded in centralized systems (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. These registers also allow researchers to follow the entire educational paths of the treatment and control groups over time, and to keep track of those students who initially failed to obtain a place to study in 2012. Most other countries do not have information on failed applications or the possibility to observe graduations, program switches and drop-outs, making the Finnish data particularly valuable.

The register data identify for each graduating high school student the set of university programs and higher vocational education programs they applied to, which ones they were accepted into and which one they eventually chose to enter. For higher vocational education 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 does not record the points obtained in that exam as that is a university specific tool for evaluating students. Based on the HAREK- and AMKOREK data, roughly 86 percent of the 2012 high school graduates applied to at least one higher education program and 64 percent to at least one university program. Only 35 percent were accepted to a program after the application process, and 20 percent were accepted to a university program. These numbers are in line with those generally reported by the Ministry of Education.

6 Estimation

The estimation of the treatment effects of our information experiment is hampered by at least two important problems. First, we are interested in the effect of the information intervention on the application *portfolio* of the applicants. This is because the applicants choose up to eleven prorgammes that they apply to. Receiving information may affect the choice of the programmes that go into the portfolio in various ways. Unfortunately, it is a priori unlcear how our intervention should affect the content of the application portfolios. Second, the fact that the randomisation is done at the school level while the application portfolio choices are done at the individual level leads to the well-known clustering problem. Since the application behaviour is likely to be highly correlated at the school level, this problem is potentially serious in our application. In this section, we describe how deal with these problems in our empirical analysis.

6.1 Portfolio choice

The first problem that we face is that it is unlcear a priori how the information should affect the application portfolio.[5] This difficulty follows from the fact that in the Finnish system students can apply to a maximum of 11 programs out of total 658 programs. Clearly analyzing each possible combination of application separately is not feasible.[6]

Our solution to this problem falls into two approaches. The first approach is to analyze the changes in the distribution of applications across programmes. We start by examining whether the intervention led to any detectable changes in the overall distribution of applications across programmes. We do this by comparing the changes in the distribution of applications between 2012 and 2011 in the treatment and control groups and testing for any statistically significant changes in the distribution with a simple likelihood ratio test. This test is basically equivalent to running differences in differences Poisson regressions where number of applications per programme are regressed on programme, year 2012, and the treatment group dummy. The test for changes in the distribution of applications is equivalent for testing the joint significance of the third order interaction of programme, year 2012, and treatment group dummies. The advantage of this approach is that is that it doesn't rely on any assumptions about the potential direction of the effects of our intervention.

While this approach analyzes the distributions of applications at the programme level, we can also analyze the effect of intervention on behaviour at the individual level, if we calculate summary statistics for the portfolios that characterize the earnings implications

[5]Existing theoretical literature is not very helpful in this respect. Although problems of this level of complexity have been analysed, the literature offers little guidance in terms of characterising the optimal strategy. Chade and Smith (2006) analyse the general problem and Chade, Lewis, and Smith (n.d.) analyse and characterise the optimal strategies in a simplified case with only two schools.

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

of the portfolio choice. The problem with such measures is that we have no way of predictong how our interventtion should change the composition of the application portfolio.

One fairly innocuous sounding prediction is that more accurate information should increase the expected earnings associated with the application portfolio. We formulate the expected income associated with the applications of each individual that we formulate 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 accepted 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 accepted and receive E_1 or be rejected and get her outside option (normalized as zero). The probability that she is accepted is p_{i1} and thus her expected income is $p_{i1}E_1$. If instead she applies to two programs, she can be accepted to her first choice and receive E_1, be rejected from the first choice but accepted 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. We can then analyse the effect of the intervention on the expected value of the portfolio at the individual level by running differences-in-differences regressions of the following form:

$$V_{its} = \alpha + \beta_T D_s \times \text{Post}_t + \gamma D_s + \delta\text{Post}_t + \epsilon_i \tag{2}$$

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.

However, it is also important to highlight the limitations of this measure. First of all, the measure may be sensitive to the ranking of applications which we do not observe in the data. We try to deal with this potential sensitivity by experimenting with different rankings such as using average earnings (in the order from the largest to the smallest) and likelihood of being accepted (from smallest to the largest) as for ranking the applications of an individual student. Second, this measure only approximates expected income, while the students supposedly maximise 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. We also lack any valuation for the outside option of the applicant which should lead us to systematically underestimate the value of the portfolios. Finally, 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 material required for 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 a measurement error.

