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STEM Graduates and Secondary School Curriculum: Does Early Exposure to Science Matter?

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Abstract
Increasing the number of Science, Technology, Engineering and Math (STEM) university graduates is considered a key element for long-term productivity and competitiveness in the global economy. Still, little is known about what actually drives and shapes students' choices. This paper focusses on secondary school students at the very top of the ability distribution and explores the effect of more exposure to science on enrolment and persistence in STEM degrees at the university and on the quality of the university attended. The paper overcomes the standard endogeneity problems by exploiting the different timing in the implementation of a reform that induced secondary schools in the UK to offer more science to high ability 14 year-old children. Taking more science in secondary school increases the probability of enrolling in a STEM degree by 1.5 percentage point and the probability of graduating in these degrees by 3 percentage points. The results mask substantial gender heterogeneity: while girls are as willing as boys to take advanced science in secondary school - when offered -, the effect on STEM degrees is entirely driven by boys. Girls are induced to choose more challenging subjects, but still the most female-dominated ones.

Keywords: university education, high school curriculum, STEM
JEL codes: J16; J24; I28; I21

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1 Introduction

In the new heavily globalized and innovation driven economy, increasing the number of Science, Technology, Engineering and Math (STEM)[1] university graduates is found to generate high social returns in terms of long-term productivity, growth and competitiveness [Winters, 2014, Peri et al., 2013, Moretti, 2012, Atkinson and Mayo, 2010, Jones, 2002]. Moreover, a STEM degree also represents a very profitable private investment for college graduates themselves. Lifetime earnings of STEM graduates are extremely high [Joseph Altonji and Maurel, 1974, Kirkeboen et al., 2016, Hastings et al., 2013, Pavan and Kinsler, 2015, Rendall and Rendall, 2014, Koedel and Tyhurst, 2010]: Altonji et al. [2012] show that nowadays intra-educational income differences are comparable to inter-educational differences. In the US in 2009 the wage gap between the average electrical engineer and someone with a degreee in general education was almost identical to the wage gap between the average college graduate and the average secondary school graduate. Moreover, graduates in STEM fields earn more independently of the quality of the institution they attended [James et al., 1989, Kirkeboen et al., 2016, Arcidiacono et al., 2016]. Non-monetary returns are also high in STEM occupations: Goldin [2014] classifies occupations based on their degree of temporal flexibility, i.e. how important it is to stay long or particular hours in the office, and STEM occupations are ranked among the first. However, despite the high social and private benefits obtained from graduating in STEM degrees, the general consensus among policy-makers is that the current supply of STEM skills is insufficient and, when combined with the forecast growth in demand, it presents a potentially significant constraint on future economic activity [UK HM Treasury and BIS, 2010, The President's Council of Advisor on Science and Technology, 2012, European Commission, 2010].[2] Despite the governments of many countries investing a very large amount of funds to induce more graduates towards STEM [Atkinson and Mayo, 2010][3], the graduation rate or even the level of interest of students in graduating in these degrees has remained pretty stable since the '80s [Altonji et al., 2012]. While the literature on choices of the educational level is very wide and consolidated (starting from the seminal work by Mincer [1974]), there is relatively little work on choices of the field of study.

This paper evaluates how much of the lack in STEM graduates can be attributed to secondary schools, and in particular to the curriculum they offer. Ellison and Swanson [2012] show that there is a large heterogeneity in secondary schools effectiveness in developing talents in technical subjects like math, which is not explained by differences in schools composition. I investigate the role of secondary school curriculum and I seek to understand whether more exposure to science in secondary school for very high ability students increases by itself the supply of STEM graduates. Moreover I explore whether changing the secondary school curriculum and increasing students' preparation in science shrinks the gender gap in STEM degrees enrollment.

The identification of the effect of studying more science in secondary school is difficult because of a double selection problem: the selection of students into different schools -based on the curriculum they offer- and that of students into different courses, within the school they chose. I address and test both sources of endogeneity: I eliminate the selection in different courses within the same school by collapsing the analysis at the school level (in the spirit

[1]Throughout the paper I define as "STEM" the following degrees: Physical science, Mathematical and Computer science and Engineering.

[2]Overall, STEM employment grew three times more than non-STEM employment over the last twelve years, and it is expected to grow twice as fast by 2018. According to a report by the Information Technology and Innovation Foundation [2010], the number of STEM graduates in the US will have to increase by 20-30% by 2016 to meet the projected growth of the economy.

[3]The US federal government for instance is considering actions with the objective of increasing STEM graduates by 34% annually [The President's Council of Advisor on Science and Technology, 2012].

of Altonji [1995]) and I address the selection of students into different schools, by exploiting exogenous variation in the timing of the introduction of an advanced science course in English secondary schools. The UK government introduced in 2004 an entitlement to study advanced science for high ability students at age 14, with the explicit aim of fostering enrollment in post-secondary science education. This resulted in a strong increase in the number of schools offering advanced science: from 20% in 2002 to 80% in 2011. As a consequence, the share of students taking advanced science increased from 4% in 2002 to 20% in 2011 and the increase was almost entirely concentrated on high ability students[4] (see Figure 1). Thanks to a novel dataset that I obtained by combining different administrative sources from England, I propose two alternative identification strategies that approach this type of selection problem from two complementary perspectives and I use different sources of variation. The first strategy uses within-school variation in the type of courses offered over time and, in the spirit of Joensen and Nielsen [2009], it exploits the three year time lag between the moment when students choose their secondary school (age 11) and the moment when they choose their field courses (age 14). I evaluate the effects on students unexpectedly exposed to the advanced science course, since their schools started to offer it only after they chose the school. The second identification strategy tests the robustness of my results by using across-school within-neighbourhood variation over time: it exploits the fact that schools in England, when oversubscribed, select students based on home-to-school distance and schools catchment areas vary (unpredictably) over time. My second instrument therefore uses variation in whether the schools were offering advanced science even before the students started to attend their school.

The empirical findings can be summarized as follows: taking advanced science at age 14 increases the probability of choosing science at age 16 by 5 percentage points and that of enrolling in STEM degrees by about 2 percentage points. Moreover, offering more science courses at secondary school does not only induce more students to enroll in STEM degrees but it also increases the likelihood that they graduate in these degrees. This is important, given the large problem with the persistence in this kind of degrees [Arcidiacono et al., 2016, Stinebrickner and Stinebrickner, 2014].[5]

Second, I find that the effect on STEM degrees (in its narrow definition) is concentrated only on boys: the gender gap in STEM degrees enrollment widens as a consequence of this policy. This is not explained by the fact that less girls take advanced science at age 14 - boys and girls at this stage select into advanced science in the same proportion - but because girls, when exposed to more science in secondary school, even if induced to take more challenging subjects[6], still opt for the most female-dominated ones.

Taken together, my findings can inform ongoing debates over government intervention to address apparent mismatches and market frictions in the supply and demand of post-secondary fields of study. My results suggest that, to reinvigorate STEM education and high-skilled STEM education in particular, governments should consider a policy aimed at offering more science courses to high ability students during secondary schools. I estimate that the policy I consider contributed to one third of the increase in the share of STEM graduates in England between 2005 and 2010.

This paper speaks to the growing literature that seeks to explain choices of university degrees. Most of the evidence so far comes from surveys or informational experiments and the results are mixed. The most common explanations look at the role of expected earnings; com-

[4]I define high ability students as those who were in the top 30 percentile of the primary school grades distribution. The increase for these students was around 35 percentage points, from 15% to about 50%.

[5]There is a problem of persistence in STEM majors also in England: in the cohort starting university in 2011, out of the 17% of students enrolled in a STEM major, only 17% graduated in the same STEM major within three years (this figure is 20% on average for the other majors).

[6]I define as challenging the subjects usually taken by students achieving very high grades in primary school.

petencies and preparation; self-confidence; preferences and innate ability [Arcidiacono et al., 2012, Arcidiacono, 2004, Beffy et al., 2012, Stinebrickner and Stinebrickner, 2014, M and Zafar, 2014]. However preferences and ability are usually considered to be constant over time, and it is therefore difficult for policy-makers to shape them; returns to STEM degrees are already very high, as stated before, and the elasticity of degree choice to expected earnings is found to be rather low [Beffy et al., 2012]. Moreover, Stinebrickner and Stinebrickner [2014] show that students start university being over-confident not under-confident about their scientific ability. There is, instead, large scope for policies that interfere with students' preparation and with the primary and secondary schools quality. Many scholars [Cameron and Heckma, 2001, Moretti, 2012], indeed, attribute the lack of STEM graduates to the low quality of the US school system. Some studies look at the effects of school inputs (usually at the university level), like peers [De Giorgi et al., 2010, Anelli and Peri, 2015], teachers [Scott E. Carrell and West, 2010], teaching structure [Machin and McNally, 2008] and university coursework [Fricke et al., 2015]. Still, excluding some recent studies that evaluate the effects of secondary school curricula using quasi-experimental evidence [Joensen and Nielsen, 2009, 2016, Cortes et al., 2015, Goodman, 2012], there is little quantitative work on the effects of secondary school courses [Altonji et al., 2012]. This is surprising given that not only every single government has to take at some point the decision about how to design its country secondary school curriculum but also, differently from other policies like changes in peers, this is not a zero sum choice: everybody may potentially benefit from a well designed curriculum.

My paper improves on the existing literature in several ways.[7]

First, I address both layers of selection of students into courses. Most studies [Altonji, 1995, Levine and Zimmerman, 1995, Betts and Rose, 2004] use across school variation in the type of curriculum offered and do not fully address the possible selection of students into schools, based on the curriculum they offer. Since family background and individual motivation are important determinants of both the choice of degrees and of the one of secondary schools, the bias in estimates that do not take into account selection into schools could be important and could lead to an overestimation of the effects. I show that, even in my context where the variation in curriculum is induced by a policy, adding school-level controls is not enough to eliminate selection bias: the inclusion of school fixed effects and the presence of an instrument turn out to be crucial to correctly identify the effect of interest.

Second, the policy I consider allows me to identify the effect of offering more (natural) science courses only, because it does not intervene on other subjects. Instead, changes in secondary school curricula usually imply a restructuring of many different courses and it is difficult to isolate the effect of one single subject [Altonji, 1995, Joensen and Nielsen, 2009, 2016, Gorlitz and Gravert, 2015, Jia, 2014]. While my treatment also has multiple components, since taking advanced science also implies a change in classroom heterogeneity and composition,[8] I disentangle the curriculum from the peer channel, using an instrument for peers that exploits within-school variation over time in the ability of predicted peers, depending on whether the school offers advanced science or not. I find that the effect of the advanced science course persists even after controlling for changes in peers' characteristics. This is key to identify the exact origin of the effect and therefore to allow policy-makers to reproduce the policy in other contexts.

Third, the compliers for my instrument are extremely high ability students: I therefore look at the effect for those students with potentially very high probability of succeeding in STEM

[7]I mention here papers that look at the effect both on earnings and on degrees, even if most of the literature looks at earnings without focusing on the effect on the choice of degree.

[8]Because the advanced science course provides the possibility of taking a course exclusively attended by other very high ability students.

degrees and of highest interest for policy-makers because they are more likely to make important contributions to scientific and technological fields. On the one side this is important because most of the existing empirical studies [Goodman, 2012, Cortes et al., 2015] analyze policies that affect almost entirely low ability students, not likely to enroll at the university at all, or students for whom taking science is rather costly [Joensen and Nielsen, 2009, 2016].[9] On the other side, it allows me to separately identify the effect on the extensive margin (i.e. the probability of attending university) from the effect on the intensive margin (i.e. the choice of degree) because, given that the students affected by the policy I consider would have enrolled at the university in any case, the policy does not have any effect on the probability of continuing to study. Any effect I find on the choice of degrees is therefore completely generated by changes on the intensive margin. Moreover, the instrument affects boys and girls in a very similar way, therefore allowing to test the gender heterogeneity of the effect without worrying about differences in compliance.

The remainder of this paper is organized as follows. In Section 2, I describe the data, the English school system and the reform of the advanced science program in UK secondary schools. Section 3 provides an overview of the main identification strategies. Section 4 presents the estimated impact of advanced science on post-16 educational outcomes and it checks the identifying assumptions and the robustness of the results. Section 5 inspects the mechanisms behind the estimates and, finally, Section 6 concludes.

