Essays on the Economics of Education and Labour

A thesis submitted for the degree of Doctor of Philosophy in Economics

by

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Declarations

No part of this thesis has been submitted for another degree.

Chapter 2 is co-authored with Professor Emilia Del Bono. The other chapters in this thesis are exclusively mine.

An early draft of Chapter 3 has been previously published in the ISER Working Paper Series (No. 2014-29, September, 2014) as “Partner ethnicity and ethnic minority socio-economic occupation. Evidence from the UK”.

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Summary

Chapter 1 provides the first evaluation of a recent educational reform in England which reduced the content of the mathematics module studied by pupils aged 16-18. Using the National Pupil Database we look at the reform's impact on the probability that secondary school students will choose mathematics, and their attainment. We use information on previous academic achievement and other individual characteristics to understand which students have been mostly affected. We show that this reform sheds new light on one of the most important questions in education research: why women are less represented in STEM fields.

In Chapter 2, we exploit variation in the labour demand to investigate whether the first job destination of graduates from different socio-economic backgrounds is differently affected by the business cycle. We use the Destination of Leavers from Higher Education survey and the Labour Force Survey across the period 2003-12. When the labour market is tight graduates from disadvantaged backgrounds are more likely to choose to study for a professional qualification. Those who become active labour market participants have more trouble finding a job, and those who find employment experience lower job quality. We provide evidence of the importance of social capital in explaining these findings.

In Chapter 3 we contribute to a recent branch of the economic literature on how social integration affects labour market opportunities. This literature compares the labour market outcomes of ethnic minorities who are in a co-ethnic partnership to those who choose a partner in the majority population . An important pre-requisite of these analyses is the extent to which these two types of partnerships can be compared. We analyse this hypothesis formally using a propensity score approach in Understanding Society data. The characteristics of these partnerships are such that they should not be compared even within narrowly defined subgroups.

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Chapter 1

Gender and the choice of Maths at post-secondary school: exploiting a curriculum reform

1.1 Introduction

The supply of workers in the fields of Science, Technology, Engineering, and Mathematics (STEM)[1] is a primary concern for policy makers. This concern dates back to the 1980s with the US report "A Nation at Risk. The Imperative For Educational Reform".[2] This was one of the first public recognitions of how the educational system and its standards, in particular in Maths and scientific subjects, are fundamental for the socio-economic well-being of a country. Although in more recent years a debate has emerged on whether there is a real shortage of STEM workers,[3] increasing the supply of such workers remains a relevant concern in most corners of the world. To increase the supply of STEM workers some countries, alongside educational programmes to increment the internal supply, have adopted

[1]The acronym STEM is widely used and stands for Science, Technology, Engineering, and Mathematics. More generally, it is used to indicate the whole spectrum of subjects and fields which require a good level of mathematical skills.

[2]Gardner, Larsen, Baker, Campbell, and Crosby (1983).

[3]https://www.bls.gov/opub/mlr/2015/article/stem-crisis-or-stem-surplus-yes-and-yes.htm

more generous migration policies to retain or attract STEM high-skilled workers.[4]

In England, the country on which we focus in this study, the supply of STEM workers has been recognized as an important issue in several reports and government enquires.[5] For example, the Council for Industry and Higher Education (CIHE) in a 2009 report (Herrmann, 2009) states that "[c]urrently we are vulnerable as a nation as our businesses and university STEM departments are over-reliant on overseas postgraduates in particular. [...] Businesses are recruiting Maths graduates from India and other Asian nations." The CIHE argues that the root of the problem lies in the post-secondary schooling system, the educational stage which is the focus of our analysis.

In this paper we exploit a reform that has changed the cost of studying Maths in post-compulsory education to investigate who the marginal students are, i.e. those that can be moved to study Maths. The reform that we study was introduced in 2005 and affected the Maths curriculum with the aim of increasing the low demand for Maths from students during post-compulsory school (16+ years old). From now on we refer to this reform as the Maths Curriculum Reform (MCR). The MCR was a large scale reform involving all post-compulsory schools in England, i.e. year 12 and 13.[6] This level of education is referred to as Key Stage 5 (KS5). About half of the population of students completing compulsory schooling keeps studying at KS5, the other half undertakes vocational courses or enters the labour market. This reform reduced the amount of material across the two-year course of Maths by dropping one module in Applied Maths. We use this change of curriculum in England as a natural experiment that provides a variation in the (expected and actual) cost of studying Maths and we look at its impacts on the choices made by students, and their attainment in this subject.[7]

[4]An example of these are the HB1 visa and the STEM Job Act 2012 and 2015 in the USA or the Blue Card Directive in Europe. The rationale behind these policies is that STEM workers are important not only for the industries and sectors in which they are employed, but they are also relevant in promoting growth through the creation of jobs in other sectors - for example, see Peri, Shih, and Sparber (2015).

[5]BIS (2014); DTI (2004).

[6]This is equivalent to the 11^{th} and 12^{th} grades in senior high school in the US.

[7]We do not expect that this reform changed the incentive to enrol in post-compulsory school.

Furthermore, we will show that this reform sheds new light on one of the most important questions in education research: why women are less represented in STEM fields. Girls are under-represented among students in STEM subjects in secondary and Higher Education, and among workers in STEM fields (Botcherby & Buckner, 2014). Decreasing the gender gap in STEM subject participation is crucial for promoting gender equality in opportunities and increasing the overall population in those fields. We know that jobs related to STEM fields are more remunerative that those in non-STEM fields.[8] If, as it has been showed, girls on average perform as good as, if not better than, boys in Science and Maths in compulsory school (DfE, 2007; C. Smith, 2014), then it is crucial to understand why they choose to opt out from the study of these subjects in post-compulsory schooling. In fact, when specialization occurs in the educational system, both boys and girls tend to specialize in those fields dominated by their gender, conditioning on previous academic performance (C. Smith, 2014). In our sample of high Maths-ability achievers, on average 47% of boys and 30% of girls study Maths in year 12 and 33% of boys and 19% of girls study Maths in year 13. The cohorts affected by the reform show an increase in the average uptake of Maths at year 13 which is of 1 percentage point for boys and of 2 percentage points for girls.

A variety of studies in economics and other disciplines (discussed in the following section), show that social forces are important in explaining why girls decide that those fields are not for them, highlighting the importance of gendered attitudes and expectations. We therefore investigate whether boys and girls of high Maths ability responded equally to the fall in the cost of studying Maths. The main hypothesis is that if they both are equally aware of their ability they will respond in similar ways.

Before investigating the relevance of gender in the choice of whether to study

[8](Dolton & Vignoles, 2002) focus on grade 12 in England and the labour market returns of the advanced Maths curriculum (known as further Maths). By analysing a cohort study on individuals born in the first week of March 1958 they find that, when keeping ability constant, studying advanced Maths A-level corresponds to a 7%-10% wage premium. This is mainly because of the way that this subject is highly valued in the labour market.

Maths, we first have to evaluate the overall impact of the MCR. We are the first to provide an exhaustive evaluation of this national curriculum reform and to exploit it as a large-scale experiment to contribute to the literature on the determinants in human capital investment. To assess whether the MCR has had any impact on uptake and attainment of Maths we use a before/after design. We compare uptake and attainment of students in Maths in post-compulsory school who obtained their compulsory schooling one and two years before the introduction of the MCR, with the uptake and attainment of those affected by the MCR. More precisely, we compare the cohorts of students who obtained their compulsory schooling in 2002 and 2003 to those who obtained it in 2004 to 2007. The reform was introduced in year 2005. The first cohort affected is the one that finished compulsory schooling in 2004 and that enrolled in year 12 in 2005. The other cohorts that we observe in our data that have been affected by the reform are those who finished year 11 in years 2005, 2006, and 2007. Students obtaining their compulsory schooling in 2002 and 2003 were meant to enter into post-compulsory school in years 2003 and 2004 respectively, and hence could not be affected by the MCR.[9]

We find that the MCR increased Maths uptake by 7% in the first year of post-secondary school. However, this did not result in a significant expansion in the following year of schooling, because the rise in uptake was offset by a fall in pass rates and grades at the end of the first year. We shed light on the heterogeneous effects of the reform across the ability distribution of students. The reform has increased the uptake of Maths by the most academically able students. Interestingly, those who have been affected by the MCR in terms of uptake are not the same students who bring the average attainment down in the post-MCR period, both in terms of passes and grades. We suggest that changes in class size and ability composition could explain these findings. We finally provide evidence of the heterogeneity of uptake and attainment by school type suggesting that some

[9]This is true unless they took gap year(s) between the two stages of education. This would be a problem especially if it occurred because of the announcement of the implementation of a curricular change in the post-compulsory school. However, given that the MCR was implemented in a sudden manner we can exclude any anticipation effect.

schools had more resources than others to enable their students to take advantage of the incentive offered by the MCR.

In the second year of post-compulsory schooling we find that the MCR has significantly affected the likelihood of students acquiring Maths for girls only. After the MCR, there has been a rise in Maths uptake for girls of 6% in year 13. We do not find that this is the case for boys who do not experience any statistically significant change in Maths uptake in the second year. This result is driven by an initial divergence in the change of Maths uptake in the first year by boys and girls after the MCR. The changes in the composition of students within Maths classes have in turns affected attainment - there is a significant decrease in Maths passes and grades for boys only. Because it is difficult to disentangle all these direct and indirect effects of the MCR, in the second part of the paper we will focus on one outcome in particular, the uptake of Maths in the first year of post-compulsory schooling and how and why girls and boys have been differently affected by the MCR.