One can also exploit the survey that we conducted with the intervention to portfolio measures that rely on reported belief updating. Our survey revealed that some of the respondents in the treatment group reported to be positively and negatively surprised about some specific fields of study. This information allows us to calculate the share of positively and negatively surprised applicants for each programme mentioned in the survey responses and to rank the programmes based on the average updating on beliefs among the treatment group students. This average updating is calculated by assigning -1 for negatively surprised respondents, 0 for no surprises, and 1 for positive surprised. Assuming that a priori beliefs are identically distributed in the treatment and control group, one would expect the information intervention to make the treatment group students more likely to apply to fields that they are positively surprised about and less likely to fields that they are negatively surprised about. Below, we analyse whether the treatment group applicants are more likely to include and drop programmes from their portfolio in line with general belief updating behaviour.

6.2 Randomisation at the school level

The second major problem that we have to deal with when estimating the effects of the interventions follows from the fact that the information treatment is constant at the school level while our outcomes are defined either at the programme or individual level. This leads to a familiar clustering problem since application patterns are very likely to be correlated at the school level. This is a common problem in field experiments in education where school often is the most natural unit of randomisation.

While cluster-correlated Huber-White standard errors would be the typical approach to deal with this programme, there is reason to believe that this adjustment would perform poorly in our application. First of all, Bertrand, Duflo, and Mullainathan (2004) show that this approach is sensitive to a small number of clusters. Second, it seems likely to that this problem is particularly severe since the application behaviour should strongly affected by peer behaviour and geographical location which are all school level variables.

An alternative approach to deal with this problem, suggested by Rosenbaum (2002), is randomisation inference. To illustrate this approach, consider the regression (2) and denote with $\{P_s\}$ the set of all possible assignments from the randomisation process over schools. An individual assignment P_s can be called a placebo random assignment. Now, consider a version of regression (2) where the treatment assignment is replaced with the placebo random assignment:

$$V_{its} = \alpha + \beta_P P_s \times \text{Post}_t + \gamma P_s + \delta \text{Post}_t + \epsilon_i \tag{3}$$

Naturally $E(\beta_P) = 0$, since P_s is simply a randomly assigned placebo.

With a sufficient number of replications of the regression (3) we can obtain an empirical c.d.f of estimator $\hat{\beta}_P$. Denote this distribution with $F(\hat{\beta}_P)$. We can now perform a hypothesis test that accounts for the clustering structure of the data by checking if our measured treatment effect, $\hat{\beta}_T$ falls in the tails of the distribution $F(\hat{\beta}_P)$. The hypothesis $H_0 : \hat{\beta}_T = 0$ can be rejected with a confidence level of $1 - \alpha$ if $\hat{\beta}_T \leq F^{-1}(\frac{\alpha}{2})$ or $\hat{\beta}_T \geq F^{-1}(1 - \frac{\alpha}{2})$.

7 Results

In this section, we present the effects of our information intervention on the application behaviour of the Finnish high school students as well as on the final allocation of study slots. We focus on the effect of the information on the overall distribution of applications across fields and on the composition of the portfolios at the individual level. As our survey evidence strongly suggests that responses to the information may vary by gender and social background, we estimate the effects also separately by subgroups.

7.1 The distribution of applications by field

In table 4, we have plotted the shares of appplicants to fields of studies in both universities and polytechnics by treatment/control group and year. If one were to trust the randomisation naively, one could simply compare the distributions of applications across fields in treatment and control groups in year 2012 and test for significant differences in the distributions. The hypothesis that the distributions are the same is easily rejected. However, having access to baseline year 2011 data allows us to test whether there were significant differences in the distributions of applications across treatment and control schools already before any intervention took place. The hypothesis that distributions are equal in 2011 is also easily rejected. This suggests that the application behaviour is sufficiently strongly correlated within schools that any random division of schools into two groups would show significant differences in application behaviour.

In column 6 of table 4, 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. Hence, these odds ratios can be interpreted as differences-in-differences tests for significant changes in applications behaviour. Column 7 of table 4 reports the standard p-values of these odds ratios and column 8 reports the p-values that are corrected for within school clustering by randomisation inference as was explained in the previous section. As can be seen from these numbers, randomisation 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 jointly not different from one, cannot be rejected when accounting for within school clustering.