2 Data and institutional setting

2.1 The English school system

Compulsory education in England is organized in four Key Stages (KS). At the end of each stage students are evaluated in standardized national exams. Figure 2 shows a timeline of the English educational system. Pupils enter school at age 4, the Foundation Stage, then they move to Key Stage 1 (KS1), spanning ages 5 and 6, and Key Stage 2 (KS2, from age 7 to age 11).[10] At the end of KS2 children leave primary school and go to secondary school, where they progress to Key Stage 3 (KS3, age 12-14) and Key Stage 4 (KS4, age 15-16). Admission to secondary school is based on criteria usually set by the school or by the local council. Usually schools give priority to children who live close to the school or whose brothers or sisters attend the school already. At KS4 students start choosing some subjects.[11] In particular, out of usually between 10 and 12 qualifications, students typically choose between 4 and 6 subjects.[12] At age 16 compulsory education ends and students may continue their secondary studies for a further two years. This phase is called Key Stage 5 (age 17-18) and may take place in the same secondary school (about 60% of the schools also offer KS5 courses) or in a different school. Again, students have many different options: they can choose more vocational or more academic-oriented type of qualifications (the so-called A levels), with slightly less than half of each cohort undertaking at least one A-level exam at age 18. Students usually take three A level or equivalent qualifications[13], and are free to choose any subject. Finally, higher education

[9] These studies exploit for instance changes in minimum math requirements across US states over time or compare students just below or just above the threshold for attending remedial classes in math and find modest effects on earnings, concentrated on low-SES students. In my setting, instead, compliers include also extremely high ability students, within the same school.

[10] KS1 corresponds to grade 1 and 2 in the US school system, KS2 to grades 3,4 and 5.

[11] A number of different qualification types are available to young people at KS4, varying in their level of difficulty. These include: GCSE (the most common qualification in England and the most academic oriented), and other more vocational qualifications. I will only consider GCSE qualifications or GCSE equivalent qualifications.

[12] The six compulsory subjects are: English, math, (single) science, information and communication, physical education and citizenship. Students in general take overall between 10 and 12 qualifications.

[13] 50% of students takes between 3 and 3.5 A level equivalent qualifications.

usually begins at age 19 with a three-year bachelor's degree. Admission to university is usually based on which subjects were chosen at KS5 and on the grades achieved.

2.2 Science in secondary school

While science is a core component of the National Curriculum at KS4, there are several different ways to fulfill the requirement. All students are required to study the basics elements of all three natural sciences (physics, chemistry and biology) and should at least take the so-called 'single science' or core science course (which is worth one KS4 qualification). They can, moreover, choose to take the 'double science' course (worth two qualifications) which leads to more knowledge in all the three subjects or the 'triple science' course (which is called advanced science and is equivalent to take one full qualification in each of the three natural science subjects). Finally students can also take more vocational science qualifications. Taking triple science implies both longer instruction time and the study of more complex science topics.[14] Double science and, more recently, triple science provide the standard routes into the fulfillment of KS4 requirements.

In 2004 the UK Government published a ten-year investment framework for science and innovation [UK Government, 2004]. The framework set out the Government's ambition for UK science and innovation over the next decade and emphasized in particular the need for more graduates in science. Taking triple science was considered extremely important, because "it gives students the necessary preparation and confidence to go on and study science" (Confederation of British Industry). The document established an entitlement to study triple science for students achieving at least level 6 or above at KS3 science (the students on the top 40% of the grade distribution).[15] The result was a very large increase in the number of schools offering triple science. While in 2002 less than 20% of schools offered triple science, by 2011 the share became more than 80% (see Figure 1). Between 2002 and 2011 the share of students choosing triple science increased from 4% to 20% and the increase was mostly concentrated among high ability students (for whom the share increased from 15% to 50%).

There are several, mainly supply driven, reasons why the exact timing of the introduction of the triple science option differs by schools. First, the lack of specialized teachers. 50% of science and math students in English secondary schools are not taught by teachers specialized in the subject. For teachers teaching outside their expertise, triple science is particularly demanding and they need more time to get familiar with the material. Second, the school size: for small schools it is difficult to offer a large number of subjects. With the ten-year investment framework, the government encouraged new collaborative arrangements with other schools (to jointly provide triple science). However, setting these agreements up takes time and many schools need the support of their Local Education Authority (LEA) and the exact timing of the conclusion of these agreements is uncertain. Finally, support and pressure on schools to fulfill the entitlement to triple science was provided at the LEA level.[16] Some LEAs were not as supportive as others regarding the introduction of triple science: the increase in the share of schools offering triple science was very heterogeneous across different LEAs.

[14] In this case students study more difficult topics such as electric current, transformers, some medical application, more quantitative topics in chemistry etc.

[15] In particular the government stated that "all pupils achieving at least level 6 [Level 6 or above is equivalent to the top 30% of students] at KS3 should be entitled to study triple science at KS4, for example through collaborative arrangements with other schools.

[16] LEAs organize courses both on how to organize the time schedule to fit the new curriculum and on the new material covered and encourage school-to-school learning. There is large heterogeneity on how actively different LEAs promoted and pushed the introduction of the Triple Science option in schools. In total there are 152 local authorities in England.

2.3 Data

By combining different administrative sources, my final dataset follows all students in maintained schools in the England,[17] from primary school till the end of their university career.

I obtain information on students demographic characteristics from The Pupil Level Annual School Census (PLASC) that collects information on students' gender, ethnicity, Free School Meal Eligibility (FSM), Special Education Needs (SEN), language group as well as their postcodes. The National Pupil Database (NPD) provides instead information on students' attainments in all their Key Stages exams (from KS1 till KS5) as well as on every single subject chosen (and the corresponding grade) in KS4 and KS5 and on school characteristics (peer groups, types of school, teachers' hirings, schools location etc.). From the NPD dataset I obtain also the information about which courses are offered by each school. In particular, I follow the official methodology used by the English Department of Education and I infer that a school offers a course if at least one pupil at the school took an assessment in that specific course and year.[18] I then link the NPD to the universe of UK university students, the Higher Education Statistical Agency (HESA) dataset. The HESA dataset provides information on whether pupils progress to university, on their degree, on the institution they attend and on whether they graduate and in which degree. I combine these two data sources to create a dataset following the entire population of five cohorts of English school children. My sample includes pupils who finished compulsory education (took KS4 examinations, at age 16) between the academic years 2004/2005 and 2009/2010. After 2010, there would be no information on university outcomes, because I only have data on university results till 2013. Before 2005, there is no information on whether the school was offering triple science when the student applied to the school, because the data collection starts in 2002 and there are three years of lag. Using information on the secondary school attended by each individual, I match the individual record with school level data on whether the school was offering triple science when the student applied and three years later, when she had to choose her KS4 subjects.
Finally, I impose a set of standard restrictions on the data. First, I exclude special schools, hospital schools, schools where there is a three tier system instead of a two tier system. Second, I only use students who can be tracked from KS2 to KS4.[19] This leaves me with approximately 530,000 students per cohort.

The data I use are a major improvement over previous studies. While the very detailed nature of the information needed on subject choices gives particularly large scope for measurement error problems in survey data, the students' administrative dataset usually available in other countries do not contain some of the elements necessary for this analysis. For instance, most datasets do not have information on university outcomes and the few administrative datasets that include post secondary school outcomes as well, refer to rather small countries, relatively homogeneous in terms of students' background and sometimes do not include information on previous test scores. The large amount of observations and the heterogeneity in the students' background available in the English dataset, provide me with enough power to accurately run my analysis and to study the heterogeneity of the effect on subgroups of the population.

[17]The dataset refers only to England and it excludes private schools, that however educate a small share (7%) of British children.

[18]My results are robust to different definitions (at least 5 pupils, at least 5% of the students, for at least two consecutive years etc.) and all different definitions are extremely highly correlated.

[19]I checked whether this selection generates any bias (i.e. is correlated with the instrument) and this is not the case. The results are available upon request.

3 Empirical strategy

3.1 The selection problem

The main identification challenge when studying the effects of secondary school courses on post secondary school outcomes, is to correct for selection bias.

To fix ideas, consider the case in which students choose between taking more science in secondary school ($D = 1$) or not ($D = 0$). The observed choice of university degree (Y) can be linked to potential degrees (Y_j where $j = 1, 0$) and the type of science in secondary school (D) as:

$$Y = Y_0 + D(Y_1 - Y_0) \tag{1}$$

The OLS estimates of the effect of choosing more science in secondary school, can be written as follows:

$$E(Y|D = 1) - E(Y|D = 0) = E(Y_1|D = 1) - E(Y_0|D = 0) \tag{2}$$

The main challenge is that students selecting into certain secondary school courses would have different potential outcomes in any case, meaning that a simple OLS does not provide the right counterfactual ($E(Y_0|D = 0) \neq E(Y_0|D = 1)$). In practice there are two layers of selection: selection of students into schools offering triple science and selection of students into triple science, for a given school.

Let's call S a dummy equal to 1 if the school attended by student i offers triple science and 0 otherwise. Then, the OLS estimates can be written as follows:

$$\begin{aligned} E(Y|D = 1) - E(Y|D = 0) = {} & \underbrace{E(Y_1 - Y_0|D = 1, S = 1)}_{\text{ATT}} + \\ & P(S = 1|D = 0)\underbrace{[E(Y_0|D = 1, S = 1) - E(Y_0|D = 0, S = 1)]}_{\text{selection into courses}} + \\ & P(S = 0|D = 0)\underbrace{[E(Y_0|D = 1, S = 1) - E(Y_0|D = 0, S = 0)]}_{\text{selection into schools+courses}} \end{aligned}$$

I address the selection problem by tackling the first and the second layer of selection in two different ways. Selection of students into courses within the same schools is addressed by collapsing the analysis at the school level, since I use instruments that vary only at the school-cohort level. Most papers (in the spirit of Altonji [1995]) use school average curriculum as instrument and therefore address this type of selection only. This leaves space, however, to endogeneity due to selection of students into schools offering different curricula. I address this other layer of selection in two different ways, that exploit two different types of variation.

3.2 First instrument

My first identification strategy is based on the following equation:

$$Y_{ist} = \gamma_1 D_{ist} + \gamma_2 X_{ist} + \zeta_s + \zeta_t + v_{ist} \tag{3}$$

where D_{ist} is the dummy equal to 1 if student i in secondary school s, in cohort t takes triple science and 0 otherwise; X_{ist} are school and student controls; δ_s are school fixed effects and δ_t are year fixed effects. Y_{ist} is the outcome variable, usually a dummy indicating whether the student takes science at KS5 or at the university (and 0 if she does not take science or does not continue studying). Finally, v_{ist} is the error term.

The school fixed effects take care of time invariant school heterogeneity, such as the overall quality of the school, of the students or of the neighbourhood. The time fixed effects absorb cohort effects or the presence of policies that uniformly affect the entire school system. Still, there may exist time varying factors, changes in cohort quality in particular, that may bias my estimates because this may be correlated both with the introduction of triple science in a school and with the willingness to take science subjects. I therefore use as instrument for D_{ist} a dummy equal to one if student i in school s and cohort t was unexpectedly exposed to the triple science option. I rely on the time span between the time when students choose secondary schools (age 11) and the time when they choose their optional subjects (age 14). I use as instrument a dummy equal to 1 if school s was not offering triple science when students from cohort t applied to secondary schools but starts to offer triple science by the time they choose their KS4 subject, three years later. I only include schools not offering triple science when students applied. I compare two types of students, a priori identical because they all selected schools not offering triple science at age 11: those whose schools unexpectedly started to offer triple science by the time they turned 14 (my treatment group) and those whose school did not offer triple science when they chose subjects at age 14 (my control group).[20]

This strategy mainly relies on two assumptions.
First, the assumption that the information set of both students in the treatment and in the control group at age 11, when choosing their schools, is the same and does not include the information on whether the school is going to offer triple science in the next three years. This is very likely, given the large time lapse and uncertainty on when exactly teachers/classrooms and time schedules would be ready. Moreover, students are not totally free to choose the school they want: there are exogenous geographical constraints in choosing schools in England, especially if schools are oversubscribed. In Section 4.3, I show that students who decided to enroll in schools offering triple science are observationally identical to students who decided to enroll in schools not offering triple science: there is no sign of strategic selection of schools based on whether the schools offer the advanced science course, even if the information is available to parents and students at age 11.
Second, the assumption that schools' decisions on when exactly to start offering triple science are related to supply-driven rather than demand-driven factors: schools must decide when to start offering triple science not based on the quality of the current cohort attending the school. In Section 2.2 I described some supply driven reasons why schools may delay the introduction of triple science. In Section 4.3 I show that the timing of the introduction of the triple science option is not correlated with (observable) characteristics of current students in the school and that school s, before starting to offer triple science, was on the same trend of all other schools.