We assume that individuals maximize their utility by choosing to study those subjects in which they fare best. However, it could be that the signal of one's own ability is a function of the social environment in which individuals interact with their peers and build the perception of themselves. For example, the gender composition of peers with respect to which the signal of one's own ability is created, could affect how individuals interpret that signal, or in other words, the weight or strength that they give to it. If academic subjects are affected by a gender stereotype (they are either for boys or girls) and if gender characteristics are stronger in a context where gender definition is more important, we could expect that the same signal of ability could be weighted differently depending on whether this is formed in an environment with a low/high share of same-sex individuals. Since we are studying the uptake of Maths, a "subject for boys", we could expect that the share of same-sex peers would be an issue especially for girls (we would expect boys to be more affected by peer gender if we were considering, for example, English literature).

We test this hypothesis empirically by comparing pupils who were in single-sex and mixed-sex schools at the educational stage just before the one affected by the MCR (i.e. when the decision on what to study at KS5 is made). We find that the percentage of girls studying AS Maths after the reform has increased much more in mixed-sex schools than in single-sex schools. For boys, the change is approximately the same in both types of schools. These estimates might be affected by endogeneity given that students select into these schools. After accounting for selection by using the endogenous switching regression model, our results change. Being allocated to an environment in which there are only girls increases the likelihood of girls positively responding to the MCR by taking Maths at KS5. We find consistent results when we consider the population of students in mixed-sex schools only, which does not present the problem of selection, where we exploit the idiosyncratic variation in gender composition of Maths classmates within KS4 school. When the share of females is high, the MCR makes girls more likely to study Maths at KS5, while for boys we do not find any statistically significant effect. One possible explanation that we offer is that girls weigh their Maths ability differently from boys. This is what makes them the marginal students who responded to the incentive offered by the reform.

The remainder of the chapter is structured as follows. Section 1.2 considers the main branches of the economics literature this paper relates to and highlights the main contributions to them. Section 1.3 describes the institutional context and the dataset that we use. Section 1.4 explains the empirical strategy that we adopt to evaluate the effects of the MCR. Section 1.5 describes and comments on the results on Maths uptake and attainment, and Section 1.6 focuses on the gender analysis. Finally, Section 1.7 concludes.

1.2 Related literature and our main contributions

We contribute to the literature in interventions on the Maths curriculum at secondary school (Cortes & Goodman, 2014; Cortes, Goodman, & Nomi, 2015; E. Taylor, 2014). The interventions studied in the cited papers are short-lived or implemented in a small setting and consist in an increase in the time (classes) allocated to Maths teaching. They are usually targeted to particular ability groups of students.[10] The MCR differs from all these interventions because, first, it affected a whole nation, second, it was not addressed to a particular group of students, and, third, it involved a change in the cost of studying Maths (rather than a compulsory change in exposure to the subject).

An intervention that is closely related to ours is studied in Joensen and Nielsen (2009, 2014), who look at the impact of choosing to study Maths on school and labor market outcomes. They study a change to the secondary school curriculum that took place in Denmark in 1988, and which lowered the cost of studying Advanced Maths by introducing the option of choosing a combination of Advanced Chemistry and Maths alongside the standard option of Advanced Physics and Maths. Joensen and Nielsen (2009, 2014) use the pilot of this reform in an IV approach and find a causal relationship between Maths and earnings, mainly driven by a resulting increase in Higher Education participation. This is true especially for high Maths ability girls, who are more likely to go to more Maths-intensive college degrees and to reach more prestigious careers.

While the papers of Joensen and Nielsen are highly related to ours, there are

[10] Cortes et al. (2015) and Cortes and Goodman (2014) show that that Double Dose Algebra classes have had positive effects on academic achievement at high school (especially for low-ability readers) as well as on school graduation and enrolment rates. In line with it, E. Taylor (2014) shows that the remedial classes in Miami schools have had positive effects in Maths achievement in the first year of high school. The effects then gradually become smaller in the following two years. Goodman (2012) instead looks at the introduction for the first time of a minimum number of years in Maths required to acquire a high school diploma. He finds that this reform closed one fifth of the earnings gap between black and white males by positively affecting black male students in non-white schools.

some important differences. First, Joensen and Nielsen look at the effect of the introduction of the option of pairing Maths with Chemistry alongside the Maths-Physics option.[11] Instead, we provide evidence on the effect of reducing the cost of studying Maths *per se*. Second, Joensen and Nielsen do not observe the Maths-specific ability of students (they only have average GPA score), while we condition on prior Maths-specific and general academic achievement. Finally, we dig deeper into the reasons why we find a gender differential in the response to the reform in terms of uptake.

This paper also contributes to the literature on human capital investment and, in particular, to the literature on the choice of the field to study. The latter focuses mostly on the choice of study at university by using elicitation of beliefs, structural models, and a mix of both (Arcidiacono, 2004; Arcidiacono, Aucejo, & Hotz, 2016; Malamud, 2010, 2011; Stinebrickner & Stinebrickner, 2014; Wiswall & Zafar, 2015). We contribute by using a quasi-experimental approach that works as an incentive (a fall in the cost of studying Maths) to make certain human capital investment.

There is a large literature which is interested in understanding how gender differences in human capital accumulation emerge. The fact that females with high mathematical ability do not choose to pursue studying Maths could be related to cultural and environmental factors which shape gender characteristics such as self-confidence in one's own ability, competition taste, and risk aversion (Niederle & Vesterlund, 2007, 2010; Niederle & Yestrumskas, 2008; Pope & Sydnor, 2010). For example, Booth and Nolen (2012a, 2012b) in a randomized experimental setting show that girls' attitudes towards risk increases in a single-sex environment, while competitiveness decreases. These hypotheses are consistent with the theory at the base of the economics of identity (Akerlof & Kranton, 2000), which suggests that conformity with the traits that defines one's identity plays an important role in the utility maximization problem. Making choices in fields that have a higher

[11] They argue that this intervention has mainly affected girls because Chemistry is a less male-stereotypical subject than physics.

gender-biased connotation, like whether to study STEM subjects when it is well known that this is over-represented by males, can be particularly affected by this behaviour of conformism.

This could explain why the gender gap in STEM subjects, both in terms of choices and performances, is reliant on cultural norms and environment as it has been shown by several studies. Pope and Sydnor (2010) show that the gender gap in several subjects correlates with gender attitudes within states in the US. Consistent results are found across PISA countries where the Maths gender gap is strongly correlated with the gender culture in the country (Guiso, Monte, Sapienza, & Zingales, 2008). However, Fryer and Levitt (2010) show that in Muslim countries, little or no gender Maths gap is found, suggesting that there is heterogeneity within cultures with strong gender oriented attitudes.

There is also much evidence on the impact of gender composition within social institutions (such as family) on choices on whether to specialize in STEM subjects, with females usually being the most affected gender.[12] In the context of school, Favara (2012) shows that single-sex schools in England are associated with less stereotypical choices in terms of gender compared to mixed-sex schools.[13] This is especially true for girls, and it remains even after controlling for selection into single-sex versus mixed-sex schools. Favara exploits complete gender segregation, while other studies exploit the idiosyncratic gender variation across cohorts. For example, it has been found that in high school a higher exposure to male peers causes boys to choose male-dominated college majors (Anelli & Peri, 2015b) while at university girls exposed to a higher share of girls are less likely to enrol in STEM subjects (Hill, Corbett, & St Rose, 2010; Zölitza & Feld, 2016).

Our contribution here is to analyse the interaction of the gender composition of peers at school with an educational reform to provide evidence on how gender stereotypes can have important consequences in the education production

[12] Anelli and Peri (2015a); Oguzoglu and Ozbeklik (2016).

[13] The difference between single-sex and mixed-sex schools is also exploited to investigate gender differences in achievement, e.g. Lee, Turner, Woo, and Kim (2014).

function, through the choice of field of study.

1.3 Data and institutional setting

1.3.1 The English educational system

The different levels of the English educational system are called Key Stages. Table 1.1 summarizes the equivalent achievement in terms of school years, the age of the students, the duration of the course, and the qualification acquired in each Key Stage (KS). For example, the fourth row of Table 1.1 shows that when students finish their KS4, which is the end of compulsory schooling, they are 16 years old and the name of the qualification obtained is GCSE, which stands for General Certificate of Secondary Education and it is equivalent to year 11. From now on we will denote the cohorts of students by the year in which they finished their KS4. For example, cohort 2002 stands for the cohort of students who finished KS4 in the academic year of 2001/2. This cohort started KS5 in 2002/3 and finished in 2003/4.

This paper focuses on KS5 because this is where the MCR was implemented.[14] A-levels (usually obtained at 18 years old, equivalent to year 13) are usually taken by students who want to go onto Higher Education. In fact, most university departments' admission policies require students to have achieved certain A-levels, and most departments also require certain grades. However, entry requirements depend on the subject studied and the university applied to. For example, if a student wants to study an undergraduate course in Economics at the University of Exeter s/he needs to have at least a combination of three A-levels with grades A*AA or AAB, including Maths. For the same undergraduate course at Oxford University, the requirements are instead at least two A-levels with grade A and one A-level with grade A* and one of these A-levels must be in Maths.[15] In the

[14]Note that we focus on the academic route of this level, which leads to the acquisition of A-levels because the MCR affected this route only. There is also a vocational KS5 track.

[15]Other examples of entry requirements for undergraduate courses in other subjects for the university of Exeter (Oxford): the Faculty of English requires A*AA-AAB, GCE A-

first year of KS5 (year 12), students take exams in the chosen subjects and can obtain an AS (Advanced Subsidiary) qualification per subject. This could be left as a stand alone qualification or the subject can be studied in year 13 to obtain the full A-level qualification.[16]

1.3.2 Data and sample selection

We use the National Pupil Database (NPD). This is an administrative educational dataset with information on educational performance and characteristics of pupils in the state sector and non-maintained special schools in England. It has rich information on the socio-economic and demographic characteristics of pupils, such as ethnicity, free school-meal (FSM) eligibility,[17] and whether any special educational needs (SEN) are required. These are collected through the Pupil Level Annual Schools Census (PLASC).[18] Alongside individual socio-economic and demographic characteristics, this dataset provides students' attainment at different stages of education from KS1 until KS5 (or KS4 if the individual is not observed studying after compulsory education). An identifier for the school attended by students in each stage of education is also provided.