The tests based on table 4 are very general and impose practically no structure on the data. However, our survey results suggest that our intervention did lead to changes in the beliefs of the students. In table 5 we have ranked the fields of studies in polytechnics and universities by average belief updating revealed in the survey responses. The average updating is calculated by assigning value -1 for negative, 1 for positive, and 0 for no surprises. Table 5 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.

Based on this evidence on belief updating, presumably a more powerful test or the effects of the intervention would be to test whether the intervention shifted applications towards fields that were associated with positive belief updating. In figure 6 we have plotted the odds ratios of changes in applications against average belief updating in fields of study. The figures are plotted by social background and gender and they reveal that whereas girls' behaviour does not seem to respond in line with belief updating, the applications of boys from less educated areas seem to shift towards fields that were associated with positive belief updating and, somewhat counterintuitively, boys from highly educated areas apply more to fields that were associated with negative belief updating.

7.2 Individual level analysis

A more natural way to test for the effects of the intervention than the analysis based on table 4 is to test for changes in the application portfolios at the individual level. In panel A of table 6 we present results from differences in differences regressions where we use the expected value of the application portfolio as the dependent variable. The derivation of this variable was explained in the previous section and is based on the average earnings of

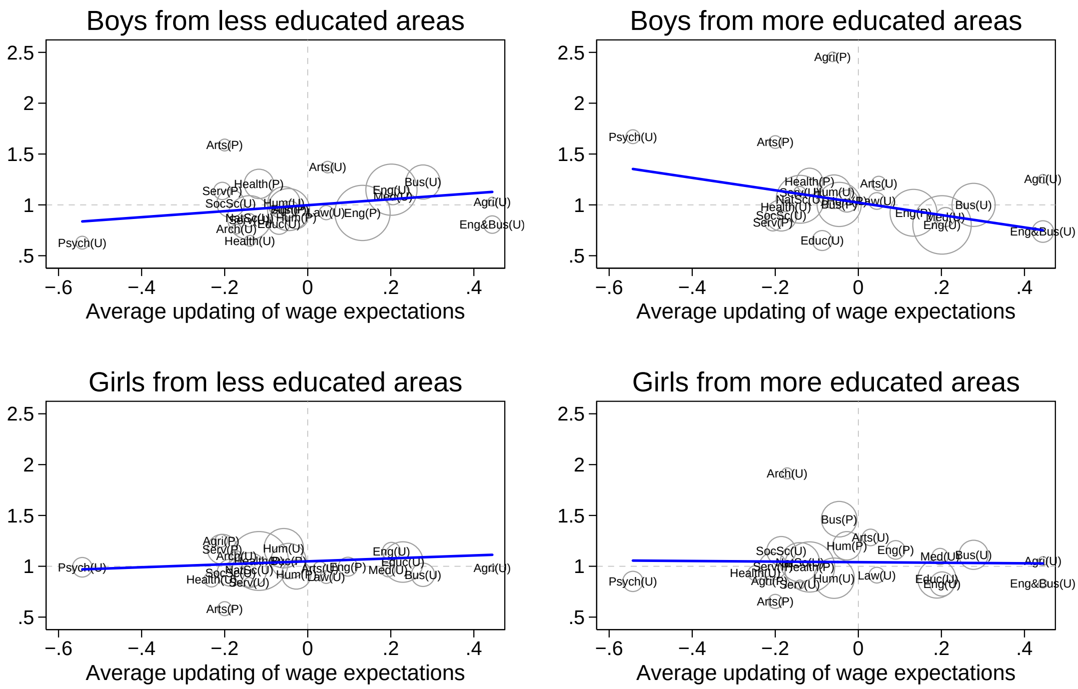

Figure 6: Differences in differences odds ratios and average belief updating

the chosen fields weighted by individual specific predicted probabilities of gaining entry to the chosen fields in the portfolio.

The effect of the intervention is estimated by the interaction of the treatment group and post-treatment dummy. As can be seen from table 6, the intervention did not affect the expected value of the application portfolio on average. The effect, 0.032 log points, is tiny and not significant at any conventional levels.

Panels B, C, and D of table 6 break the expected value of the portfolio into its components. These results reveal that the intervention did not increase the number of applications in the portfolio on average. Nor did it lead the average student to apply to fields where he or she had higher had a higher probability of gaining entry or where average wages would be simply higher.