3.3 Second instrument

Still, even if there is no evidence that schools decide when to offer triple science depending on observable characteristics of their current cohort, it may still be that unobservable characteristics matter. This is impossible to test. My second instrument however is not subject to this last concern because it exploits variation in available courses that existed even before current students started to attend their secondary schools. This excludes the possibility that the choice of offering triple science depends on specific shocks to the particular cohort in the school.
This instrument compares students living in the same neighbourhood but who are more or less likely to enroll in schools offering triple science, because of exogenous changes in schools' catchment areas.

[20] A similar idea, with only one year lag, has been used in Joensen and Nielsen [2009, 2016], to evaluate the effects of increasing secondary school curriculum flexibility, that induced students to take more math at secondary school in Denmark. I study a different policy that affects very high ability students and identifies the effect of more science only. Thanks to the availability of data on previous test scores and of many cohorts, I am able to use within school variation and to explore more in details the effect on choices of university degrees.

I exploit the fact that when schools in England are oversubscribed, usually prioritize students based on geographical distance.[21] Therefore, in each year there will be a maximum distance between the school and the students' addresses above which students will not be accepted. I build my instrument in two steps: first, I compute the school catchment areas for each year, the area delimited by the circle whose centre is the school and ray is the maximum observed home-to-school distance,[22] and I define the set of 'reachable' schools for each student. Second, I compute the share of 'reachable' schools that offered triple science when student i applied. Figure 3 shows how the instrument is constructed. Student address refers to the lower level output area (LLOA)[23] where student i used to live at age 10. Around i's house there are two schools with different catchment areas, whose ray is indicated by the black dashed line. The instrument used in this section of the analysis counts how many schools, out of the set of schools reachable by students i in year t, offered triple science when i applied to secondary school (in this case the instrument in year $t-1$ was 1 and in year t was 0.5). The instrument varies both because of (unpredictable) variations in schools catchment areas and because of the overall increase in the number of schools offering triple science. I estimate the following equation:

$$Y_{ipt} = \theta_1 D_{ipt} + \theta_3 X_{ipt} + \theta_t + \theta_p + v_{ipt} \tag{4}$$

where D_{ipt} is the usual dummy indicating whether student i in year t, who used to live in neighbourhood p when she was 10 year old, takes triple sciende and 0 otherwise; X_{ipt} are individual controls and θ_t and θ_p are cohort and neighbourhood fixed effects respectively; v_{ipt} is the error term.

I then instrument D_{ipt} using the share of schools reachable in year t, when i applied to secondary school, by student i, residing in block p, that were offering triple science in year t (z^2_{pt}). This instrument compares students attending schools that offer triple science with students attending schools not offering it, i.e. it uses across school within neighbourhood variation (instead of within school over time variation). Offering triple science is likely to be related to other school characteristics, like school quality, that may directly affect the choices of degree at the university. This issue may be more relevant when we use across school rather than within school variation because differences in quality across schools are likely to be much more sizable than differences within schools over time. Section 4.4 addresses this concern by including as control the average quality level of the set 'reachable' schools in each catchment area over time.

4 Results

This section shows results obtained with the first instrument. I first show the overall effect of taking more science in secondary school in term of post-16 outcomes (Subsection 4.1) and I explore whether the effect is stronger for girls than for boys. Second, I describe who decides to take triple science, when exposed to the option of taking it, by characterizing compliers (Subsection 4.2) and, in particular, by analyzing whether boys are more likely than girls to select triple science at age 14. Finally I check the identifying assumptions and whether the main findings are robust to the second identification strategy (Subsections 4.3 and 4.4).

[21] With some exceptions for students with siblings attending the same school or for students with special education needs. Since I do not have the full set of information necessary to simulate the exact admission formula for each school, I can't adopt an RDD strategy.

[22] In order to exclude exceptions I eliminated outliers (the distances higher than the 5th percentile for every school.

[23] In total there are more than 30,000 LLOAs in England and Wales and each LLOA contains on average 1500 households.

4.1 Main Results

Table 2 presents the main estimates of the effect of taking triple science at age 14 on the probability of choosing at least one natural science subject at age 16 (KS5) and a STEM degree at the university.[24] The Table proceeds by estimating the effect of interest under different specifications. Column 1 displays results from a simple OLS regression; in column 2 I add school fixed effects; column 3 follows Altonji [1995] and uses as instrument for triple science the share of students taking triple science in school s and year t; column 4 uses my first instrument (z_{st}) and some school time varying controls[25], but does not include school fixed effects; column 5 shows results from my preferred specification that uses my instrument and exploits within school over time variation only; finally column 6 adds a school-specific trend. Reassuringly, the coefficients of columns 5 and 6 are very similar, suggesting that schools offering triple science are on a similar trend. Column 7 estimates the specification of equation 3, but it eliminates controls (X_{ist}). The coefficients of columns 5 and 7 are again very similar, suggesting that -conditional on my fixed effects- the instrument is quasi randomly assigned. As expected the bias in the OLS estimates is upward: the coefficient indeed gets smaller as I correct for all different layers of selection. The Table shows that, if a student strengthens her science preparation at age 14, she is 5 percentage points more likely to take science at age 16 and 1.5 percentage points more likely to choose a STEM degree at the university.

Table 3 shows the coefficients obtained from estimating equation 3 on other outcomes at age 14 (KS4), age 16 (KS5) and university. The top panel shows results on KS4 grades and on the number of exams taken in KS4 and KS5. Since triple science is more difficult, taking it reduces the average science grade at KS4. Columns 2 and 3 show that there are not spillovers on other subjects' grades. Columns 4 and 5 investigate whether the total number of qualifications taken at age 14 and 16 changes, as a consequence of the new course offered. The results show that the number of exams taken at age 14 slightly increases.

The second panel refers to outcomes at age 18, the results of KS5 exams. Column 1 shows that the policy does not have any effect on the probability of continuing to study at age 16, probably because the instrument mainly affects high ability students, who would continue to study in any case. Since a change in the probability of enrolling in science subjects at age 16 may be driven both by a change in the likelihood of continuing to study after age 16 and by a change in the likelihood of choosing science subjects - conditional on continuing-, column 1 shows that the coefficient estimated on KS5 subjects comes entirely from an increase in the second component, because the first is not affected by the policy. The result displayed in column 2 shows that the effect of studying triple science is not limited to the pure natural science subjects but it has spillovers on math, for instance. The third panel refers to university outcomes. Column 1 shows again that the policy does not have any effect on the probability of continuing to study at the university.[26] The other columns show the effect on choice of degree and on the quality of the institution attended. Students taking triple science are more likely to attend institutions belonging to the Russell group.[27] Moreover studying more science in secondary school also increases the probability of graduating on time in STEM degrees.[28] This is extremely relevant given the large debate that is taking place in many countries, the US in particular, about

[24] The dependent variables in all cases are dummies equal to one if students attend a certain course and equal to 0 if they do not attend those courses or do not continue studying.

[25] In particular, the share of girls attending school s in year t and the share of FSME (Free School Meal Eligible). In the spirit of Joensen and Nielsen [2009, 2016].

[26] Note that even if the magnitude of the coefficient is similar to the other coefficients, the baseline in this case in much larger: the average is 36% in this case.

[27] The Russell group represents 24 leading UK universities in terms of research and teaching.

[28] The results on university outcomes are estimated on students taking the final KS4 exam in the years 2005-2007 only, otherwise there is no information on whether the students graduated from university.

the low persistence of students in scientific fields [Arcidiacono et al., 2016, Stinebrickner and Stinebrickner, 2014].

Table 4 shows that the effect masks substantial gender heterogeneity[29]: while girls are affected by the policy- for instance they are induced to take more medicine or biological sciences-, the effect on pure STEM degrees is entirely driven by boys. Some studies claims girls may shy away from STEM degrees because of fair for competition or lack of confidence about their ability [Buser et al., 2014, Niederle and Vesterlund, 2010], suggesting that increasing preparation and fostering scientific culture in secondary schools may shrink the gender gap in STEM degrees. My results suggest instead that strengthening the science curriculum at age 14 is not helpful. It may increase the share of girls taking science at age 14 and age 16, but it does not affect the share of girls choosing STEM subjects at the university. This is in line with the findings of some recent studies [Gemici and Wiswall, 2014, Zafar, 2013] showing that differences in preferences are the main driver behind the gender gap in college degrees; and preferences are difficult to be shaped by secondary school courses. My results are complementary to what is found in Joensen and Nielsen [2016] for Denmark. Joensen and Nielsen [2016] estimate very positive effects both for boys and for girls on the probability of choosing technical subjects at the university for students taking advanced math in secondary school. A first reason behind the difference in our results may be that they find a rather large effect on the probability of attending university as well, given their instrument affects slightly lower ability students than in this case. Their effect may therefore be the combination of changes in the pool of students attending university and changes in the willingness to choose STEM subjects, conditional on going to university; my effect instead comes exclusively from the second component. A second reason is related to differences in the type of compliers. As also pointed out by Joensen and Nielsen [2016] and extensively addressed for the regressions on earnings, the policy they analyze affects girls much more than boys and compliers for the two groups of students are likely to be very different. This makes the coefficients of the IV diffucult to compare across genders. As I will address more extensively in Subsection 4.2, my instrument affects boys and girls in a very similar way.

Tables A4 and A5 explore moreover the extent and the presence of subjects complementarity and substitutability. If one takes more science at age 14, which other (complement) subjects is she more likely to take and, more importantly, from which (substitute) subjects does she opt out? Table A3 in the Appendix shows the coefficients and standard errors obtained from estimating equation 3 using each time a different KS4 subject as dependent variable. Tables A4 and A5 report the same type of estimates but with respect to KS5 subjects and university degrees, respectively. Students who take triple science at KS4 tend to drop more vocational subjects, some foreign languages like German and some other core subjects like history. In terms of KS5 courses, taking triple science induces students to choose more natural science subjects and math later on, and to drop more vocational subjects, like media and accounting. Finally, triple science increases the probability of choosing scientific subjects at the university, like physics, engineering and medicine, but also non scientific but more challenging subjects, like classical languages. It decreases, instead, the probability of enrolling in law and architecture. The effect are different for boys and girls, especially for what concerns university degrees.

It is difficult to draw general conclusions from the coefficients of Tables A3, A4 and A5: anecdotal evidence may suggest that a vocational course in music is very different from an advanced course in science at age 14, but to evaluate each subject according to some objective

[29] As shown in Table A1 of the Appendix, there are other interesting source of heterogeneity. The group mostly affected by the policy are the middle-high ability students. The very high ability students would probably be very well prepared in any case and are less likely to be at the margin, the low ability students are instead less likely to be affected by the policy at all. Moreover the effect on science at age 16 is slightly stronger for low SES students, the effect on university outcomes is instead more difficult to estimate with enough precision for low SES students because of the small share (20%) of low SES students attending university.

criteria, Table 5 uses a more formal procedure. I define courses along two dimensions: (i) 'high achievers' courses, characterized by a high average primary school grade of students choosing them in out-of-sample academic years; (ii) 'female dominated' courses, characterized by a high share of girls attending the courses in out-of-sample academic years (2002-2005). Figure 4 describes each subject, along these dimensions. In particular it shows three scatterplots where for each course is displayed on the x-axis the share of girls usually enrolled in it and on the y-axis the average primary school grade of student attending it. Triple science stands out as the course at KS4 that is attended by the best students, followed by foreign languages, history and geography. With respect to KS5 options, math is the most challenging course, followed by physics, chemistry and foreign languages. For university degrees, medicine, languages and STEM subjects are attended by very good students while education, subjects allied to medicine and art are attended by the worst students on average. The correlation between the ability of students usually attending each course and the share of girls enrolled in those courses is negative. This is surprising, given that on average girls have higher grades than boys in primary school. Table 5 shows whether students start choosing more 'high achievers' courses at age 18 (KS5) and at the university as a consequence of taking more science at KS4.[30] Taking advanced science at age 14 induces students to choose more challenging subjects later on. Students taking triple science are induced to choose at age 16 courses usually attended by students whose average grade in primary school is about 0.2 standard deviations higher. The same is true for university degrees, but the magnitude of the effect is smaller. Moreover, for KS5, I disentangle how much of the reported increase is automatically due to the higher probability of choosing natural science subjects and how much to the fact that students choose other (complement) more 'high achievers' subjects, different from the three natural sciences. I find that the increase is partly driven by an higher probability of choosing science courses (63%) and partly due to a higher willingness to enroll in other difficult subjects not strictly in the natural science field (37%).[31]

The other columns look at the sample of boys and girls separately. The first row shows that girls who take triple science are induced to choose more challenging subjects (i.e. more 'high achievers' subjects) in about the same proportion as boys, the second row shows that they still opt for female-dominated subjects (like medicine for instance). This is an interesting result: while at age 16 girls taking triple science still opt for more male-dominated subjects (physics or math for instance - even if to a lower extent than for boys), strengthening the science preparation in secondary school does not have any effect on the likelihood that girls opt for STEM (male-dominated) subjects at the university. This suggests that once the subject choice is actually related to the characteristics of their future jobs, girls still prefer the most female-dominated degrees.