Our sample includes those young people who acquired their KS4 qualification

level English Literature grade A, GCSE English Literature or English Language grade A, and candidates may offer either GCE A-level English Literature or English Language and Literature (A-level in English Literature or in combined English Language and Literature with a standard conditional offer AAA, e.g. at least 3 A-levels with grade A). For an undergraduate course in Engineering the requirement instead is AAA-ABB including A-level Maths grade B, another science subject at grade B, and candidates may offer A-levels Further Maths (A*A*A to include Maths and Physics. The A*s must be in Maths, Physics or Further Maths if taken). Sources: `http://www.exeter.ac.uk/undergraduate/degrees` and `http://www.ox.ac.uk/admissions/undergraduate/courses-listing`

[16] This was the system operating at the time that we consider in the paper. Since 2015 it has been gradually modified to drop the AS and become a 2-year A-level course.

[17] This is a commonly used indicator to proxy the socio-economics of pupils. It indicates whether students are eligible for free meals at schools. In order to be eligible, pupils have to come from a household recipient of benefits.

[18] Some schools (i.e. independent) do not provide information on socio-economic and demographic characteristics of their students. In the whole sample of students who left KS4 in the years 2002-2007 around 7% of pupils attended independent schools. Since we want to include them in the analysis, in the regression we include a missing information dummy that is equal to 1 for all these schools and 0 otherwise. In this manner we can keep the educational information of the pupils going to independent schools even if they do not provide any information on students' individual characteristics.

in 2001/2 to 2006/7, as these are the cohorts that we can follow through KS4 to KS5 in the NPD. We separate the students into different cohorts according to the year in which they obtained their KS4. Those students who finished their compulsory education (year 11) in years 2004-7 have been facing the new system introduced by the reform. The MCR was for the first time implemented for year 12 students in 2005 and for year 13 students in 2006. Thus, KS4 cohorts 2002-3 have been studying in the regime pre-MCR, and KS4 cohort 2004-7 in the regime post-MCR. We follow students for two academic years since the year in which they start their KS5 to observe whether they have obtained an AS or A-level qualification (the standard duration to get A-level qualification is of two years). If an exam is re-taken we consider only the first attempt.

We keep only full time students from non-special schools. Our intermediate sample is composed of 1,648,282 young people. Furthermore, since to study Maths at KS5[19] it is necessary to have a high grade in Maths at KS4, we restrict the sample to those students with grade A*, A, and B in KS4 Maths. These consist of 31% of all pupils who left KS4 in the years 2002-2007.[20] Our sample is then composed of 990,689 pupils.[21]

Notice that in England some schools offer both KS4 and KS5 in sixth forms, while others, the colleges, offer KS5 qualifications only. If students studied KS4 in a sixth form school they have the option to keep studying their KS5 qualification in the same school, otherwise they have to change school. In the rest of the paper we hence refer to KS4 schools and KS5 schools. For half of the sample the school attended for KS4 qualifications coincides with the school attended for KS5 qualifications. We keep only those KS5 schools that we observe for each cohort of students, achieving a final sample of 969,862 pupils who are observed studying in 14,892 KS5 schools.

[19] In this paper we focus on a non-advanced course in Maths. However, at KS5 there are other courses on advanced Maths that could be chosen alongside the standard one. Appendix A1 shows all the Maths courses available in our sample and briefly comments on them.

[20] Students with a grade A*-B in KS4 Maths represent 98% and 96% of overall A-level and AS Maths takers, stable across all cohorts considered.

[21] Appendix A2 describes the sample selections and restrictions in more detail.

Table 1.2 shows the summary statistics of the main socio-economic and demographic variables that we use in our analysis. The first two columns show the mean of the variables for the whole sample divided by the KS4 cohorts who have not been affected by the MCR (2002-3), "pre", and those who have been affected (2004-7), "post". We then report the difference of the means of the two sub-samples, followed by standard errors, and p-value of the t-test when implementing clustering at KS5 school level. We can see that most of the differences between the two periods of time, pre- and post-MCR, are statistically significant, although their magnitude is very small - most of the differences are <0.010. The most important differences arise because of the improvement of the quality of the data collection and the consequent decrease in missing values - the first year that we have in our sample coincides with the first year of data collection of the NPD. For example, the missing values of variables such as ethnicity, SEN status, and FSM eligibility decrease over time.

1.3.3 The Maths Curriculum Reform

To understand why the MCR was introduced and to predict its possible implications, it is important to know the historical context and the determinants of its implementation.[22] Until the KS5 examination year 2000/1, all courses were *linear*. Students decided what they wanted to study in the first year of post-compulsory schooling and took exams in these (usually 3) subjects at the end of

[22]Notice that this reform has been one of several measures implemented by governments in the last years to increase the quality and the quantity of STEM students and teachers in England. In 2005 the Higher Education Funding Council for England (HEFCE) has invested around 50 million pounds to support programmes to increase the number of students in STEM subjects. In the same year, the Further Maths Support Programme (FMSP) started a pilot in some areas in England to promote and support post-16 Maths. After more than ten years the FMSP is still running successfully. In 2011, a generous bursaries scheme to bring graduates in STEM subjects to teach in schools has been implemented. Furthermore, in the last decades there have been several curricular and systemic reforms at secondary level. A Triple Science option was introduced in 2008 at secondary school - De Philippis (2016) evaluates this intervention and finds that the offer of more intensive scientific courses has positively affected the scientific orientation and preparation of students in STEM subjects up to university level. All these initiatives, however, do not overlap in terms of time with the cohorts that we consider in this paper because they mainly affect more recent cohorts of pupils. In Section 1.5.2 we will expand on the possible threats to our empirical strategy.

the second year. This system generated a concern that, especially in certain subjects, a high number of students failed the exams in their second year. There was also demand for widening the KS5 curricula, which was considered very narrow, especially compared with other European countries.

These were the main reasons for the introduction of an earlier reform, Curriculum 2000. This reform introduced a *modular* system at KS5 (AS and A-level). With the *modular* system students decide what they want to study in the first year (usually 4 subjects) and at the end of this year they have exams that give AS qualifications (a stand-alone qualification). This qualification was not meant to be considered by universities for entry requirements, and usually it is not, but it might be considered by prospective employers. After the first year pupils can drop the subject in which they fared worse or did not like, and keep the others[23] in the second year, for which, after the final exam, they would get A-level qualifications. Even though the Maths curriculum was unchanged by this *modular* system, a few years after its implementation, the uptake of A-level Maths had dropped by 20% (Kidwell, 2014). In this year the number of A-level Maths entries was little more than half the number it had been 25 years previously (MEI, 2005). This happened because the changes in the way this subject was taught (i.e. from *linear* to *modular*) and examined (i.e. one exam at the end of each year instead of a unique exam at the end of the second year) made the study of this subject particularly difficult. Students could not cope with the amount of the material to study within the new timetable (A. Smith, 2004).

The Curriculum 2000 reform changed the composition of students studying Maths at A-levels: after the *modular* system was introduced those doing Maths were generally more able students. Figures 1.1.a-1.1.d show the changes that occurred in KS5 qualification uptake and attainment by KS5 year of examination.[24]

[23] Usually universities require three A-levels.

[24] This time series on AS and A-level entries for each academic year is provided by the Department for Education. This is not the data that we will use in the analysis of this paper (since it does not contain any further information than what is displayed in the graphs) but it is useful for looking at the trends given the large number of years available. A description of this dataset and its comparison with the dataset that we use in our analysis (National Pupil

The three vertical lines denote the first KS5 cohort of students affected by Curriculum 2000 (long-dash line), by the MCR (solid line), and by other changes[25] (short-dash line). After the implementation of Curriculum 2000, the uptake in A-level Maths fell (Figure 1.1.a) while passes and grades increased (Figure 1.1.c). AS and A-level, if not failed, are graded from A (A* was introduced for A-level in 2010), the highest mark, to E, the lowest mark.

The decline in post-16 Maths study was so important that an enquiry was launched (A. Smith, 2004). This enquiry even envisaged the possibility of introducing financial incentives to bring more students to study Maths after compulsory school if the situation did not improved. The fall in the number of entries in Maths at secondary school negatively affected the enrolment in STEM subjects at university and some STEM departments had to be incorporated in others or shut down (MEI, 2005).[26] Higher Education representatives, employers, and other parts of the society asked for another change in the system only four years after the reform (year of KS5 exams 2001/2-2004/5). This is when the MCR was introduced.

The main aim of the MCR was to adjust what was considered as a disastrous outcome of Curriculum 2000 for the provision of Maths at KS5. The MCR exclusively changed the curriculum of Maths. Changes in the AS Maths curriculum were introduced in the academic year 2004/5 and changes in the A-level Maths curriculum in the academic year 2005/6 so that the first cohort of students affected was the one that obtained secondary education qualifications in 2004. The main change was a reduction in the Maths curriculum which was achieved by dropping one module of Applied Maths. A more detailed explanation of the reform is available in the Appendix in Section A4.

Database) is available in the Appendix A3.

[25] The changes that affected firstly the cohort obtaining their A-levels in 2010 are the following: introduction of A* and reduction of modules to study from 6 to 4 for all subjects except than for Maths and natural sciences at KS5; introduction of 2-tier GCSEs at KS4.

[26] Here note that universities and UCAS (the central organisation through which applications are processed for entry to Higher Education) did not change their entry requirement when the reform was introduced.

After the introduction of these changes the uptake of A-level Maths gradually increased, and nowadays A-level Maths is the most taken subject. While the trend in uptake during the period before the MCR is stable (apart from the sudden drop due to the Curriculum 2000 reform), it monotonically increases after the introduction of the MCR for both AS and A-levels (Figures 1.1.a and 1.1.b). More specifically, since the year of the introduction of Curriculum 2000 there was a decreasing trend in AS uptake which reversed after the introduction of the MCR.