The only subgroup that seems to respond to the intervention according to the results in table 6 are the boys from less educated areas. The expected value of their application portfolio increases by 0.14 log points which is a statistically significant effect. This increase in the expected value of the portfolio of these boys seems to come both from higher probability of entry and from larger average earnings.

Figure 6 revealed that, at least among the boys, the changes in application patterns were correlated with the average belief updating associated with the fields of study. In table 7 we present results from regressions where we attempt to test for the effects of our information on the shifts in application patterns more formally. More precisely, in panel A of table 7 we use average surprise of the portfolio, i.e. the average updating related to fields of studies in the portfolio, as a dependent variable in the same kind of differences in differences regressions ain previous tables.

Again, the results in table 7 show that, on average, the intervention did not shift the applications towards any direction that would be correlated with belief updating.

However, as figure 6 suggested, boys from less educated areas do seem to respond to the intervention in ways that in line with belief updation. As panel A of table 7 reveals, the intervention increased the share of programmes that were associated with poisitive belief updating in the portfolios of boys that come from less educated areas. At the same time, however, the application portfolios of boys from highly educated areas shifted towards fields that were associated with negative updating.

The results in tables 6 and 7 tell us about the effects of the intervention on the application behaviour. In the context of the Finnish educational system where the most popular fields are heavily oversubscribed it is important to distinguish applications from the final allocation of study slots. In table 8 we present results on the effect of the information intervention on the number of programmes that the applicant is accepted to, on the probability of being enrolled in post-secondary studies after the application process has closed in 2012, and on the log average earnings in the programme that the applicant finally enrolled in. The effects in panels A, B, and C of table 8 are very robust zeros. Our information intervention apparently had no effect whatsoever on the actual allocation of study slots. Hence, any effects on beliefs and application behaviour that we detected did not transalte into effects on enrollment.

8 Conclusions

The alleged suboptimality of educational choice is a widely shared concern. Many commentators, politicians, and parents feel that students are not making the kind of choices that would prepare for a succesful entry into the labour market. Often the suboptimality of educational choice is blamed on the lack of information about the actual labour market prospects associated with alternative choices. In particular, the choice of the field of study in post-secondary education is thought to be especially ill-informed. However, since educational choice is also shaped by preferences, the role of information in explaining these allegedly suboptimal choices is an empirical question.

Here, we test the effect of providing correct information about the average earnings and employment prospects associate with different degrees on educational choice. This test is done by running a randomised field experiment were students in the treatment schools were given a presentation on the labour market prospects. We follow the application behaviour of both treatment and control group students by using the Finnish application register data.

Our results confirm the findings from the previous literature that these kind of information interventions do lead to belief updating. Roughly a third of our treatment group students 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 behaviour. In particular, the treatment group students that were negatively surprised about the labour market prospects associated with the field that they had ranked as their first choice 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 behaviour and especially on enrollment should make one skeptical about claims that this kind of belief updating would lead large changes in educational choice. We detect no changes in the application behaviour on average. The only subgroup whose appilcation behaviour seems to robustly respond to our information intervention are boys from low educated ares. These boys do apply more to fields with better labour market prospects and also to fields that were associated with positive updating. Still, we fail to find any effect on the actual enrollment for anyone.

Our results should be contrasted with the important studies that have been conducted with information interventions in developing countries. For example, Jensen (2010) finds that information decreases the probability of dropping out from high school in the Dominican Republic. An important difference between our setting and the one studied by Jensen (2010), apart from the obvious developing/developed country difference, is that the students in our study face a choice that is much more severly constrained than the choice of staying or dropping out of high school. The feasible set of fields of study where on can apply to is already restricted by past educational choices and achievement at the time of our information intervention. Moreover, as serious applications in our context imply important effort costs, such as preparing for and attending entrance examinations, it is likely that an information intervention targeted at high school seniors is too late to affect actual choice. Therefore, earlier interventions, or indeed a student guidance system that continuously reminds the students about the potential labour market implications of their choices, would be more effective in shaping application behaviour and enrollment.

References

Altonji, J. G., Blom, E., & Meghir, C. (2012). Heterogeneity in human capital investments: High school curriculum, college major, and careers. *Annual Review of Economics*, *4*(1), 185–223.

Bertrand, M., Duflo, E., & Mullainathan, S. (2004). How much should we trust differences-in-differences estimates? *The Quarterly Journal of Economics*, *119*(1), 249–275.