4.2 Compliers' characterization

This Section analyses who decides to take triple science, when the school offers it. This helps understand how students make decisions about which subject to take at age 14 and whether the heterogeneity in the β_1 coefficient, especially along the gender dimension, is actually driven by differences in the treatment effect or by differences in compliance across genders. Even if teachers in England usually make recommendations about which field courses to choose, the actual choice of whether to take triple science or not is a free decision made by students.[32]

[30] To obtain these results I multiply the coefficients displayed in Tables A3, A4 and A5 by the numbers displayed in Figure 4 and I sum the series. Standard errors are computed through the Delta method.

[31] This result is available upon request.

[32] One caveat should be considered when interpreting the results: sometimes supply of triple science is constrained since classes in England cannot be larger than 30. Since schools mainly prioritize based on previous science and math scores, any differences in the probability of taking triple science based on previous test scores

Pupils will choose to take triple science if their expected utility when $D = 1$ is higher than their expected utility when $D = 0$. This may happen because triple science reduces their costs (or their perception of the cost) of graduating in certain degrees or of graduating at all or because triple science directly increases their productivity, and therefore wage. The contribution in terms of utility of taking triple science with respect to the second best option, will not be the same for all students: those already very good in science or with very strong preferences towards other subjects may not find it as beneficial to take triple science.[33] This means that the likelihood of taking triple science will not be the same for everybody: it will depend on preferences, on innate ability and on perceptions towards their ability.

The first row of Table 6 shows results from the first stage regression. Being unexpectedly exposed to the offer of taking triple science increases students' probability of enrolling in it by 15 percentage points. The F statistics is around 2800.
Table 6 then characterizes compliers for the entire population and for boys and girls separately (columns 2 and 3, respectively). I obtain information on compliers' characteristics looking at the first stage for several subgroups of the population. For instance the ratio between the instrument's coefficient of the first stage estimated on the sample of females only (0.149) and the coefficient of the first stage estimated on the entire sample (0.163) represents the relative likelihood that a complier is female.[34] The Table shows that compliers are more likely to be very good students in primary school: the relative likelihood a complier is in the top 20th percentile of test scores in primary school is more than two. Moreover compliers tend to be high income students and, interestingly, there does not seem to be any particular gender difference in compliance. The second and the third columns compare compliers for the subgroups of girls and boys respectively and show that compliers' characteristics are very similar between these two groups.

4.3 Checks to the identification strategy

As stated in Section 3, the instrument used in the analysis relies on some assumptions.

First, the assumption that the information set of both the treatment and the control groups of students at age 11 is the same and does not include the information on whether the schools not offering triple science when students apply are going to offer it in three years. To check this assumption I include all schools in the sample (both offering and not offering triple science when student i applies) and I estimate the following equation:

$$W_{ist} = \alpha_1 z_{st}^{11} + \alpha_2 z_{st} + \alpha_3 X_{ist} + \xi_s + \xi_t + \eta_{ist} \tag{5}$$

where W_{ist} are several outcomes (like the dummy for whether student i chooses a STEM degree or whether he graduates in it) or pre-determined characteristics (like the average science grade in secondary school, his gender etc); z_{st}^{11} is a dummy equal to 1 if school s attended by student i in cohort t offered triple science when the student was 11 and chose her secondary school and z_{st} is my usual instrumental variable. In this way I test the extreme assumption that, even when parents or students know the school is offering triple science when applying, they do not select schools accordingly. Table 7 shows the results with (panel 1) and without (panel 2) school specific trends. The coefficient α_1 is not significant for most variables and in any case is usually extremely small: students applying to schools already offering triple science

may not be driven by students' willingness to take triple science, but by schools admission rules.

[33]Unless triple science has a positive effect also in reducing the cost of taking exams in other subjects, for instance through changes in self confidence.

[34]First stages in this case do not include any control a part from year and school fixed effects. This does not affect the effect of interest because controls are not correlated with the instrument.

or not offering it appear very similar- at least in terms of observable characteristics. This is consistent with the notion that students cannot freely choose their schools because schools, when oversubscribed, have to select students based on geographical distance.

Second, the assumption that schools decide when to start offering triple science not based on the quality of the current cohort attending the school and not because the school is already on an increasing trend. Table 8 provides evidence that, when using my identification strategy, the timing of the introduction of the triple science option is not correlated with (observable) characteristics of current students in the school. The Table runs a set of placebo tests, where I estimate the reduced form of equation 3 (without controlling for X_{ist}) and where the dependent variable is a pre-determined characteristic, the grade in the science course in primary school. The triple science dummy (TS) in this case should not be significant, because the instrument should not be correlated with the grade at KS2, unless my specification does not take full care of selection. The Table has the same structure of Table 2 and it shows how different identification strategies may fail to address selection. Column 1 shows results from a simple OLS regression, column 2 adds school fixed effects, column 3 replicates the specification used by Altonji [1995] and uses as instrument the share of students taking triple science in school s and year t, Column 4 uses my instrument but does not include schools fixed effects.[35] Column 5 includes also school fixed effects. Reassuringly, the effect in this case is 0. Finally column 6 adds school specific time trends, and the coefficient is again 0. Table A2 in the Appendix shows results from a set of other balancing tests obtained estimating the same specifications as in columns 5 and 6 for a bunch of other predetermined observable characteristics. All balancing tests show that the treatment is not correlated with observable characteristics of the current students in the school.

Moreover, I check for the presence of parallel trends. In particular, I check whether, before school s started to offer triple science, the trend was parallel to that of all other schools still not offering triple science. I augment my reduced form regression with leads and lags of the instrument (following Autor [2003]):

$$y_{ist} = \sum_{t=0}^{m} \gamma_{\tau-t} z_{s(\tau-t)} + \sum_{t=0}^{q} \gamma_{\tau+t} z_{s(\tau+t)} + \zeta_t + \zeta_s + u_{ist} \tag{6}$$

where z_{st} is my instrument, τ is the year school s starts offering triple science, ζ_s and ζ_t are the usual school and year fixed effects and u_{ist} is the error term. I then check for the presence of parallel pre-treatment trends by evaluating whether all coefficients $\gamma_{\tau-t}$ are close to 0, for every τ. Figure 5 shows that the trends are parallel before the introduction of the advanced science course and there is a jump in the outcomes and in the treatment correspondingly exactly to the year of the introduction of the new course.[36] This confirms the results obtained in Table 7 and 8.

Another possible concern is that, once a school sets up all arrangements in terms of teaching qualifications and staff in order to offer triple science, it may start to offer more science courses at KS5 as well. In England about 60% of the schools offer both KS4 (age 14) and KS5 (age 16) exams. This would imply that part of the effect I find may be purely mechanical: students take more KS5 science courses because the set of options changes also at KS5. I address this concern in Table 9. Columns 1 and 2 look at how the probability of offering science at KS5 evolves over time and whether it corresponds exactly to the cohort when the school starts offering triple science at KS4. The correlation is 0. Columns 3 and 4 look at whether the effect of studying triple science on the probability of choosing science at KS5 is larger for schools offering both

[35] This column partly replicates, even if in a very different context, Joensen and Nielsen [2016]

[36] I also estimated the same graphs but using predetermined characteristics as dependent variables: in this case there is no jump at year 0, nor at year -3, that correspond to the time when students know, when applying, that the school offers triple science. These results are available upon request.

KS4 and KS5 courses than for schools offering KS4 courses only. The effect is identical. If part of the effect I find in my results was mechanical, it would be stronger for schools offering both KS4 and KS5 exams.

Moreover, one may worry that taking triple science could potentially directly affect the possibility of being admitted to STEM degrees at the university. However, while universities often require some KS5 subjects in order to admit students to certain degrees, in no case they require specific KS4 subjects. For instance, in 2013, a KS5 exam in math was required in 13% of the cases (i.e. of degree-university combinations) and at least one KS5 exam in science was required in 12% of the cases. In no case[37], in 2013, there was a specific requirement for age 14 (KS4) subjects.

Finally, it may be that the simple fact of having the possibility of being enrolled in advanced science but having been excluded, for example because the class was oversubscribed and schools had to select students, may generate a direct effect on some students and may therefore violate the exclusion restriction assumption. This is impossible to test. Table A6 however exploits some of the institutional features of English school system to evaluate how problematic this may be. Figure 6 plots the distribution of the size of triple science courses in each school. From the Figure it is clear that class size bunches at multiples of 30. There is a discontinuity both corresponding to 30 students and corresponding to 60 students. Since class size in England is required to be lower than 30, this Figure suggests that in some cases the triple science course was oversubscribed, and schools had to select students. Unfortunately the exact admission rule is different for each school and is not publicly available. Table A6 exploits this feature of the system and runs the main specification (using equation 3) on the sample of schools where the triple science course was very likely not oversubscribed, because the number of enrolled students was not close to the maximum.[38] The results of this exercise are very similar to the main ones.

4.4 Second instrument

Table 10 shows the results obtained from my second identification strategy.[39] The first three columns refer to the probability of choosing a natural science subjects at Key Stage 5 (age 18), the last three columns refer to the probability of attending a STEM degree at the university.[40] The first and the forth columns do not include neighbourhood fixed effects, but control for the lagged value of my instrument: they compare neighbourhoods which had the same share of reachable schools offering the triple science course the previous year and they exploit variation between t and $t-1$. All other columns include neighbourhood fixed effects.

This instrument compares students living in the same neighbourhood but attending different schools which offer or do not offer triple science. However, the probability of offering triple science is likely to be related to other school characteristics, like school quality, that may directly affect the choices of degrees at the university. Since the variation in school quality may be much larger when using across school rather than within school over time variation, like with the previous instrument, in Columns 3 and 6 I include the average quality of the set of reachable schools in year t as a control. I proxy school quality using the school value added in the out of sample years (2002-2005).

[37]Data are taken from http://www.thecompleteuniversityguide.co.uk/courses/search

[38]Those schools where the number of students enrolled in the triple science classes was not between 28 and 32 or between 58 and 62.

[39] Since there is no information on postcode in primary school for students who finished secondary school in the years before 2007, this section only refers to the years 2007-2010. For these cohorts, however, I have information on whether they graduated only for the students who took KS4 exams in the year 2007, so I only analyze effects on enrollment and on KS5 outcomes.

[40]The effect on the probability of attending university is 0, as for the previous instrument.

The results confirm the robustness of the first identification strategy: the estimated effects are positive and significant and the effects on STEM dergrees are stronger for boys than for girls[41]. The estimates obtained through this strategy are however slightly larger, this may be related to the different type of variation, and therefore of compliers, exploited. While compliers for the first instrument are all individuals who take triple science because their school unexpectedly starts to offer it, which also include very good students who happened to be enrolled in a school not offering triple science; compliers in the second instruments are students who take triple science because, thanks to a larger supply of triple science in the set of reachable schools in their neighbourhood, they manage to enroll in a school offering it. In this second case, very good students would probably have enrolled in a school offering triple science in any case. This suggests compliers for the second strategy exclude the extremely high ability students. Since, as shown in Table A1 in the Appendix, those mostly affected by the policy are middle-high ability students, this may explain the larger effect found in Table 10.