Grades and pass rates, especially for AS Maths, have changed as well.[27] Passes slightly increased for both AS and A-level for the cohorts affected by the MCR. Average grade also increases, mainly driven by a decrease in B grades (Figure 1.1.c) and a decrease in C/E grades (Figure 1.1.d). In our data we observe two cohorts pre-MCR and four cohorts post-MCR and these coincide with the KS5 exam year 2003/4 and 2005/9 in Figures 1.1.a-1.1.d. From the KS4 cohort 2008, while the MCR remained unaltered, other changes both at KS4 and at KS5 were implemented. The changes in the trends after 2008 are to be attributed to these.

Figure 1.2.a shows the average percentage of AS and A-level uptake by KS4 cohort in the National Pupil Database in our analysis population (described in the previous subsection). The first two cohorts (2002 and 2003) are the pre-reform cohorts and the others (2004-2007) are the post-reform cohorts. The uptake of AS Maths has gradually increased over these cohorts from 38% in 2002 to 40% in 2007, while the uptake in A-level Maths has increased by two percentage points (from 25% to 27%). Notice that, as shown in Figure 1.1.a, there is a downward trend for AS uptake in the pre-MCR period resulting in a drop from 2002 to 2003. If we consider the sub-population of students who took AS Maths, the percentage of students getting A-level Maths did not change much, i.e. the line A-level|AS Maths. Figures 1.2.b and 1.2.c show that after the implementation of the MCR, there is an increase in A grades and a decrease in B grades for A-level Maths. For AS Maths, the proportion of A grades increased, of C/E decreased, and the

[27]However, it is difficult to get a comparison in terms of the Maths ability of students with the previous systems because of the curricular changes.

percentage who failed fell for AS Maths.

From the mentioned figures it appears that the MCR has increased both the uptake and attainment of AS and A-level Maths. However, these are only raw data. In order to establish whether the MCR has had any effect at all, we need to condition on the composition of the cohorts.

1.4 Empirical framework

Our main outcomes, y, are: whether Maths has been chosen to be studied (0/1), whether a pass grade has been achieved (0/1), and the grade. We denote the choice of studying Maths "uptake". At year 13 we have two different uptake outcomes. One is on the overall population and the other is on the population of students who studied AS only, i.e. A-level|AS uptake. While the former shows the total effect of the reform across the two years of schooling, the latter provides information on whether the students change their likelihood of continuing to study Maths from year 12 to year 13. Grades range from A to E. We attribute to each of them a numerical value, five to A, four to B, and so on until one to E. Then, we normalize them to have the mean equal to zero and the standard deviation equal to one within each cohort to address the possible issue of grade inflation over time.

We have a before/after design where we compare two cohorts of students who have not been affected by the MCR (those who completed KS4 by 2003) to four cohorts of students who have been affected (those who finished compulsory schooling from 2004 onwards). The effect of the MCR is captured by the dummy $Post$: $Post = 0$ for individuals in the pre-MCR cohorts (KS4 years 2002-3) and $Post = 1$ for individuals in the post-MCR cohorts (KS4 years 2004-7).

Our main aim is to identify the *true* effect of the MCR and disentangle it from other time trends. For example, practitioners and students could have taken some time to adapt to the new system. To show how we do this we implement several specifications as shown in the equations below. In each equation subscript

i stands for individual and s for school. y denotes one of the outcomes listed above. The individual and school characteristics, which we describe at the end of this subsection, are represented by the matrix X. Equation 1.1 is the most flexible one because it allows the effect of the reform to differ by each post-MCR cohort. Equation 1.2 instead captures in the coefficient β the average effect of the reform. Equation 1.3 adds a linear control for time $Trend$, and Equation 1.4 allows the trend pre-MCR to differ from the trend post-MCR through the interaction of the $Post$ dummy with the linear time trend.

1. Cohort dummies:

$$y_{is} = \alpha + \sum_{k=2004}^{2007} \beta^k Cohort_i + X'_{is}\delta + \phi_s + \mu_{is}; \tag{1.1}$$

2. Post dummy:

$$y_{is} = \alpha + \beta Post_i + X'_{is}\delta + \phi_s + \mu_{is}; \tag{1.2}$$

3. Post dummy with linear time trend:

$$y_{is} = \alpha + \beta Post_i + \gamma Trend_i + X'_{is}\delta + \phi_s + \mu_{is}; \tag{1.3}$$

4. Post dummy interacted with linear time trend:

$$y_{is} = \alpha + \beta Post_i + \gamma Trend_i + \zeta Post_i * Trend_i + X'_{is}\delta + \phi_s + \mu_{is}. \tag{1.4}$$

We cluster the standard error by KS4 school because all characteristics in X_{is} are collected by KS4 schools. In order to account for KS5 school-specific and time invariant characteristics, we include KS5 school fixed effects (ϕ_s).

In the results section we will discuss the estimates of all specifications. For this specification we also show the Average Marginal Effect (AME from now on) of the reform. This considers the effect of the MCR on both the level and trend of the outcome of interest at one point in time. More specifically, the AME is calculated as $(\hat{\zeta} * \overline{Trend}) + \hat{\gamma}$. $\overline{Trend}$ is equal to 3.5, i.e. the average value of $Trend$ which takes the values from 1 to 6 where 1 identifies cohort 2002 and 6 identifies cohort 2007. Thus, the AME gives us the predicted mean of the outcome of interest at approximately one year and a half after the introduction of the MCR by taking into account the changes in both the level and in the trend.

In all these specifications we treat the first two cohorts (2002-3) as the control group. However, this is not a proper counterfactual group, i.e. a group showing what would have happened if there was no MCR. This is because the pre-MCR cohorts could have been affected by different factors alongside the MCR compared to the post-MCR cohorts just because they studied in different years. The main assumption underlying our before/after strategy is that the MCR was the only phenomenon that affected uptake and attainment of Maths over the time period considered. Among all specifications, 4 is our favourite because it partly reduces this drawback of the empirical framework by including a time trend which should capture what would have otherwise happened if the MCR was not implemented. In section 1.5.2 we discuss the limitations of our empirical strategy and implement some robustness checks to show evidence for the plausibility of the assumption that the changes in uptake and attainment of Maths is attributable to the MCR only.

The school and individual characteristics we condition on are: gender, ethnicity, month of birth, free-school meal eligibility (FSM), indicator of the deprivation of the area where student is from (Income Deprivation Affecting Children Index, IDACI, rank divided into 50 quantiles), whether the child has been classified as having Special Educational Need (SEN), and the type of KS4 school (e.g. Academy, Community, Independent) attended.

We also condition on KS4 attainment as a proxy for general academic ability. A reasonable way of dividing students in ability groups is to use the total score that they obtained in the previous stage of education (KS4). This is plausibly exogenous because the MCR was introduced suddenly and we do not see how students or teachers could have anticipated it and adjusted to it accordingly, for example by changing the effort taken in studying/teaching certain subjects at KS4. This ability measure is capped which means that it is based on the sum of the grades achieved in the best eight GCSEs (or fewer if the individual has less that eight GCSEs).[28] We divide the pupils in five ability-groups (quintiles) by each KS4 year. This measure of ability is rather general because it is based on a general score grouping different subjects. However, students at KS4 already choose, under the advice of schools, the number and subjects that they study (the only compulsory subjects are Maths, English, and Science, either single, double, or triple). We assume that students prefer, and hence choose the optional subjects in order to maximize their grades. Thus, this score, even if it allows for some specialization, should reflect their ability.

1.5 Results

We first investigate how the uptake and attainment in Maths has been affected by the MCR. We implement the four different specifications described in section 1.4. Results are shown in Table 1.3. For each of them we first include as covariate(s) the variable(s) capturing the effect of the MCR only (column 1); a specification follows with the inclusion of the covariates on the characteristics of students and KS4 schools (column 2); we then add fixed effects by KS5 school to control for all unobserved differences fixed in time within each school (column 3). In the final specification, we cluster the standard errors by KS4 school given the potential error correlation across individuals within schools (column 4).

For brevity, we discuss the different results of the specifications with respect to one outcome only, AS Maths uptake, as shown in Table 1.3. Specification I shows the effect of the reform on each post-MCR cohort. Overall, the uptake of AS Maths increases over time and the impact of the MCR is highly statistically significant.

[28]The average number of GCSEs taken by individuals is 9 in each cohort. Note that this capped score is used as measure of ability in other papers, such as Nicoletti and Rabe (2016).

In column 2 we condition on the characteristics discussed in Section 1.4 and the effect of the MCR increases with respect to column 1. It slightly decreases when conditioning on unobserved time-invariant characteristics at school level (column 3). These changes suggest that there is heterogeneity across schools. Allowing for the error term to be correlated within KS4 school does not importantly affect the standard errors (column 4).

The same patterns are found for Specification II, where the effect of the MCR is now captured by the coefficient on a dummy variable, *Post*, which identifies whether the cohort has been affected by it. In Specification III, where alongside the *Post* dummy we include a general linear time trend, we find instead a negative average effect of the MCR on uptake. This is attenuated, and becomes no longer statistically significant, once we include the covariates and the school fixed effects. This result could be explained by the fact that the inclusion of the linear time trend absorbs the positive effect of the MCR. This is consistent with the results of Specification IV where the coefficient of the time trend is negative, indicating a downward slope in uptake before the MCR, while the coefficient of the interaction term ($Post * Trend$) is actually positive indicating a positive trend after the introduction of the MCR. The *Post* coefficient shows that the average level of uptake was lower in the pre-MCR period compared to the post-MCR period. The last row of Specification IV shows the average marginal effect (AME) of the MCR in column 4. This is calculated at one point in time, which is at one year and half after the introduction of the MCR. The AME shows that the average uptake of Maths increased by 2.5 percentage points, which is statistically significant at the 1% level. This is the same as the coefficient on *Post* in Specification II and it is the average of the non-linear effects across cohorts found in Specification I. We hence choose the fourth Specification as seen in column 4 as our preferred one, and we will use it in the rest of the analysis.