Bettinger, E. P., Long, B. T., Oreopoulos, P., & Sanbonmatsu, L. (2009). *The role of simplification and information in college decisions: Results from the h&r block fafsa experiment* (Tech. Rep.). National Bureau of Economic Research.

Betts, J. R. (1996). What do students know about wages? evidence from a survey of undergraduates. *Journal of Human Resources*, 27–56.

Brunello, G., Lucifora, C., & Winter-Ebmer, R. (2004). The wage expectations of european business and economics students. *Journal of Human Resources*, *39*(4), 1116–1142.

Carvajal, M. J., Bendana, D., Bozorgmanesh, A., Castillo, M. A., Pourmasiha, K., Rao, P., & Torres, J. A. (2000). Inter-gender differentials between college students' earnings expectations and the experience of recent graduates. *Economics of Education Review*, *19*(3), 229–243.

Chade, H., Lewis, G., & Smith, L. (n.d.). Student portfolios and the college admissions problem.

Chade, H., & Smith, L. (2006). Simultaneous search. *Econometrica*, *74*(5), 1293–1307.

Dominitz, J., & Manski, C. F. (1996). Eliciting student expectations of the returns to schooling. *Journal of Human Resources*, *31*(1), 1–26.

Hoxby, C., & Turner, S. (2013). *Expanding college opportunities for high-achieving, low income students* (Tech. Rep.).

Hoxby, C. M., & Avery, C. (2012). *The missing" one-offs": The hidden supply of high-achieving, low income students.* (NBER WP 18586)

Jensen, R. (2010). The (perceived) returns to education and the demand for schooling. *The Quarterly Journal of Economics*, *125*(2), 515–548.

McGuigan, M., McNally, S., & Wyness, G. (2012). *Student awareness of costs and benefits of educational decisions: Effects of an information campaign* (Tech. Rep.). Centre for the Economics of Education, LSE.

Nguyen, T. (2008). Information, role models and perceived returns to education: Experimental evidence from madagascar.

Nordin, M., Persson, I., & Rooth, D.-O. (2010). Education–occupation mismatch: Is there an income penalty? *Economics of education review*, *29*(6), 1047–1059.

Oreopoulos, P., & Dunn, R. (2013). Information and college access: Evidence from a randomized field experiment*. *The Scandinavian Journal of Economics*, *115*(1), 3–26.

Robst, J. (2007). Education and job match: The relatedness of college major and work. *Economics of Education Review*, *26*(4), 397–407.

Rosenbaum, P. R. (2002). Covariance adjustment in randomized experiments and observational studies. *Statistical Science*, *17*(3), 286–327.

Wiswall, M., & Zafar, B. (2011). Determinants of college major choice: Identification using an information experiment. *FRB of New York Staff Report*(500).

Table 1: : Post-secondary degree characteristics

Major	Share of applicants	% female	% adv. sec. school Math	Matriculation Exam Score Average	Matriculation Exam Score Std. dev.	Employ-ment rate	Mean monthly wages	p10 monthly wages	p90 monthly wages
A: Polytechnics									
Humanities	5.08	0.75	0.21	3.75	1.01	0.80	2255	905	3395
Arts	1.20	0.72	0.26	3.89	1.01	0.55	1784	645	2890
Business	9.23	0.57	0.29	3.80	1.01	0.90	2875	1308	4488
Engineering	7.84	0.19	0.59	3.52	0.91	0.94	3463	2340	4686
Agriculture	1.04	0.53	0.38	3.73	1.00	0.88	2575	1577	3592
Nursing	14.95	0.88	0.24	3.65	0.96	0.89	2228	936	3080
Services	4.60	0.84	0.18	3.67	0.97	0.87	2459	1076	3867
B: University									
Education	7.09	0.88	0.29	3.98	1.00	0.75	2291	958	3195
Arts	1.34	0.71	0.30	4.08	1.04	0.79	2319	837	3659
Humanities	9.33	0.73	0.31	4.42	1.04	0.83	2606	1133	3723
Business	5.68	0.47	0.50	4.36	1.04	0.92	4287	1742	6690
Social sciences	5.35	0.62	0.40	4.29	1.04	0.86	2926	1247	4356
Psychology	1.93	0.81	0.37	4.37	1.00	0.88	2613	1003	3476
Law	1.32	0.61	0.43	4.45	1.09	0.93	4102	1925	6347
Natural sciences	10.35	0.54	0.81	4.60	1.05	0.83	3012	1592	4406
Engineering	8.15	0.21	0.96	4.38	1.07	0.95	4179	2576	5837
Eng. & business	1.05	0.23	0.93	4.38	1.05	0.95	4832	2720	7112
Architecture	0.72	0.64	0.79	4.37	1.12	0.91	3065	1827	4104
Agriculture	0.45	0.60	0.62	4.31	1.03	0.86	3143	1343	4651
Medicine	1.51	0.55	0.86	4.70	1.09	0.93	4721	2127	6847
Other health care	1.12	0.79	0.62	4.22	1.02	0.90	3009	1387	4333
Services	0.66	0.51	0.40	3.81	0.91	0.95	3499	2271	4612