5 Alternative Mechanisms

This Section explores the mechanisms that may generate the effect found in Section 4 and explores whether the effect obtained is actually generated by changes in curriculum or, since the treatment has multiple components, it is also driven by changes in the peer composition of the courses attended or in the type of teachers in the school.

5.1 Peers

First, I analyse the peers channel. In particular, I use the following measure of peer quality in science (Q_{ist}) for student i, attending school s in year t who takes science courses D_{ist}:

$$Q_{ist} = \overline{X}^{D}_{(-i)st} \tag{7}$$

where $\overline{X}^{D}_{(-i)st}$ is the average science grade in primary school of students taking age 14 science course D[42], in school s in year t (excluding i).

The first panel of Figure 7 shows how peers' composition in the science course taken at age 14 changes for schools offering triple science or not. The dashed line plots the density of Q_{ist} in the age 14 science course for students attending schools not offering triple science. The solid line refers instead to schools offering triple science. The figure shows that when schools offer triple science there is a concentration of very high ability students able to attend the science class with peers of much higher quality than before. Column 1 of Table 11 confirms this finding: it shows how peers' quality in science courses changes after the school starts offering the advanced science course, depending on students' primary school grade in science. The quality of peers in the science class decreases for lower ability students and increases quite extensively for higher ability students.

To control for this dimension and check whether the effect found in Table 3 comes mostly from changes in the peer composition or from changes in the curriculum, I control for peer quality in equation 3. Since students self-select into different types of science course at age 14, peers' quality may be endogenous. I therefore instrument peer quality by using within-school over-time changes in peers' composition (following Hoxby [2000]). In particular, I use the fact that classes in England cannot be larger than 30 (as shown in Figure 6).[43] I therefore

[41]results available upon request

[42]Since there is no information about the exact class but only about the type of science course, I use the average grade in primary school of students taking the same course.

[43]While for primary schools this requirement is compulsory, it is just recommended for secondary school.

predict, based on predetermined characteristics like previous test scores and demographics,[44] the probability of being enrolled into triple science and I take the average science grade in primary school of the 30 or 60 students (depending on the number of triple science classes offered) with the highest probability of being enrolled into triple science. I then exploit within school over time variation in the average quality of these students and of all other students in school s and year t, allowing the effect to be different depending on whether the school offers (unexpectedly) triple science or not. My first stage equation is:

$$Q_{ist} = \theta_1 z_{st} + \theta_2 \widehat{Q^{top30}_{st(-i)}} + \theta_3 \widehat{Q^{others}_{st(-i)}} + \theta_4 \widehat{Q^{top30}_{st(-i)}} * z_{st} + \theta_5 \widehat{Q^{others}_{st(-i)}} * z_{st} + \theta_5 X_{ist} + \theta_s + \theta_t + \eta_{ist} \quad (8)$$

where z_{st} is the first instrument - the dummy equal to 1 student i was unexpectedly exposed to the option of choosing triple science- $\widehat{Q^{top30}_{st(-i)}}$ is the average science grade in primary school of the 30 (or 60) students with the highest predicted probability of being enrolled in triple science and $\widehat{Q^{others}_{st(-i)}}$ is the average science grade in primary school of all other students; θ_s and θ_t are school and year fixed effects and η_{istj} is the error term. Panel b of Figure 7 shows how the instrument works. The solid line refers to the average science grade in primary school for students predicted to attend the triple science class, the dashed line refers to all other students.

Table 11 displays the results. Columns 2 to 6 show that the effect of triple science is very similar to what found before, even after controlling for changes in peers' quality. The joint F statistic is 35.

5.2 Teachers

Unfortunately, it is not possible in England to link data on individual teachers to administrative data on individual students. In this section I use the yearly number of teachers and of qualified teachers in each school. Table A7 in the Appendix shows that neither the overall number of teachers nor the number of qualified teachers in a school change significantly once the school introduces the triple science option. This suggests that teachers' quality and quantity do not increase as a result of the introduction of the advanced science course.

6 Conclusions

This paper uses a reform that increased the probability of taking an advanced science course in English secondary schools for students at the top of the ability distribution to analyze whether secondary school curriculum affects post-16 outcomes, and in particular the probability of enrolling and graduating in a STEM degree. Moreover, by separately investigating the effect on boys and girls, this paper seeks to understand whether strengthening school preparation in science shrinks the gender gap in enrollment in STEM degrees.

Since the policy I consider affected very high ability students, who would have continued studying in any case, I find that a stronger science curriculum in secondary school has no effect on university enrollment. Still, my estimates suggest that offering more science in secondary school improves educational outcomes in many domains. It induces students to attend higher quality universities and significantly increases the probability of enrolling and, very importantly, of graduating from university with a STEM degree. This effect masks a substantial and interesting gender heterogeneity: at age 14 when exposed to the option of studying more science

[44] In particular, KS2 and KS3 science grades (both teacher assessed and from standardized exams) , gender, Free School Meal Eligibility.

in secondary school, there is no gender difference in the take-up probability. However, the difference arises later on, at the university, when subject choices are likely to be correlated with occupations and jobs: both boys and girls are induced to take more challenging courses on average, but girls still choose more female-dominated subjects like medicine, instead of engineering and math. This seems to be in line with the recent literature relating preferences towards job attributes to choices of university degrees [Wiswall and Zafar, 2016, Reuben et al., 2015, Zafar, 2013] that shows that job characteristics play an important role in the choice of subjects at the university, with women and men displaying very different preferences, even if at the very top of the ability distribution.

My findings show that there is a certain degree of persistence between what is studied at secondary school and what is studied at the university. An optimal design of the secondary school curricula may be useful to improve the match between supply and demand of specific skills.

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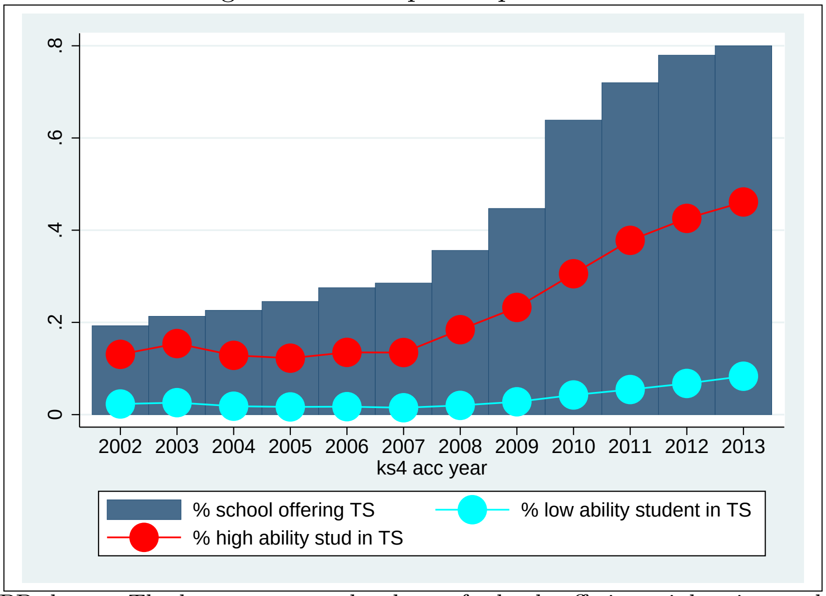
Figures

Figure 1: Take up in triple science



Source: NPD dataset.The bars represent the share of schools offering triple science; the red dots represent the share of high ability (based on English, math and science primary school grade, top 40 %) students taking triple science and the blue dots show the share of low ability (based on primary school grades, bottom 60 %) students taking triple science, by year.

Figure 2: Timeline of the English educational system

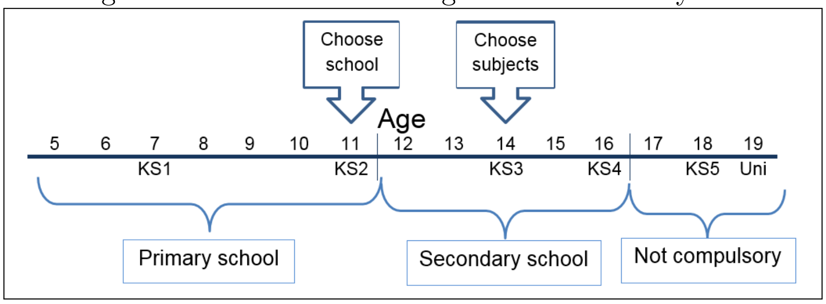


Figure 3: Second instrument

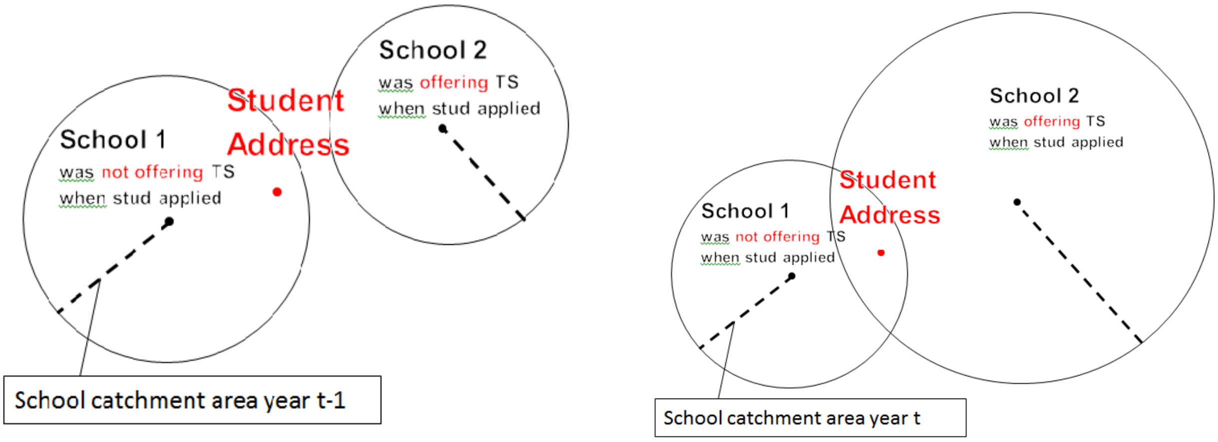
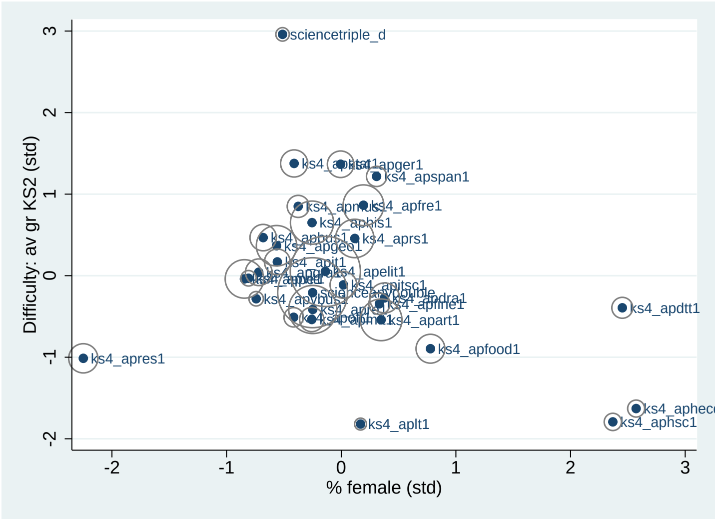
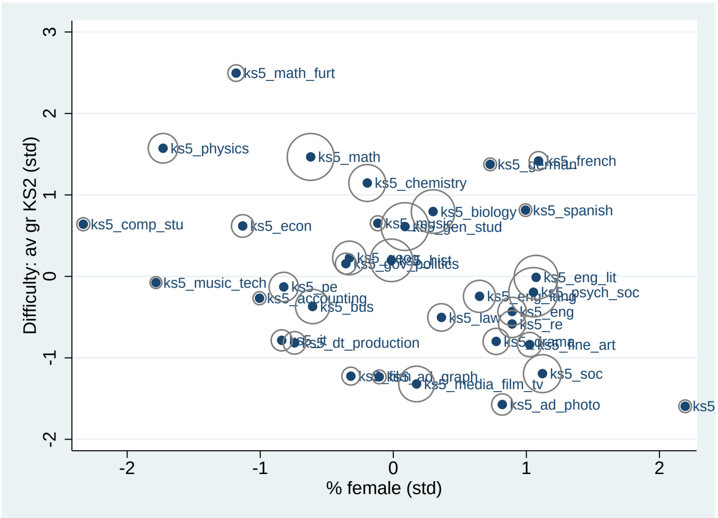