Table 1.4 reports the coefficients of interest and the AMEs for each of the outcomes of interest. The slope coefficient on AS uptake for the post-MCR cohorts is positive and statistically significant at the 5% level. By considering both the change in the intercept as well as in the slope, the increase in the share of pupils who study Maths just after the implementation of the MCR is equivalent to a 7% change with respect to the average AS uptake rate. There is an increase in students failing AS Maths and the average AS grades falls - see column 2 and 3, respectively. As a result, when we restrict the sample to those students who studied AS Maths, we find that the cohorts affected by the MCR are less likely to continue studying Maths in the second year (a reduction of 6%). The positive impact of the MCR on Maths uptake in the first year of school fades out after the first year of schooling. We do not find any statistically significant effect on the uptake of A-level Maths (column 7) because not all students continued studying Maths in the second year (column 4). Finally, we do not find any statistically significant effect on A-level attainment.

Some of these results, mainly the negative impact of the MCR on AS attainment and the null effect on A-level uptake, differ from what we would expect by looking at the raw data discussed in section 1.3.3. This is because in the regression analysis we condition on several characteristics of pupils and schools which allows us to control for changes in the composition of students across cohorts.

Unlike most educational interventions, the MCR was not targeted at a particular ability group of students. Furthermore, our empirical strategy is an intention-to-treat strategy and is informative about the average effects of the MCR. In the next subsection we investigate whether the MCR has had heterogeneous effects across the students' ability distribution and schools. We accomplish this by implementing several interactions of the main variables with student and school characteristics, as described below.

1.5.1 Who responded to the MCR?

a. Heterogeneity in academic ability

First, we test the hypothesis of whether the MCR has had non-linear effects on uptake and attainment across the ability distribution. Any changes in patterns of uptake of Maths could lead to changes in average class size or in the ability composition of classes. These in turn could affect attainment.

We look at the change in the ability composition within Maths classrooms in two ways. First, we use pupil level data and we implement our preferred specification (specification 4 in section 1.4) with an interaction of quintile of the KS4 academic ability score with the variables capturing the impact of the MCR, i.e. $Post * Ability$, $Trend * Ability$, and $Post * Trend * Ability$. Second, we investigate how the MCR separately affected school-level mean, median, mode, and absolute deviation from the mean ability.

Figures 1.3.a-1.3.g shows the AME of Post across the different ability quintiles. The first three figures (1.3.a, 1.3.b, and 1.3.c) show that the MCR has had a positive impact on AS uptake for the individuals with the highest academic ability (quintiles four and five) by 6 and 7 percentage points, respectively. However, those pupils in the lowest three quintiles have seen a decrease in their passes and grades. As a result, these groups of students are less likely to keep studying Maths in the second year of schooling, as shown in Figure 1.3.d. We do not find any statistically significant effects across ability groups for A-level passes (Figure 1.3.e). However, those students in the second and third quintiles see a decrease in the average Maths grades because of the MCR (Figure 1.3.f). The average impact of the MCR on uptake of A-level Maths for the whole population of students has been negative for the two lowest ability quintiles, and positive for the two highest ability quintiles (Figure 1.3.g). These results suggest that the composition of AS level classes has changed such that we have a higher average ability, and even more so at A-level, as those at the bottom of the ability distribution are now less likely to proceed with A-level.

Next, we estimate the impact of the MCR on measures of ability composition within KS5 school/KS4 cohort cells. Results are shown in Table 1.5. The mean, median, and mode of the ability distribution rise while the absolute deviation from the mean falls. This is true for both years of schooling, and it means that there has been a rise in the average ability of students in Maths classes which has made classes more homogeneous. However, these estimates are not statistically significant at the conventional levels.

We conclude that the MCR has affected the ability composition in Maths classrooms by increasing the share of high ability students. However, those with low general academic ability have experienced a fall in attainment. This could have been driven by the increase in the number of classmates or the increase in the share of students with higher general academic ability, although we do not separate these two effects.

b. School heterogeneity

Because the intervention affected all schools in England, we can examine which sorts of schools have been affected most by the MCR. Because of sorting, students within the same school share similar observable and, presumably, unobservable characteristics. Additionally, through social interaction in the school, peer effects arise. These are usually further magnified by social multiplier effects (Glaeser, Sacerdote, & Scheinkman, 2003). We hence expect that the impact of the MCR varies across the different types of schools. We investigate this by interacting the characteristics of interest with the variables capturing the policy change. We focus on: the funding status of the school, its "propensity" towards Maths, and whether it is a single-sex or mixed-sex school. Given that here we are interested in the heterogeneous response of individuals across different types of schools, alongside the school and individual characteristics described in Section 1.4, we also condition on several characteristics at the KS5 school and KS4 cohort level: whether the school is single-sex or mixed sex, its size, the share of students who are FSM eligible and have SEN, the share of students in each of the seventeen ethnicity groups, and the share of students within each national ability quintile.

Across all schools, independent or private schools are the only ones charging fees and, because of this, their intake is mainly composed of pupils coming from wealthy households. In these schools, 27% of students in the pre-MCR sample obtained A-level in Maths, versus 22% of students in government funded schools. The average ability of students in these schools in our sample of students with grade A*-B KS4 Maths is 3.4 (on a scale from one to five, i.e. the ability quintiles), while for non-private schools this is 2.6. We condition on this characteristic. However, *ceteris paribus*, we still expect that students in non-private schools might have replied differently to the changes in the Maths curriculum compared to students in private schools, because pupils in these schools are subjected to a different investment by their families and school.

Panel I in Table 1.6 shows that, on average, there have not been any statistically significant different responses of AS uptake between private and non-private schools. However, in private schools there has been an increase of four percentage points in A-level Maths uptake after the implementation of the MCR. This is mainly driven by the increase in the percentage of AS passes or the increase in students who kept studying Maths after the first year of schooling.

Next, we divide schools into five quintiles depending on the share of students studying A-level Maths in the pre-MCR period. The first quintile has a share of students ranging [0,0.14], the second (0.14,0.20], the third (0.20,0.25], the fourth (0.25,0.32], and the fifth (0.32,0.89]. We call this measure the "Maths propensity" of the school and it indicates how specialized the school is in teaching Maths.

Panel II of Table 1.6 shows that the higher the "Maths propensity" the greater the attainment in Maths after the MCR, both in year 12 and 13 - suggesting that the overall negative effect of the MCR on attainment is driven by those schools who are not specialized in teaching Maths. For the schools with the highest "Maths propensity" this results in an increase in A-level uptake driven by an increase of students continuing study Maths in the second year. These results could be explained by the fact that schools where the demand for Maths was traditionally relatively high have better resources (in term of teaching experience) to deal with the changes brought about by the MCR.

Finally, we consider differences in the outcomes by the share of female students within KS5 school and KS4 cohort, and between schools that are single-sex versus mixed-sex schools.[29] This analysis will give us insight into gender differences that will explored in more detail later.

Panel III of Table 1.6 shows that the share of female students within KS5 school has no statistical significant interaction with the MCR effect for any of the outcomes considered. Panel IV shows that single-sex schools responded more positively to the MCR both in terms of uptake and passes of AS and A-level Maths than mixed-sex schools. Finally, Panel V shows that the results for uptake are not driven by boys-only or girls-only schools, and that those for attainment are mainly driven by the difference in response of boys in single-sex and mixed-sex schools, i.e. after the MCR boys in single-sex schools fare better in AS passes and grades than boys in mixed-sex schools.

Given that our empirical specification conditions on school's fixed and changing-over-time characteristics of its student intake, these differences in the response to the MCR can be attributed to variation in schools' resources and organization. Students in private schools, in schools with a high "Maths propensity", and single-sex schools are those who benefited the most from the MCR both in terms of uptake and attainment.

1.5.2 Threat to identification

Since we are evaluating the impact of a policy reform, the first threat we can think of is whether the reform had already been anticipated. If this were the case, teachers or students could have changed their effort put into teaching or studying Maths in the previous educational stage (KS4) to increase the students' chances of being able to study A-level Maths at KS5. This hypothesis is ruled out by the late announcement of the policy, which occurred around one academic year before

[29] Notice that in our sample 43% of boys-only schools are private and 50% of girls-only schools are private, so that gender segregation importantly overlaps with the private status of KS5 schools.

its implementation (Porkess, 2003). Furthermore, all high-stake exams in England are externally marked and so it is not possible for the teacher to systematically affect the grades of their students (classwork accounts in a negligible way towards the final marks of both KS4 and KS5 qualifications).

Another concern is that KS5 schools might have responded to the MCR (and the consequential higher demand for Maths) by changing the number of classes and ability sorting within them, or by increasing the number of Maths teachers. Unfortunately, we do not have any information on these potential responses. However, given the scarcity in the supply of Maths teachers in secondary and post-secondary schools, the fact that the MCR was implemented suddenly, and that we observe the cohorts immediately affected by it, we doubt that schools managed to respond so quickly to the changes produced by the MCR. It is more plausible therefore that the changes in the attainment are driven by the change in exposure to Maths classmates of different ability.

Another threat to our strategy is that we might capture the effect of the MCR in a manner that confounds it with the effect of other phenomena. The interaction between $Post$ and $Time$ should help in cancelling out any other confounding trends affecting our outcomes of interest. One important change that took place across the period that we consider is the gradual increase in the provision of Triple Science at KS4, which has been shown to have increased the uptake in STEM subjects at subsequent levels of education (De Philippis, 2016).[30] In our sample, we see that the percentage of students who went to a KS4 school that offered the Triple Science option has increased from 18% within the 2002 KS4 cohort to 20% within the 2007 KS4 cohort. More specifically, there is a difference of 45 KS4 schools that offered this option between KS4 cohort 2002 and 2007 in our sample. As a robustness check, we re-run the main model to investigate the average effect of the MCR by including an additional variable: whether the

[30]However, the increase in the period that we consider is small, especially if compared to the increase in the provision of Triple Science that has taken place since KS4 cohort 2008. Figure 1 in De Philippis (2016) offers a time-line of the average offer of Triple Science from KS4 cohort 2002 to 2013.