Table 2: Average background variables in treatment and control schools

	Control schools		Treatment schools		Difference	
	Mean	St.dev.	Mean	St.dev	Diff.	St.error
Average matriculation grade 2007-2010	4.254	0.427	4.256	0.394	0.003	0.055
Share of high school graduates in the region	0.080	0.031	0.078	0.034	-0.002	0.004
Share of university graduates in the region	0.102	0.068	0.100	0.081	-0.003	0.009
Average household income	32 220	17 652	29 717	18 608	2 504	2 110
Regional unemployment rate	0.089	0.044	0.099	0.046	0.010	0.005

Table 3: 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	

Table 4: Applications by Field

	2011		2012		Odds	p-values	
	Cont.	Treat.	Cont.	Treat.	ratio	Stand.	Rand. Inf.
			A: Polytechnics				
Humanities	5.2	4.7	4.4	3.9	0.99	0.90	0.93
Arts	1.2	1.3	1.2	1.0	0.82	0.04	0.22
Business	9.3	9.2	9.5	10.2	1.09	0.01	0.17
Engineering	7.7	8.3	7.4	7.5	0.94	0.13	0.46
Agriculture	1.0	1.1	0.9	1.1	1.12	0.27	0.46
Health	15.0	14.7	14.7	15.0	1.05	0.05	0.32
Services	4.7	4.4	3.7	3.8	1.10	0.09	0.29
			B: Universities				
Education	7.1	7.0	8.2	7.6	0.95	0.19	0.53
Arts	1.4	1.2	1.2	1.2	1.16	0.12	0.22
Humanities	9.5	9.0	8.9	8.8	1.06	0.13	0.40
Business	5.8	5.4	6.4	6.3	1.06	0.20	0.49
Social sciences	5.2	5.8	4.8	5.3	0.99	0.90	0.95
Psychology	1.9	2.0	2.2	2.1	0.94	0.40	0.58
Law	1.3	1.5	1.4	1.4	0.94	0.46	0.58
Natural sciences	10.3	10.6	10.3	10.2	0.97	0.39	0.65
Engineering	8.1	8.3	8.7	8.6	0.97	0.35	0.63
Eng. & business	1.0	1.1	1.1	1.1	0.92	0.44	0.53
Architecture	0.8	0.5	0.7	0.6	1.50	0.00	0.04
Agriculture	0.4	0.5	0.4	0.4	1.03	0.84	0.88
Medicine	1.5	1.5	1.8	1.8	1.01	0.92	0.92
Other health	1.1	1.3	1.2	1.2	0.86	0.13	0.27
Services	0.6	0.7	0.8	0.8	0.88	0.31	0.41

Note: Columns 1 to 4 report the distribution of applications from the treatment and control high-schools in 2011 (pre-treatment) and 2012 (post-treatment). Column 5 reports odds ratios for the change between years 2011 and 2012 by treatment status. Column 6 reports p-values for the odds ratios using the standard methods. Column 7 reports p-values from randomization inference. Test for homogenous association: $\chi^2 = 42.2$; p-values 0.004 (standard), 0.687 (rand. inf.)