Figure 4: Subject descriptives

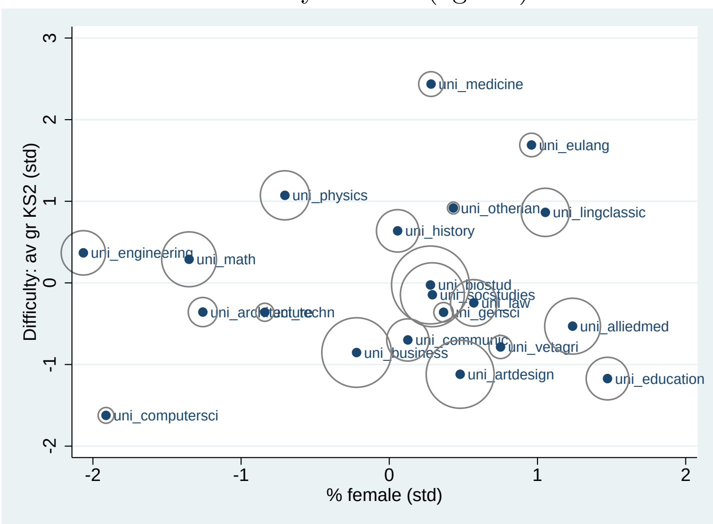
KS4 courses (age 14)



KS5 courses (age 16)



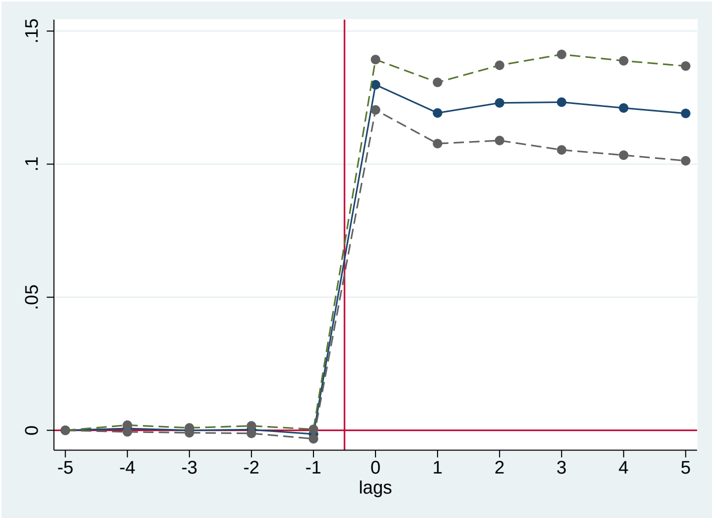
University courses (age 18)



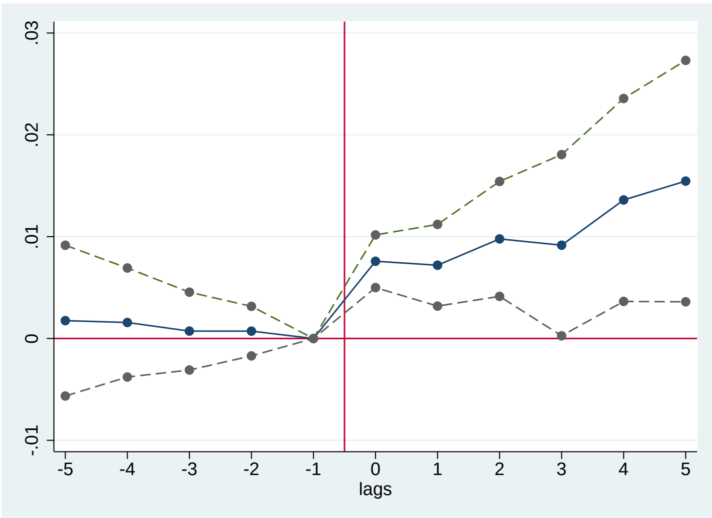
Source: NPD dataset. Subjects are described along two dimensions: the average primary school grade (in English, math and science) of students taking the course in out of sample years and the share of girls taking the course in out of sample years. The circles around each observation represent the number of students attending these courses.

Figure 5: Parallel Trends: Leads and Lags of the instrument

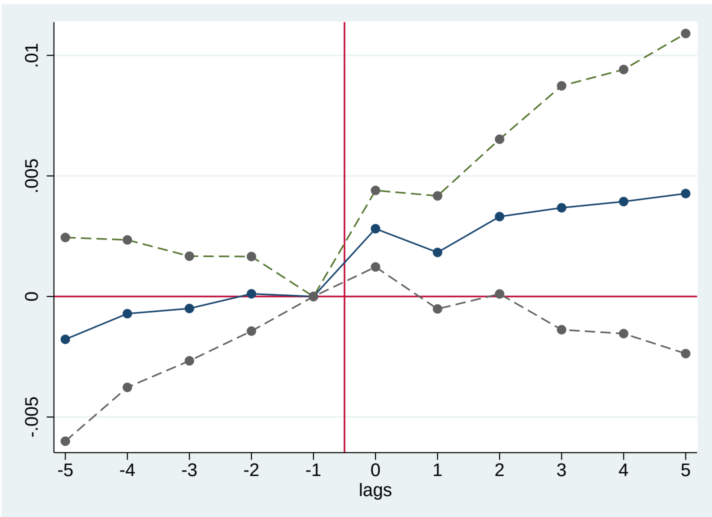
Dep var: 1=Triple Science



Dep var: 1=A lev Science

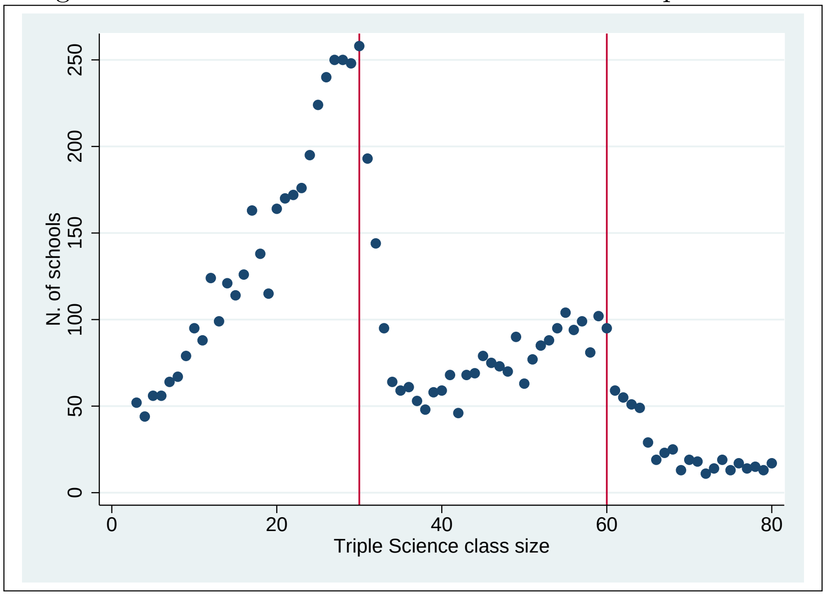


Dep var: 1=Uni STEM



Source: NPD dataset. The continuous line represent coefficients, the dashed lines the 5% confidence intervals, obtained from estimating equation 6. Omitted category: one year before the treatment.

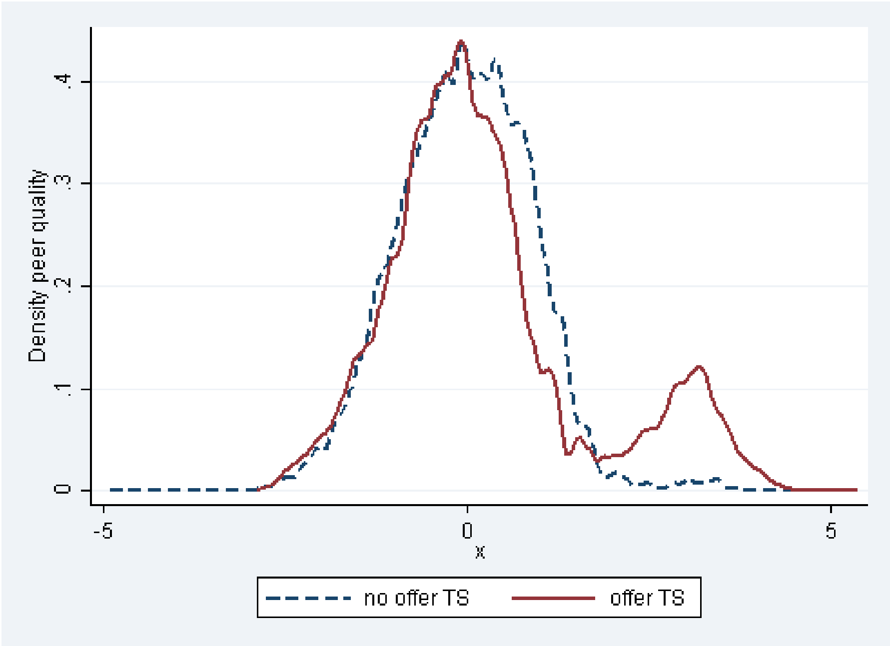
Figure 6: Class size and number of students in triple science



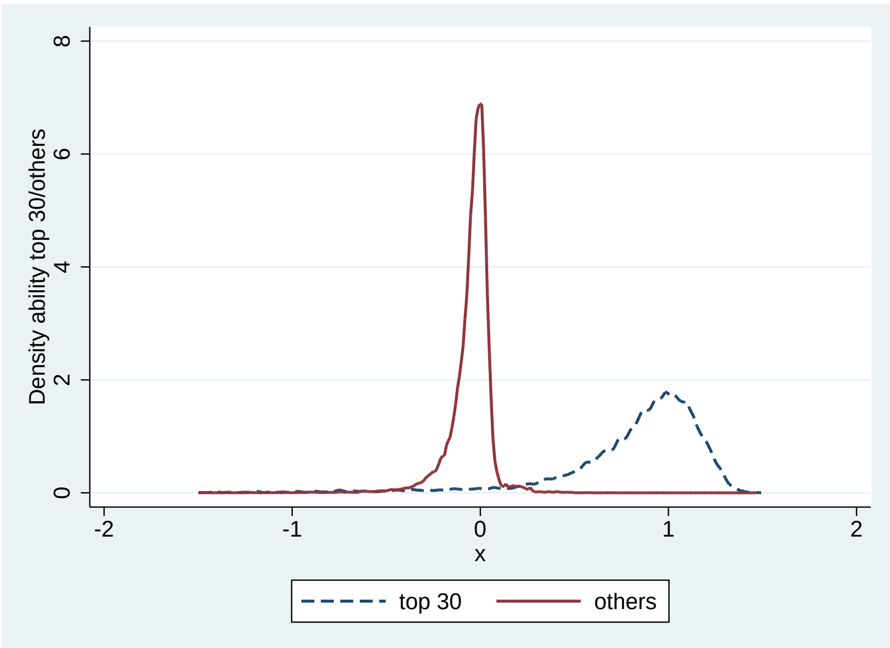
Source: NPD dataset. The dots are the number of schools, by triple science class size .

Figure 7: Peers

Actual peers' quality



Instrument



Source: NPD dataset. The first panel plots the distribution of science peers' quality, distinguishing whether the school offers triple science or not. The second panel plots the average peers quality for students predicted to take the TS class and students not predicted to take the TS class.