KS4 school attended by students offered Triple Science. Panel A of Table A4 in the Appendix shows the coefficients of interest. It is evident that including the provision of Triple Science by school and cohort does not affect our results, suggesting that the effect that we attribute to the MCR is not confounded with possible changes deriving from the policy of increasing the offer of Science at KS4.

1.6 Has the MCR affected boys and girls differently?

We now investigate whether girls and boys have been affected differently by the MCR. We implement a strategy similar to what we have just undertake to capture the heterogeneity across student ability and school characteristics; that is, we interact the variables that capture the effect of the MCR with the dummy $Female$. Panel A of Table 1.7 shows the difference in the trend of uptake between girls and boys after the MCR (given by the coefficient on the interaction of $Post$, $Trend$, and $Female$), the coefficients on ability quintiles, and the AME of $Post$ for boys and girls, separately. Girls, on average, are more likely to respond positively to the MCR in terms of uptake. The coefficient of the interaction term suggests that girls in the cohorts that have been affected by the MCR have seen an average increase in the uptake of Maths by 1 percentage point more than boys, both for AS and A-level. The MCR increased AS grades and pass rates for girls more than for boys. The AME for girls shows a statistically significant increase of 3.3 and 1.5 percentage points in AS and A-level uptake. For boys, we see an increase of 1.5 percentage points for AS only, which is only marginally statistically significant. Furthermore, the changes in AS and A-level passes after the MCR is mainly driven by a fall in the attainment of boys. This suggests that the change in the composition of the classroom might have had a detrimental effect on boys' performances. Overall, the MCR has benefited the female population in terms of studying Maths. One year after the implementation of the MCR, girls' uptake of

A-level Maths increased by 8%.

1.6.1 Gender and Maths ability

Why are girls the marginal students, i.e. those who are mainly affected the MCR? In order to reply to this question we need to further explore the definition of ability. In the Appendix A5 we set out a simple theoretical model that explains the importance of perceived ability for subject choice. Girls, on average, are higher academic achievers than boys, especially at this stage of education. Figure A2.a in the Appendix shows that the share of girls within ability quintiles increases with ability, and it is more than half in the three highest ability quintiles. This reflects that girls at KS4 get higher grades than boys in their best 8 GCSE qualifications (notice that, on average, boys and girls take the same number of GCSEs). However, in our analysis we condition on the ability quintile, so that this characteristic is taken into account - we compare boys and girls within the same ability quintile.

One aspect that this measure does not capture, however, is the Maths-specific ability. It could be that girls are the marginal students because their grade in Maths is lower with respect to their other subjects compared to boys, whom tend to be better in Maths compared to their other subjects. So that while the choice of Maths at KS5 for boys is obvious, girls have a wider range of subjects to choose from. This would put the choice of whether to choose Maths at the margin, and hence it is more likely to be affected by external factors such as the incentive introduced by the reform. We hence create a variable that captures the students' relative ability in Maths: this is the ratio of KS4 grade in Maths to the average grade of all other subjects taken. In the rest of the paper we refer to this as "Maths relative ability". Figure A2.b shows that this ratio is normally distributed around one for girls, while the boys' distribution is lightly shifted towards the right with respect to girls. This suggests that girls are more likely to have a grade in Maths which is closer to the grade in the other subjects at KS4.

Furthermore, the signal of one's own Maths ability could be measured with some degrees of noise. We capture this by using the variance of the KS4 Maths score within the KS4 school attended by students with respect to their own cohort. In the rest of the paper we refer to this as "Maths dispersion". The rationale behind conditioning on this variable is that students perceive whether they are good in a subject by comparing their grades with those of their peers.[31] For example getting an A in Maths in a school where most of the schoolmates get a A* might differently affect the perception of one's own Maths ability compared to getting an A where most of the schoolmates achieve a C. The higher the dispersion of grades within a school, the more informative the comparison of one's own achievement with one's peers is, i.e. the stronger the signal provided by one's KS4 exam results is. While the dispersion of Maths grade within school is approximately the same for boys and girls (see Figure A2.c), the way they respond to it could differ.

Panel B of Table 1.7 shows that the results on gender heterogeneity are robust to the inclusion of the measures of Maths relative ability and Maths dispersion.[32] Girls are still more likely to study Maths in the post-MCR period in both years of schooling, and the only statistical significant AME for boys is found for the negative effect of studying Maths as an A-level for those who studied it in the first year. Also, the impact of the MCR on attainment remains approximately the same in both magnitude and statistical significance as those in Panel A, i.e. boys achieving lower passes and grades under the MCR.

The coefficients of the general academic ability (capped score quintiles), as well as those of Maths relative ability and Maths dispersion, are highly statistically significant in determining the outcomes. Furthermore, as we would expect, the coefficients on the Maths relative ability and Maths dispersion are positive, suggesting that the higher the grade in Maths with respect to the other subjects

[31] Notice that the English system in secondary schools amply uses the practice of tracking students by subject specific performances, so that it is simple for students to understand where they are in the overall school distribution. A more detailed description of the tracking practice follows in the next section.

[32] Also general results of the effect of the MCR shown in the previous section are not altered by including the variables on Maths relative ability and Maths dispersion - see Panel B in Table A4 in the Appendix.

and the strength of the signal, the higher the likelihood of choosing Maths at KS5 and of performing well. Notice that the general ability quintiles maintain the same statistical significance as in Panel A and their magnitude is only marginally affected by the introduction of the new variables. Hence, the fact that boys and girls differ in their response to the MCR is not explained by the difference in their *objective* Maths ability.

We further investigate another mechanism that might explain why boys and girls differ in their attainment in Maths following the MCR. This is whether they choose a different number or type of subjects to study at KS5 alongside Maths. There is no difference in the average number of AS and A-level subjects studied by girls and boys (4.2 AS and 2.8 A-levels). However, boys and girls might cope differently in situations where there are several and different pieces of information to acquire. The most studied subjects paired with Maths are other STEM subjects, mainly Biology, Chemistry, Physics and Further Maths. However, girls' predilection for some subjects differ to that of boys. For example, the uptake of A-level Biology is 18% for boys and 24% for girls; for A-level Chemistry this is 17% and 16%, for A-level Physics 20% and 5%, and for A-level Further Maths 5% and 2%.

We replicate the analysis on gender heterogeneity in response to the MCR by first conditioning on the number of subjects simultaneously studied with Maths and then by additionally adding dummy indicators on the most common types of subject studied (Chemistry, Biology, Physics, and Further Maths). Results are shown in the Appendix in Table A4. Even conditioning on all these pieces of information does not affect the results on Maths attainment. One remaining explanation for the gender differential in attainment under the MCR could be that girls and boys responded differently to the change in the composition of Maths classmates induced by the MCR.[33]

[33]The gender gap is only one of the gaps that are found in Maths and STEM subjects participation across different socio-economic and demographic groups. Ethnicity, as well as socio-economic status are also important characteristics for which a disparity is observed in uptake and attainment of Maths (DfE, 2007). We hence replicate the same model as for gender

To conclude, two main results emerge from this analysis. First, after the MCR, more girls are brought to study Maths both in year 12 and 13. Second, under the MCR boys get lower grades and passes in year 12 and are less likely to keep studying Maths in year 13. In the next section we investigate the possible mechanisms underlying the former finding.

1.6.2 Is gender composition important in determining subject choices?

Once we include relative ability measures, the gender differential with respect to the response to the MCR persists. It is hence plausible that some unobservable elements, such as preferences or perception of one's own ability, play a role in driving these results. The literature has highlighted how these characteristics are shaped by the social context in which individuals interact with each other. In particular, the gender composition of peers has found to be particularly relevant to understand educational outcomes (see Section 1.2). We hence investigate whether gender composition in the classroom has had any effect in influencing the decision to take Maths after the MCR, and whether it has affected boys and girls differently.

Notice that for this section our focus is on the gender composition at KS4 school, not KS5 school because the choice of whether to study Maths at KS5 is made in the previous stage of education. Because of the empirical strategy used (KS4 school FE), we maintain in our sample only those students who attended KS4 schools that are observed in each year that we consider (i.e. we use a balanced sample of KS4 schools/cohorts).

a. Single-sex vs. mixed-sex schools: fixed effect model

(results shown in Appendix, Table A6) focusing on whether pupils are of white origin, speak English as their first language, and are eligible for Free School Meals. Non-white, non-English mother-tongue and FSM students are those who have negatively been affected by the MCR in terms of achievement (AS and A-level passes). No main differences between groups are found in uptake. These results provide suggestive evidence that the students with the mentioned characteristics are more susceptible to peers class composition in the classroom. This is because this is likely to be the element that can explain a decrease in attainment for the cohorts post-MCR who have been exposed to an easier curriculum compared to the pre-MCR cohorts.

We first investigate whether girls (boys) have been differently affected by the MCR in terms of the likelihood of choosing to study Maths at KS5 for the pooled sample of girls (boys), and then separately for girls (boys) who went to single-sex or mixed-sex KS4 schools. We implement a KS4 school fixed effect model where we look at the within-school change in the likelihood of studying Maths at KS5 for the cohort pre and post-MCR.

Panel A of Table 1.8 shows the estimated coefficients of interest for the subsample of girls and boys, separately. For both genders the trend in AS uptake has increased for the cohorts post-MCR compared to the cohorts pre-MCR. However, the AME is statistically significant for girls only. Panel B shows the regressions separately for gender and type of school. One year after the implementation of the MCR, the uptake for girls in mixed-sex schools has increased by 18% and it is highly statistically significant. For girls in single-sex schools the increase is just 4% and not statistically significant. For boys, the increase is more similar across the two types of schools (2% and 7%, respectively, although only marginally statistically significant for single-sex schools).