Table 5: Updating Beliefs about Average Wages by Field

	% updating					
	↓	0	↑	na.	Mean	Obs.
A: Polytechnics						
Engineering	13	64	18	5	0.05	137
Business	17	69	12	3	-0.05	133
Hum. Arts, SocSc.	20	54	14	13	-0.07	133
Health and welfare	19	69	8	4	-0.12	264
Agriculture	26	57	13	4	-0.14	22
Services	24	60	7	10	-0.19	160
B: Universities						
Agriculture	0	64	36	0	0.36	11
Eng. & business	4	54	38	4	0.36	25
Business	5	61	31	3	0.27	271
Medicine	4	68	25	2	0.22	216
Engineering	8	62	27	3	0.20	125
Law	9	78	13	1	0.04	158
Arts	22	49	22	8	0.00	47
Humanities	20	64	13	4	-0.07	192
Services	22	60	13	5	-0.10	91
Natural sciences	23	56	12	8	-0.12	111
Social sciences	24	60	9	6	-0.16	101
Architecture	26	55	11	8	-0.17	35
Other health care	32	51	11	6	-0.23	114
Education	37	55	6	2	-0.32	154
Psychology	57	35	5	4	-0.54	105
Total	17	57	14	12	-0.04	2,619

Table 6: Impact of the Information Intervention on the Excpected Value of the Application Portfolio

		Boys		Girls	
	Everyone	Less educated	More educated	Less educated	More educated
	A: log Expected value of application portfolio				
Constant	11.323	11.578	11.509	11.127	11.232
	(0.018)	(0.022)	(0.027)	(0.020)	(0.032)
Treatment	-0.007	-0.063	0.006	0.011	0.004
	(0.033)	(0.045)	(0.059)	(0.039)	(0.059)
Post	-0.016	-0.034	0.046	-0.005	-0.048
	(0.012)	(0.025)	(0.032)	(0.021)	(0.025)
Treatment	0.032	0.139	-0.024	0.035	-0.031
× Post	(0.024)	(0.053)	(0.068)	(0.039)	(0.052)
	[0.186]	[0.000]	[0.744]	[0.362]	[0.546]
	B: Number of applications				
Constant	4.443	4.216	4.173	4.659	4.530
	(0.039)	(0.054)	(0.057)	(0.048)	(0.068)
Treatment	-0.023	-0.073	0.050	-0.056	0.039
	(0.084)	(0.096)	(0.110)	(0.104)	(0.147)
Post	0.038	0.108	0.161	0.021	-0.106
	(0.036)	(0.067)	(0.079)	(0.053)	(0.063)
Treatment	0.051	0.152	-0.076	0.083	-0.034
× Post	(0.082)	(0.125)	(0.153)	(0.110)	(0.147)
	[0.498]	[0.206]	[0.602]	[0.476]	[0.788]
	C: Probability of being accepted to at least one program				
Constant	0.430	0.479	0.451	0.397	0.417
	(0.005)	(0.006)	(0.007)	(0.005)	(0.009)
Treatment	0.002	-0.009	0.017	-0.001	0.007
	(0.009)	(0.013)	(0.014)	(0.011)	(0.017)
Post	-0.007	-0.017	0.009	-0.003	-0.013
	(0.004)	(0.007)	(0.009)	(0.005)	(0.007)
Treatment	-0.002	0.022	-0.020	0.003	-0.021
× Post	(0.007)	(0.014)	(0.018)	(0.010)	(0.013)
	[0.746]	[0.120]	[0.252]	[0.750]	[0.130]
	D: Average log earnings of the programs applied to				
Constant	7.968	8.076	8.096	7.871	7.916
	(0.005)	(0.005)	(0.007)	(0.004)	(0.007)
Treatment	0.002	-0.011	0.014	0.002	0.004
	(0.008)	(0.008)	(0.014)	(0.006)	(0.012)
Post	0.012	0.007	0.016	0.014	0.012
	(0.003)	(0.005)	(0.006)	(0.003)	(0.005)
Treatment	-0.003	0.013	-0.028	0.000	0.004
× Post	(0.005)	(0.009)	(0.013)	(0.006)	(0.012)
	[0.608]	[0.228]	[0.032]	[0.946]	[0.726]

Note: ITT estimates. Standard errors (in parantheses) clustered at high-school level. P-values [in brackets] from randomization inference using 500 replications

Table 7: Impact of the Information Intervention on the “Surprise Content” of Application Portfolios