Tables

Table 1: Summary statistics

Variable	Mean	Std. Dev.
Key Stage 4		
offer TS (unexpected)	0.196	0.397
1=Triple Sci	0.076	0.264
1=Double Sci	0.764	0.425
1=Single Sci	0.163	0.369
Key Stage 5		
1=KS5 science (if KS5)	0.198	0.282
1=KS5 math (if KS5)	0.142	0.252
University		
1=uni	0.348	0.470
1=STEM[a]	0.126	0.198
1=Russell	0.046	0.211
1=graduate[a]	0.481	0.361
Demographics		
1=female	0.497	0.500
1=FSM eligible[b]	0.144	0.356

The summary statistics reported in the Table refer to the entire sample of students taking their final KS4 exams (at age 16) between 2005 and 2010.
[a] Conditional on going to university.
[b] Free School Meal Eligible.

Table 2: Results for science at age 17 and 19

	OLS [1]	OLS-Fe [2]	Altonji [3]	IV [4]	IV-Fe [5]	IV-Fe tr [6]	IV-Fe [7]
Dep var:				1=KS5 Science			
1=TS	0.334***	0.257***	0.147***	0.072***	0.051***	0.048***	0.054***
	(0.005)	(0.005)	(0.014)	(0.010)	(0.006)	(0.008)	(0.006)
1=female		-0.009***	-0.004***	-0.011***	-0.010***	-0.010***	
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
I sch gr sci		0.020***	0.019***	0.019***	0.021***	0.022***	
		(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	
N	1690451	1690451	1690451	1690451	1690451	1690451	1690451
Fstat			559372	2234	2065	1742	2066
Dep var:				1=STEM university			
1=TS	0.104***	0.072***	0.039***	0.024***	0.014***	0.012**	0.015***
	(0.002)	(0.002)	(0.005)	(0.004)	(0.004)	(0.006)	(0.004)
1=female		-0.034***	-0.034***	-0.035***	-0.034***	-0.034***	
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	
I sch gr sci		0.005***	0.005***	0.005***	0.006***	0.006***	
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	
N	1690451	1690451	1690451	1690451	1690451	1690451	1690451
Fstat			559372	2234	2065	1742	2066
School Fe	No	Yes	No	No	Yes	Yes	Yes
School trends	No	No	No	No	No	Yes	No
School contr	No	No	Yes	Yes	No	No	No
Stud contr	No	Yes	Yes	Yes	Yes	Yes	No

Additional controls: year and school fixed effects; student controls: gender, Free School Meal Eligible, Special Education Needs, primary school grade in science, math and english; schools controls: school size. All dependent variables are set equal to 0 if students do not continue studying or if they do not take the considered subjects. Robust standard errors clustered by school in parentheses. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

Table 3: Results for other outcomes

	[1]	[2]	[3]	[4]	[5]
Panel 1: KS4 (age 14) outcomes					
	Grades			N. Exams	
Dep var:	KS4 Eng gr[a]	KS4 Math gr[a]	Ks4 science gr	n exams ks4	n exams ks5[c]
1=TS	0.001	-0.026	-0.065**	0.438**	-0.021
	(0.031)	(0.028)	(0.027)	(0.210)	(0.022)
N	1332413	1339792	1690325	1690451	860615
ymean	0.022	0.021	0.000	10.303	3.416
Panel 2: KS5 (age 16) outcomes					
Dep var:	1=KS 5	1=KS5 math	1=KS5 Bio	1=KS5 Che	1=KS5 Phy
1=TS	-0.009	0.035***	0.037***	0.025***	0.024***
	(0.010)	(0.005)	(0.004)	(0.003)	(0.005)
N	1690451	1690451	1690451	1690451	1690451
ymean	0.509	0.056	0.040	0.026	0.065
Panel 3: University outcomes[b]					
Dep var:	1=uni	1=grad	1=Russell	1=uni med	1=grad STEM
1=TS	0.044*	0.041	0.022*	0.013**	0.033***
	(0.025)	(0.025)	(0.011)	(0.007)	(0.011)
N	966777	966777	966777	966777	966777
ymean	0.318	0.207	0.046	0.019	0.034

Additional controls: year and school fixed effects; student controls: gender, Free School Meal Eligible, Special Education Needs, primary school grade in science, math and english; schools controls: school size. All dependent variables are set equal to 0 if students do not continue studying or if they do not take the considered subjects. Robust standard errors clustered by school in parentheses. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

[a] Grades go from 0 to 7, but are standardized to have mean 0 and standard deviation 1.

[b] The results on university outcomes use only the 2005-2008 sample because otherwise there will be no information on the graduation outcomes.

Table 4: Gender Heterogeneity

Dep var:	1=KS5 sci	1=Russell	1=STEM	1=medicine	1=grad	1=grad STEM
	[1]	[2]	[3]	[4]	[5]	[6]
				Girls		
1=TS	0.047***	0.027	0.003	0.023**	0.049	0.015
	(0.008)	(0.021)	(0.015)	(0.009)	(0.040)	(0.013)
N	849149	486068	486068	486068	486068	486068
ymean	0.080	0.053	0.020	0.030	0.239	0.019
				Boys		
1=TS	0.053***	0.018	0.037**	0.005	0.033	0.045***
	(0.007)	(0.013)	(0.017)	(0.006)	(0.029)	(0.016)
N	841234	480646	480646	480646	480646	480646
ymean	0.088	0.040	0.054	0.008	0.174	0.049

Additional controls: year and school fixed effects; student controls: gender, Free School Meal Eligible, Special Education Needs, primary school grade in science, math and English; schools controls: school size. All dependent variables are set equal to 0 if students do not continue studying or if they do not take the considered subjects. Robust standard errors clustered by school in parentheses. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

Table 5: Summarizing effects on other subjects

	Δ ks5 courses			Δ uni major		
	All	Girls	Boys	All	Girls	Boys
High achievers	0.197***	0.168***	0.220***	0.022***	0.021**	0.028***
	(0.019)	(0.028)	(0.023)	(0.007)	(0.011)	(0.008)
Female-dominated	-0.042***	-0.016	-0.058***	-0.007	0.014	-0.023**
	(0.018)	(0.027)	(0.020)	(0.008)	(0.011)	(0.010)

The coefficients are computed as $\sum_j \beta_j q_j$ where j indicates subjects, β_j is the subject specific coefficient estimated in Tables A4 and A5 and q_j is either 'high achievers'(the average primary school grade of taking the course j in out of sample academic years (2002-2005), standardized to have mean 0 and standard deviation 1) or 'female dominated' (the share of girls attending course j in out of sample academic years). Standard errors are computed through the delta method.

Table 6: Characterizing compliers

Sample	Everybody	Only Girls	Only Boys
	[1]	[2]	[3]
Panel 1: Entire Sample			
Z_{st}	0.175***	0.161***	0.188***
	(0.004)	(0.005)	(0.005)
N	1690451	849184	841267
Panel 2: Quintiles science grade in primary school			
	subgroup: 1st quintile av. primary school grade		
Z_{st}	0.009***	0.008***	0.009***
	(0.001)	(0.001)	(0.001)
N	339951	174093	165858
Ratio wrt tot FS	0.051	0.050	0.048
	subgroup: 2nd quintile av. primary school grade		
Z_{st}	0.038***	0.035***	0.041***
	(0.001)	(0.002)	(0.002)
N	341063	171845	169218
Ratio wrt tot FS	0.217	0.217	0.218
	subgroup: 3rd quintile av. primary school grade		
Z_{st}	0.099***	0.092***	0.105***
	(0.003)	(0.003)	(0.004)
N	336767	168450	168317
Ratio wrt tot FS	0.566	0.571	0.559
	subgroup: 4th quintile av. primary school grade		
Z_{st}	0.222***	0.208***	0.234***
	(0.005)	(0.006)	(0.006)
N	344551	171725	172826
Ratio wrt tot FS	1.269	1.292	1.245
	subgroup: 5th quintile av. primary school grade		
Z_{st}	0.449***	0.417***	0.479***
	(0.009)	(0.011)	(0.010)
N	328119	163071	165048
Ratio wrt tot FS	2.566	2.590	2.548
Panel 3: Socio-Economic Status			
	subgroup: Low SES students (yes FSM[a])		
Z_{st}	0.084***	0.077***	0.092***
	(0.002)	(0.003)	(0.003)
N	223375	114446	108929
Ratio wrt tot FS	0.480	0.478	0.489

The Table reports results from the first stage for different subgroups of the population. Dependent variable: a dummy equal to 1 if the student takes triple science. Additional controls: year and school fixed effects. Robust standard errors clustered by school in parentheses. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

[a] Free School Meal Eligible.

Table 7: Selection

	av KS2 gr[a]	sci KS2 gr[b]	1=FSM	1=KS5 sci	1=uni	1=STEM	1=grad STEM
	[1]	[2]	[3]	[4]	[5]	[6]	[7]
Without school specific trends							
Z_{st}^{11}	-0.005	-0.008	0.002	0.005***	-0.002	0.001	0.001
	(0.005)	(0.006)	(0.002)	(0.001)	(0.004)	(0.002)	(0.002)
N	2882341	2882341	2882341	2882341	1468169	1468169	1468169
School fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School trend	No	No	No	No	No	No	No
With school specific trends							
Z_{st}^{11}	0.002	0.002	0.007**	0.004**	-0.003	0.001	0.001
	(0.006)	(0.002)	(0.003)	(0.002)	(0.005)	(0.002)	(0.002)
N	2285735	2285735	2285735	2285735	1309004	1309004	1309004
School fe	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School trend	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Additional controls years dummies, school fixed effects. Robust standard errors clustered by school in parentheses. The dependent variables in column 4, 5 and 7 are set equal to 0 if students do not continue studying or if they do not take that subject. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

[a] average grade in English, math and science.

[b] grade in science.

Table 8: Balancing Test

	OLS	OLS-Fe	Altonji	IV	IV-Fe	IV-Fe tr
	[1]	[2]	[3]	[4]	[5]	[6]
Dep var:	1=Average Grade prim school[a]					
1=TS	0.927***	0.788***	0.802***	0.363***	0.042	0.045
	(0.013)	(0.015)	(0.054)	(0.052)	(0.026)	(0.034)
mfemale				0.232***		
				(0.053)		
mfsm				-1.545***		
				(0.051)		
N	1337202	1337202	1337202	1337202	1337202	1337202
School Fe	No	Yes	No	No	Yes	Yes
School time trends	No	No	No	No	No	Yes

Additional controls: years dummies. Robust standard errors clustered by school in parentheses. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

[a] Average grade in the KS4 exams in English, math and science.

Table 9: Robustness: offer KS5 Science

Dep var:	Sch level regr (offer) 1=Offer KS5 Science	1=offer KS5 Math	Stud in schools wo sixth form All schools Dep var: 1=KS5 Science	only offer KS4
	[1]	[2]	[3]	[4]
offertriple0	0.002	-0.000		
	(0.004)	(0.004)		
1=TS			0.050***	0.053***
			(0.006)	(0.009)
N	5294	5294	1690451	751721
ymean	0.477	0.467	0.084	0.060

Column 1 and 2 are run at the school-year level. Columns 3 and 4 are run at the student level. Additional controls: year and school fixed effects; student controls: gender, Free School Meal Eligible, Special Education Needs, primary school grade in science, math and English; schools controls: school size. The dependent variables in columns 3, and 4 are set equal to 0 if students do not continue studying or if they do not take the considered subjects. Robust standard errors clustered by school in parentheses. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

Table 10: Identification based on the second instrument

Dep. Var.:	1=KS5 Science			1=STEM major		
	[1]	[2]	[3]	[4]	[5]	[6]
1=TP	0.111***	0.120***	0.108**	0.028***	0.042	0.035
	(0.013)	(0.042)	(0.043)	(0.010)	(0.054)	(0.060)
% reach school off TS_{t-1}	0.001			-0.002		
	(0.002)			(0.002)		
av. qual reach school			0.018**			0.010
			(0.007)			(0.007)
N	2847133	2850675	2850675	2392486	2395787	2392319
Neigh Fe	No	Yes	Yes	No	Yes	Yes

Additional controls: year fixed effects; student controls: gender, Free School Meal Eligible, Special Education Needs, primary school grade in science, math and English. All dependent variables are set equal to 0 if students do not continue studying or if they do not take the considered subjects. Robust standard errors clustered by neighbourhood in parentheses. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

Table 11: Peers

Dep var:	$Q_{ist}{}^{a}$ [1]	1=KS5 sci [2]	1=Russell [3]	1=STEM [4]	1=medic [5]	1=grad [6]	1=grad STEM [7]
Z offer*ks2 sci q1	-0.095***						
	(0.011)						
Z offer*ks2 sci q2	-0.060***						
	(0.008)						
Z offer*ks2 sci q3	-0.031***						
	(0.007)						
Z offer*ks2 sci q4	0.024***						
	(0.007)						
Z offer*ks2 sci q5	0.055***						
	(0.007)						
Z offer*ks2 sci q6	0.099***						
	(0.008)						
1=TS		0.053***	0.022**	0.024**	0.013*	0.042*	0.034***
		(0.006)	(0.011)	(0.012)	(0.008)	(0.025)	(0.011)
qual peer (std)		0.021***	0.018***	0.003	-0.001	0.014	0.004
		(0.005)	(0.004)	(0.004)	(0.003)	(0.009)	(0.004)
N	1648926	1621765	935630	935630	935630	935630	935630

Additional controls: year and school fixed effects; student controls: gender, Free School Meal Eligible, Special Education Needs, primary school grade in science, math and english; schools controls: school size. All dependent variables are set equal to 0 if students do not continue studying or if they do not take the considered subjects. Gr sci refers to sixtiles of the grade distribution in the science exam at the end of primary school (KS2). F statistic: 35.