One possible explanation of this is that students in different types of schools receive different signals about their own Maths ability. Table A7 shows that, for both boys and girls, single-sex schools have a higher average general academic ability (Panel I). Single-sex and mixed-sex schools do not differ much in terms of Maths relative ability (i.e. the ratio of the Maths grade on the average grades, Panel II), but they differ a lot in terms of the strength of the signal on Maths ability with respect to peers (Panel III). Hence, the differences in the response to the MCR that we find between girls in single-sex and mixed-sex schools could be driven by these differences in the Maths dispersion, i.e. the strength of the signal on one's own Maths ability is much higher in mixed-sex schools.

We next interact the variables of interest with a dummy specifying whether the school is single-sex or mixed-sex separately for boys and girls. In this way, we constrain the model to take into account the differences in the signal provided by the different types of schools. Panel C of Table 1.8 shows the interaction of $Post{*}Trend$ with the dummy variable of the type of school. This coefficient shows the differential in pre/post-MCR uptake for single-sex vs. mixed-sex schools. We obtain a very similar result to the results in Panel B. While for boys there is no difference in the AS Maths uptake for the cohorts post MCR period in single/mixed-sex schools, girls in mixed-sex schools replied more positively than girls in single-sex schools. As a result, the differential in signals provided by single and mixed-sex schools cannot explain why girls in these schools respond differently to the MCR.

Our next step is to understand whether these differences between different types of schools can be explained by selection. Selection could be an issue if unobserved characteristics that influence the enrolment in a single-sex or mixed-sex KS4 school are related to the likelihood of studying Maths at KS5. Endogenous switching regression models (Quandt, 1972) take this into account by correcting for selection bias in the main equations.[34] We explain how this works in our context in the next subsection.

b. Single-sex vs. mixed-sex schools: switching endogenous regression

Each individual is observed being in a single-sex or mixed-sex KS4 school. This is equivalent to the following specifications:

$$\begin{aligned} \text{Single-sex school: } Y_{1i} &= X_i\beta_1 + \epsilon_{1i} \text{ if } I_i = 1 \\ \text{Mixed-sex school: } Y_{0i} &= X_i\beta_0 + \epsilon_{0i} \text{ if } I_i = 0, \end{aligned} \tag{1.5}$$

where Y is the outcomes of interest, i.e. whether pupil studies Maths in year 12. X_i is a vector of individual characteristics, β_1 and β_0 are vectors of parameters, and ϵ_1 and ϵ_0 are disturbance terms. I_i is the observed realization of latent variable I_i^*, which identifies the school selection equation:

[34]We follow Favara (2012) in the implementation of this method for dealing with sorting in single-sex and mixed-sex schools.

$$
\begin{aligned}
I_i^* &= \delta(Y_{1i} - Y_{0i}) + Z_i\gamma + u_i \\
I_i &= 0 \text{ if } I_i^* > 0 \\
I_i &= 1 \text{ otherwise}
\end{aligned}
\tag{1.6}
$$

In the selection equation Z_i is a vector of characteristics affecting the likelihood of going to a mixed- or single-sex school. Among these, we include an exclusion restriction, otherwise the identification would be coming from non-linearities of the model only (Wooldridge, 2010). The estimation is computed simultaneously for the system of equations containing the two outcome equations and the selection equation by Full-Information Maximum Likelihood method.[35] This provides consistent standard errors. The error terms of each of the outcome equations ϵ_i are assumed to be correlated with u_i and have trivariate normal distribution with mean vector zero and $var(u) = \sigma_u^2$, $var(\epsilon_1) = \sigma_1^2$, $var(\epsilon_2) = \sigma_2^2$, $cov(u_i, \epsilon_{1i}) = \sigma_{1u}$, and $cov(u_i, \epsilon_{2i}) = \sigma_{2u}$.

Alongside the covariates already discussed in section 1.4, in the selection equation we condition on: pupil's KS2 grades (English, Maths, and Science - standardized by KS4 cohort with mean 0 and standard deviation equal to 1), mean KS2 grades by KS4 school/cohort,[36] and a linear time trend. Our exclusion restriction is the share of single-sex schools in the local authority where the student resides, and we call it *Density*. Local authorities are the best approximation of the neighbourhood in which we assume that pupils live and go to school at KS4. Even if families sort in neighbourhoods by socio-economic background (we condition on the IDACI of the area in which pupils have their domicile) and their intention to send their kids into local schools, the gender composition of these schools can

[35] To implement the switching regression model we use the command "movestay" in Stata, written by M. Lokshin (DECRG, The World Bank) and Z. Sajaia (Stanford University).

[36] For attainment at KS2 we use the total marks achieved in each of the mentioned subjects that have a range 0-100. Unfortunately, conditioning on KS2 attainment results in a loss of observations because KS2 attainment is not available for all pupils. About 14% of pupils do not have this information for KS4 cohort 2002 and the percentage decreases to 8% among students in KS4 cohort 2007.

still have some margins of randomness. The *Density* measure for our sample of students has an average of single-sex schools of 15% within a range of 0%-50% for a total number of 150 LAs.[37]

Table 1.9 shows the results of the endogenous switching regressions separated by boys and girls. We report the coefficients capturing the impact of the MCR, and, for the selection equation, the coefficient on the instrument, i.e. the density of single-sex schools within the LA. At the bottom of the table, we report the correlation between the error term of the selection equation with the outcome equations, and the Wald test for the independence of the equations. The Wald test suggests that we reject the null hypothesis of independence of the equations in the system. The sign of the correlation between the error term of the selection equation and the outcome equation for mixed-sex schools is negative and statistically significant for both genders, suggesting that pupils in mixed-sex schools have unobserved characteristics which make them less likely to choose Maths at KS5 compared to a random pupil in the sample. The error correlation between outcome and selection equation for single-sex schools is instead statistically significant for girls only and, again, it is negative. The coefficient *Density* in the selection equation is highly statistically significant and of an important magnitude, suggesting that it is a good predictor of the kind of school attended by students.[38]

After accounting for selection into the type of school, girls in single-sex schools increase their overall uptake trend in the period post-MCR by 2.2 percentage points, which is statistically significant at 1% level. The coefficient on uptake trend for girls in mixed-sex schools is not statistically significant. For boys, the effect of the MCR on AS Maths uptake is very similar between single and mixed-

[37]From our dataset we do not know whether schools are selective. However, DfE (2007) shows that 12% of secondary schools are single-sex in England and, among those, 33% are grammar schools and 60% are independent schools. In total, 75% of grammar schools and 26% of independent schools are single-sex. Hence there is an important overlap between KS4 school gender composition and type of school.

[38]Also the coefficients on KS2 grades at individual and aggregate level as well as the coefficient of the linear time trend (not shown in Table 1.9) are highly statistically significant.

sex schools. These results provide evidence that, after taking into account the selection into the kind of schools and allowing for heterogeneity in the effects of the covariates across single and mixed-sex schools, girls that studied in KS4 single-sex schools have responded to the MCR while girls in mixed-sex schools have not. The response of boys is unaffected by the kind of school attended.

These results show that girls are more affected than boys by gender composition in shaping their preferences towards a subject mainly studied by boys. More specifically, they are more sensitive to external incentives that affect the cost of studying Maths when their signal of ability is generated with respect to a population of other girls than with respect to a mixed-sex population. We next check whether this hypothesis is consistent by using another identification strategy, which allows us to surpass the selection issue by only considering students in mixed-sex schools.

c. Mixed-sex schools: Idiosyncratic changes in the gender classroom composition

We consider students in mixed-sex schools only and we exploit idiosyncratic variation in the gender composition of the Maths classroom within KS4 schools across different cohorts. In our dataset we do not have an indicator for classrooms within school. However, we exploit the way in which the educational system works in secondary school to infer Maths classmates at KS4 by using the grade obtained in KS4 Maths. In England it is very common to have a track system by subject. If an individual is particularly good in subject J s/he will be allocated in a classroom of high achievers in the same subject. However, if the same person does not fare particularly well in subject K s/he will be sharing the classroom with lower achievers in that subject. More precisely, in the period that we consider the system of teaching and assessing KS4 Maths was a 3-tier system. This means that students, based on their previous achievement, were divided into different classes where the material studied would differ by its complexity, as would the exam papers. The three different tiers were: foundation, which is the lowest with students examined on topics which range from grade D to grade G; intermediate, in which possible grades vary from B to E; and higher, which ranges from A* to C. Our sample is composed of students with a KS4 Maths grade A*/B, who come from the higher tier. As a result, we define their Maths classmates at KS4 as those students who studied in the same school/cohort and that have a KS4 Maths grade between the range A*/C.[39]

Table 1.10 shows the estimated coefficients of a regression for AS uptake where we interact the $Post * Trend$ with a continuous variable capturing the share of female classmates within cohort/school, and the dummy on whether the student is a girl. The AME of Post shows the percentage points associated with the likelihood of choosing Maths when the MCR is implemented for boys and girls at four different points: when there are 20, 40, 60, and 80 percent of girls in the classroom. The higher the percentage of girls in the classroom, the higher the likelihood of choosing Maths for the post-MCR cohorts for both girls and boys. However, the effect is statistically significant for girls only. These results strengthen the validity of the previous findings: girls are more responsive to changes in the expected effort to study Maths, a male-dominated subject, when the signal on one's own ability derives from the comparison between peers mainly of the same sex. For boys, gender composition is instead not relevant.

1.7 Summary and conclusions

This paper contributes to our understanding of the process of subject choice. We do this by exploiting a national reform, which reduced the cost of studying Maths in post-compulsory education in England by changing the content of the curriculum. We study whether the variation in the cost of studying Maths affects the likelihood of students to enrol into Maths courses, and their subsequent attainment. We find that the reform resulted in an increase in the uptake of Maths by 7% in year 12. However, this did not result in any changes in year 13 uptake.