		Boys		Girls	
	Everyone	Less educated	More educated	Less educated	More educated
		A: Average surprise			
Constant	-0.049	0.019	0.027	-0.105	-0.085
	(0.002)	(0.003)	(0.004)	(0.002)	(0.004)
Treatment	0.000	-0.008	0.005	0.002	-0.003
	(0.004)	(0.006)	(0.008)	(0.004)	(0.007)
Post	0.003	0.002	0.011	0.001	0.002
	(0.002)	(0.004)	(0.004)	(0.002)	(0.004)
Treatment	-0.001	0.014	-0.017	-0.003	0.006
× Post	(0.004)	(0.007)	(0.009)	(0.005)	(0.008)
	[0.854]	[0.052]	[0.060]	[0.432]	[0.444]
	B: Has a negative surprise program in the applicatio portfolio				
Constant	0.675	0.521	0.551	0.792	0.742
	(0.006)	(0.010)	(0.012)	(0.007)	(0.010)
Treatment	0.006	0.000	0.010	0.000	0.024
	(0.011)	(0.019)	(0.021)	(0.014)	(0.018)
Post	-0.009	-0.008	-0.029	-0.011	0.004
	(0.006)	(0.013)	(0.015)	(0.008)	(0.011)
Treatment	0.009	0.011	0.025	0.015	-0.025
× Post	(0.012)	(0.024)	(0.030)	(0.015)	(0.019)
	[0.386]	[0.654]	[0.396]	[0.324]	[0.254]
	C: Has a positive surprise program in the applicatio portfolio				
Constant	0.393	0.627	0.621	0.207	0.277
	(0.008)	(0.009)	(0.012)	(0.007)	(0.012)
Treatment	0.011	0.001	0.011	0.012	0.007
	(0.013)	(0.018)	(0.027)	(0.012)	(0.019)
Post	0.017	0.005	0.039	0.021	0.011
	(0.006)	(0.012)	(0.015)	(0.008)	(0.012)
Treatment	-0.009	0.030	-0.039	-0.018	0.007
× Post	(0.013)	(0.024)	(0.031)	(0.017)	(0.026)
	[0.480]	[0.244]	[0.220]	[0.230]	[0.768]

Note: ITT estimates. Standard errors (in parantheses) clustered at high-school level. P-values [in brackets] from randomization inference using 500 replications

Table 8: Impact of the Information Intervention on Enrollment

		Boys		Girls	
	Everyone	Less educated	More educated	Less educated	More educated
		A: Number of programs accepted to			
Constant	0.653	0.773	0.688	0.596	0.594
	(0.017)	(0.019)	(0.026)	(0.019)	(0.028)
Treatment	-0.006	0.002	0.033	-0.031	-0.005
	(0.026)	(0.036)	(0.046)	(0.031)	(0.047)
Post	-0.024	-0.044	0.007	-0.025	-0.022
	(0.011)	(0.021)	(0.025)	(0.018)	(0.020)
Treatment	-0.014	-0.010	-0.080	0.034	-0.039
× Post	(0.020)	(0.043)	(0.052)	(0.032)	(0.036)
	[0.584]	[0.794]	[0.150]	[0.368]	[0.306]
		B: Enrolled			
Constant	0.438	0.531	0.469	0.393	0.387
	(0.009)	(0.009)	(0.014)	(0.010)	(0.014)
Treatment	0.001	0.004	0.012	-0.009	0.003
	(0.013)	(0.020)	(0.027)	(0.017)	(0.023)
Post	-0.014	-0.031	0.001	-0.008	-0.014
	(0.006)	(0.012)	(0.013)	(0.010)	(0.012)
Treatment	-0.007	-0.004	-0.034	0.018	-0.024
× Post	(0.012)	(0.024)	(0.032)	(0.017)	(0.023)
	[0.610]	[0.856]	[0.274]	[0.354]	[0.282]
		C: log Average eanings in the program enrolled to			
Constant	12.501	12.637	12.652	12.362	12.400
	(0.007)	(0.006)	(0.009)	(0.008)	(0.014)
Treatment	0.011	0.000	0.030	-0.003	0.012
	(0.012)	(0.012)	(0.017)	(0.013)	(0.021)
Post	0.008	0.003	0.020	0.001	0.024
	(0.006)	(0.008)	(0.011)	(0.009)	(0.014)
Treatment	-0.020	-0.019	-0.024	0.004	-0.022
× Post	(0.011)	(0.016)	(0.025)	(0.016)	(0.022)
	[0.060]	[0.250]	[0.260]	[0.856]	[0.356]

Note: ITT estimates. Standard errors (in parantheses) clustered at high-school level. P-values [in brackets] from randomization inference using 500 replications