[a] quality (based on science grade in ks2 (age 11) of peers in the same science class. Robust standard errors clustered by school in parentheses. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

7 Appendix

Table A1: Heterogeneity

Dep var:	1=KS5 sci	1=Russell	1=STEM	1=medicine	1=grad	1=grad STEM
	[1]	[2]	[3]	[4]	[5]	[6]
Panel 1: Quintiles science grade in primary school						
			3rd quintile			
1=TS	0.019	-0.002	-0.002	0.015	0.036	0.032
	(0.015)	(0.035)	(0.037)	(0.028)	(0.089)	(0.036)
N	336723	203148	203148	203148	203148	203148
ymean	0.045	0.024	0.026	0.017	0.188	0.023
			4th quintile			
1=TS	0.032***	0.041*	0.076***	0.017	0.084*	0.086***
	(0.010)	(0.021)	(0.021)	(0.014)	(0.046)	(0.019)
N	344500	197276	197276	197276	197276	197276
ymean	0.104	0.053	0.045	0.024	0.277	0.042
			5th quintile			
1=TS	0.053***	0.018	0.010	0.005	0.016	0.012
	(0.007)	(0.016)	(0.015)	(0.008)	(0.023)	(0.015)
N	328076	181689	181689	181689	181689	181689
ymean	0.254	0.146	0.097	0.040	0.414	0.090
Panel 2: Socio-Economics Status						
			High SES students (no FSM)			
1=TS	0.048***	0.024**	0.020	0.015*	0.037	0.033***
	(0.006)	(0.011)	(0.013)	(0.008)	(0.026)	(0.012)
N	1431595	818880	818880	818880	818880	818880
ymean	0.093	0.052	0.041	0.020	0.226	0.037
			Low SES students (yes FSM)			
1=TS	0.063***	-0.008	0.042	-0.003	0.100	0.024
	(0.018)	(0.044)	(0.039)	(0.035)	(0.090)	(0.036)
N	258804	147854	147854	147854	147854	147854
ymean	0.034	0.015	0.018	0.010	0.103	0.016

Additional controls: year and school fixed effects; student controls: gender, Free School Meal Eligible, Special Education Needs, primary school grade in science, math and English; schools controls: school size. All dependent variables are set equal to 0 if students do not continue studying or if they do not take the considered subjects. Robust standard errors clustered by school in parentheses. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

Table A2: Other balancing tests

	RF [1]	RF [2]	IV [3]	IV [4]
Dep var:	1=Grade English prim school			
Z_{st}	-0.000	0.005		
	(0.004)	(0.005)		
1=TS			-0.001	-0.002
			(0.023)	(0.023)
N	1690451	1690451	1690451	1690451
ymean	0.015	0.015	0.015	0.015
Dep var:	1=female			
Z_{st}	-0.002	-0.001		
	(0.001)	(0.002)		
1=TS			-0.009	-0.009
			(0.009)	(0.009)
N	1690451	1690451	1690451	1690451
ymean	0.502	0.502	0.502	0.502
Dep var:	1=FSM			
Z_{st}	-0.000	-0.000		
	(0.001)	(0.002)		
1=TS			-0.001	-0.001
			(0.008)	(0.008)
N	1690451	1690451	1690451	1690451
ymean	0.153	0.153	0.153	0.153
School Fe	Yes	Yes	Yes	Yes
School trend	No	Yes	No	Yes

Additional controls years dummies. All dependent variables are set equal to 0 if students do not continue studying or if they do not take that subject. Robust standard errors clustered by school in parentheses. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

Table A3: Effect on other KS4 subjects (age 14)

Dep. var	All		Girls		Boys	
	[1]	[2]	[3]	[4]	[5]	[6]
	Coeff.	Se	Coeff.	Se	Coeff.	Se
English lit	0.068**	(0.030)	0.075**	(0.030)	0.061*	(0.032)
Statistics	0.011	(0.034)	0.010	(0.038)	0.011	(0.034)
DT food	-0.027*	(0.016)	-0.047**	(0.024)	-0.009	(0.013)
DT graphics	-0.015	(0.014)	-0.002	(0.017)	-0.027	(0.017)
DT material	-0.014	(0.014)	0.000	(0.011)	-0.024	(0.022)
Art design	-0.008	(0.019)	0.001	(0.025)	-0.015	(0.019)
History	-0.032*	(0.019)	-0.045*	(0.023)	-0.022	(0.021)
Geogr	0.007	(0.020)	0.010	(0.024)	0.005	(0.022)
French	-0.015	(0.028)	-0.010	(0.033)	-0.020	(0.027)
German	-0.065***	(0.018)	-0.072***	(0.022)	-0.060***	(0.018)
Business	-0.012	(0.019)	-0.012	(0.020)	-0.014	(0.021)
Drama	0.007	(0.014)	-0.001	(0.020)	0.013	(0.014)
Inf tech	-0.034	(0.031)	-0.020	(0.032)	-0.048	(0.035)
Music	-0.001	(0.008)	-0.012	(0.011)	0.009	(0.010)
Media	-0.012	(0.022)	-0.016	(0.025)	-0.009	(0.023)
Fine art	0.005	(0.014)	0.007	(0.019)	0.004	(0.013)
Office technology	0.016	(0.028)	0.008	(0.032)	0.022	(0.028)
Applied buss	-0.001	(0.014)	-0.004	(0.015)	0.000	(0.015)
Health care	0.003	(0.011)	0.009	(0.022)	-0.002	(0.004)
Applied IT	-0.009	(0.021)	-0.009	(0.021)	-0.008	(0.024)

Each line represents a different regression. Columns 1, 3 and 5 display the coefficients on the independent variable $1 = TS$. All dependent variables are set equal to 0 if students do not take that subject. Usual controls. Robust standard errors clustered at the school level. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%. I exclude math and English because compulsory in KS4.

Table A4: Effect on other KS5 subjects (age 16)

Dep. var	All		Girls		Boys	
	Coeff.	Se	Coeff.	Se	Coeff.	Se
Biology	0.035***	(0.005)	0.037***	(0.008)	0.034***	(0.006)
Chemistry	0.037***	(0.004)	0.032***	(0.006)	0.040***	(0.005)
Physics	0.025***	(0.003)	0.012***	(0.003)	0.036***	(0.005)
Math	0.024***	(0.005)	0.016**	(0.007)	0.031***	(0.007)
AD textile	-0.003*	(0.002)	-0.005	(0.003)	-0.001*	(0.000)
History	0.005	(0.005)	0.004	(0.008)	0.005	(0.006)
Economics	0.003	(0.003)	0.002	(0.003)	0.004	(0.005)
Law	-0.007**	(0.003)	-0.007	(0.005)	-0.008**	(0.004)
Psychology	-0.010*	(0.006)	-0.015	(0.011)	-0.006	(0.005)
Media film tv	-0.012***	(0.005)	-0.013*	(0.007)	-0.011**	(0.005)
German	-0.003**	(0.001)	-0.002	(0.002)	-0.003**	(0.001)
Music tech	-0.004***	(0.001)	-0.001	(0.001)	-0.008***	(0.002)
Accounting	-0.002*	(0.001)	-0.002	(0.002)	-0.002	(0.002)

Each line represents a different regression. Columns 1, 3 and 5 display the coefficients on the independent variable $1 = TS$. All dependent variables are set equal to 0 if students do not continue studying or if they do not take that subject. Usual controls. Robust standard errors clustered at the school level. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

Table A5: Effect on other university majors (age 18)

Dep. variables	All		Girls		Boys	
	Coeff.	Se	Coeff.	Se	Coeff.	Se
Physics	0.006***	(0.002)	0.001	(0.003)	0.009***	(0.003)
Math	0.001	(0.002)	-0.002	(0.002)	0.003	(0.004)
Engineering	0.007***	(0.002)	0.003**	(0.001)	0.011***	(0.003)
Biology	-0.001	(0.003)	-0.001	(0.005)	-0.002	(0.004)
Veterinary agric	-0.001	(0.001)	-0.001	(0.002)	0.000	(0.001)
Computer sci	-0.001	(0.001)	-0.001	(0.001)	-0.000	(0.002)
Technology	-0.000	(0.001)	-0.000	(0.001)	-0.000	(0.001)
General science	-0.000	(0.001)	-0.001	(0.002)	0.000	(0.001)
Medicine	0.003*	(0.001)	0.006**	(0.002)	0.001	(0.001)
Allied medicine	0.004*	(0.002)	0.008*	(0.004)	0.000	(0.002)
Architecture	-0.003***	(0.001)	-0.002*	(0.001)	-0.004**	(0.002)
Other languages	0.000	(0.000)	-0.000	(0.001)	0.000	(0.001)
History	0.001	(0.002)	0.003	(0.003)	-0.001	(0.002)
Art design	-0.000	(0.003)	0.001	(0.005)	-0.002	(0.003)
Education	-0.001	(0.002)	-0.001	(0.004)	-0.001	(0.001)
Soc studies	0.003	(0.003)	0.005	(0.005)	0.001	(0.003)
Law	-0.004*	(0.002)	-0.006*	(0.003)	-0.002	(0.002)
Business	0.001	(0.003)	0.001	(0.004)	-0.000	(0.004)
Communication	0.000	(0.002)	0.001	(0.003)	-0.001	(0.002)
Ling classic	0.005**	(0.002)	0.004	(0.004)	0.006***	(0.002)
Eu languages	-0.000	(0.001)	-0.000	(0.002)	-0.000	(0.001)

Each line represents a different regression. Columns 1, 3 and 5 display the coefficients on the independent variable $1 = TS$. All dependent variables are set equal to 0 if students do not continue studying or if they do not take that subject. Usual controls. Robust standard errors clustered at the school level. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

Table A6: Robustness: exclusion restriction

Dep var:	1=KS5 sci	1=Russell	1=STEM	1=medicine	1=grad	1=grad STEM
	[1]	[2]	[3]	[4]	[5]	[6]
1=TS	0.057***	0.024*	0.022	0.010	0.039	0.026**
	(0.007)	(0.014)	(0.013)	(0.009)	(0.028)	(0.012)
N	1613226	948058	948058	948058	948058	948058
ymean						

The sample includes only schools where the triple science class is not likely to be oversubscribed (class size not around a multiple of 30). Additional controls: year and school fixed effects; student controls: gender, Free School Meal Eligible, Special Education Needs, primary school grade in science, math and English; schools controls: school size. The dependent variables in columns 3, 4, 5 and 6 are set equal to 0 if students do not continue studying or if they do not take the considered subjects. Robust standard errors clustered by school in parentheses. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

Table A7: Teachers

Dep. variable:	N teachers	N qualified teachers
	[1]	[2]
1=TS	1.604	1.577
	(1.267)	(1.249)
N	1022489	1022489
ymean	70.567	66.654

Additional controls: year and school fixed effects; student controls: gender, Free School Meal Eligible, Special Education Needs, primary school grade in science, math and english; schools controls: school size. Robust standard errors clustered by school in parentheses. * denotes significance at 10%, ** denotes significance at 5%, *** denotes significance at 1%.

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