[39] Notice, however, that results are not sensitive to a more/less generous definition of classmates.

This is because the rise in uptake was offset by a fall in grades and pass rates in year 12. On average, attainment in Maths falls after the MCR. We go one step further by understanding which students responded to the reform, and in which institutional settings they studied. We discover substantial heterogeneity in the response to the reform, both in uptake and attainment.

First, we show that those students who responded positively to the MCR in terms of uptake (high achievers) are not the same students who bring the average attainment down in the post-MCR period (low achievers). We provide evidence suggesting that changes in class size and ability composition of Maths classmates could explain these findings.

Second, we provide evidence on the importance of some schools' characteristics to enable students to best respond to the incentives provided by the reform.

Third, we investigate heterogeneity in socio-economic and demographic characteristics and we show that while some of them matter in terms of attainment, the trait that stands out for both uptake and attainment is gender. Females are the only group of the population that has seen an increase in A-level uptake after the reform was implemented. Furthermore, for this group we do not find any statistical significant negative effects on attainment. For boys instead we find a marginal increase in uptake of Maths in the first year of schooling, but not in the second one, and we find negative effects on attainment.

In the second part of the paper we hence focus on gender differences. We first check whether the differences in gender are driven by the fact that we do not condition our analysis on Maths ability. Hence, in addition to the general academic ability that we have used until that point, we condition on the relative Maths ability to the average grades in the other subjects studied and on the Maths grade dispersion within school. Even after conditioning on these, results do not change.

Finally, we try to understand whether gender heterogeneity in Maths uptake could be driven by gender differences in interpreting the signal on Maths ability. We do this by comparing single and mixed-sex schools (after taking into account selection into the type of school) and by looking at the share of female Maths classmates within mixed-sex schools. We show that female students who responded the most to the reform are those who formed their Maths ability signal with respect to other girls. For boys, the gender of the peer group does not matter for subject choice.

These results are consistent with what has been found in the literature. Decreasing the cost of studying Maths increases its uptake and this happens especially for girls (Joensen & Nielsen, 2014). We also try to show why this is the case. As in Favara (2012), we find that while for girls the choice of subjects in which boys are over-represented is sensitive to the gender of their peers, this is not the case for boys. It is not simple to disentangle which mechanisms create the link between the choice of Maths and the gender of classmates. Lavy and Sand (2015) found that teacher's bias in favour of boys in Maths and Science has a positive effect on achievement for boys and a negative one for girls. It further affects students' enrolment in advanced level Maths courses in high school in the same direction.

In our case, we do not know the mechanisms underlying our results. We can only speculatively think of possible explanations related to the cited literature on why we find different responses to class gender composition for boys and girls. It could be that teachers pay more attention or encourage more male than female high achievers in the same Maths classrooms because boys are those supposed/expected to specialize in STEM subjects in the next stages of education. This would mean that the higher the number of boys in the classroom, the lower the investment towards girls. Since students are very responsive to teachers,[40] this can affect girls' perception on their own scientific ability. Additionally, we could think about other factors that might play a role in gender differences towards subjects. For example, gender peer composition affects risk aversion and

[40]For example, it has been found that students respond to teacher's gender (Carrell, Page, & West, 2010).

competitiveness and these characteristics could be relevant for a decision such as subject choice,[41] especially when the subject has attached to it a strong gender stereotype.

Whatever the mechanisms, the evaluation of MCR highlights that there is an important pool of students that could be encouraged to take scientific subjects. Furthermore, the results on attainment suggest that the students who would not have studied Maths in the period pre-reform fare rather well once they are induced to enrol in this course. There is hence scope for policies to modify Maths participation at post-16 education. We suggest that this could be achieved by decreasing the gender stereotype attached to the subject at school and in other public institutions.[42]

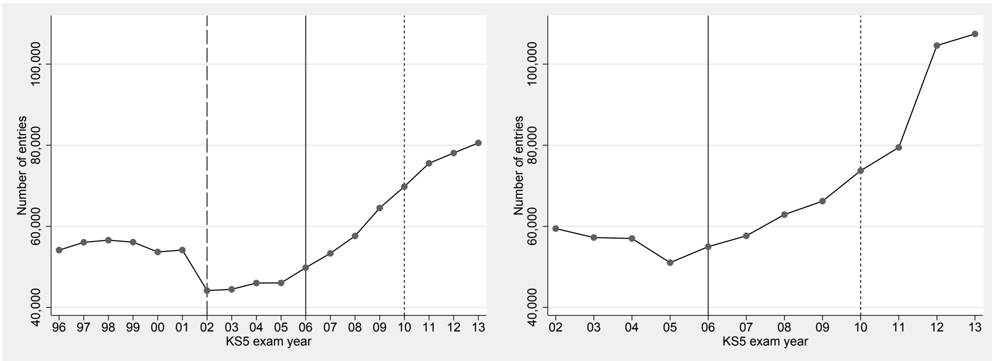
In this paper we only look at short term effects of the reform due to being limited by the available data, and different reforms affecting the cohorts after 2007. Joensen and Nielsen (2009, 2014) show that decreasing the cost of studying Maths, as seen in the 1980s reform that they study, has important consequences in the labour market outcomes of those affected by the reform. Future research should investigate whether the short-term effects that we find for a much more recent reform have longer-term consequences. This could be achieved, for example, by looking at outcomes in Higher Education and in the labour market.

[41] Apesteguia, Azmat, and Iriberri (2012).

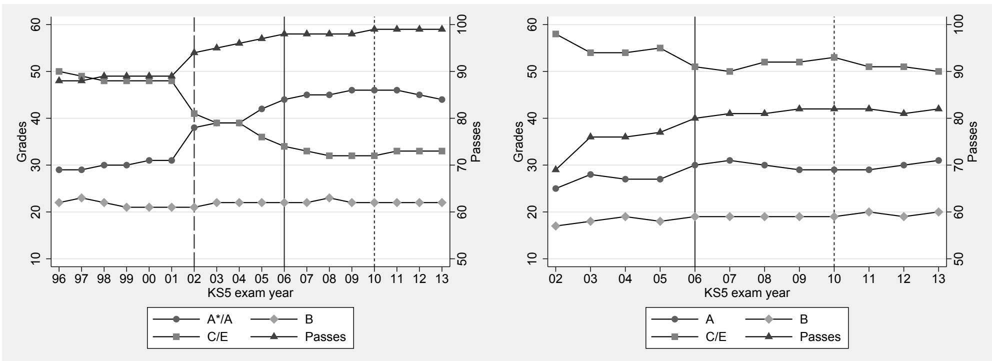
[42] The Science Museum in London in 2016 was suggesting to the public that intelligence has a gender by promoting a test that asked "Is your brain pink or blue?" https://www.theguardian.com/world/2016/sep/14/science-museum-under-fire-exhibit-brains-pink-blue-gender-stereotypes

Figure 1.1: A-level and AS Maths entries 1996-2013

(a) Uptake - A-level Maths (b) Uptake - AS Maths



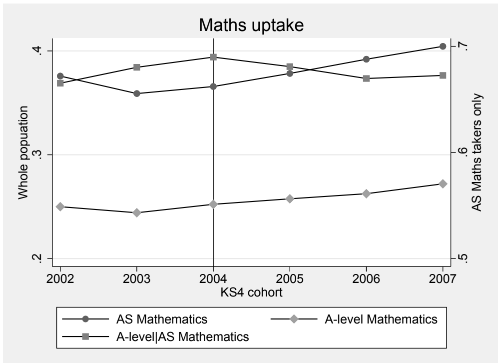
(c) Attainment - A-level Maths (d) Attainment - AS Maths



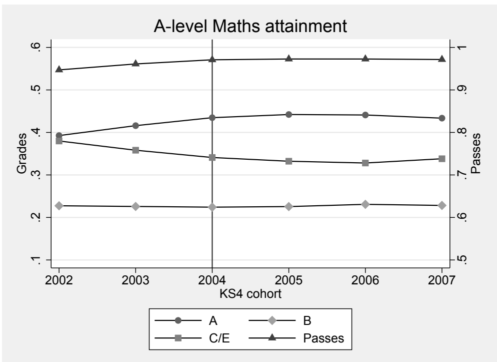
Notes. Time series provided by the Department for Education. On the x-axis the years of KS5 exams are shown. The vertical lines show the first KS5 cohorts who have been affected by: the Curriculum 2000 (long-dash line), the MCR (solid line), and by several other changes at both KS4 and KS5 level (introduction of A* and reduction of modules to study from 6 to 4 for all subjects except than for Maths and natural sciences at KS5, and introduction of 2-tier GCSEs at KS4 - short-dash line).

Figure 1.2: A-level and AS Maths by KS4 cohort

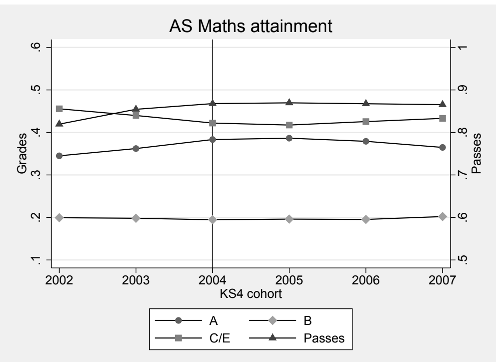
(a) Uptake: A-level and AS Maths



(b) Attainment: A-level Maths



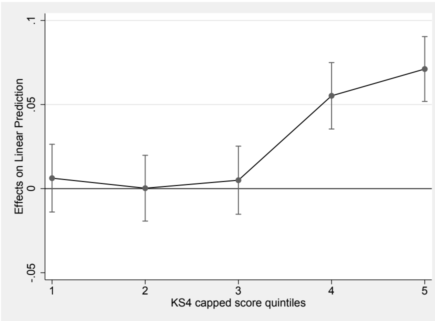
(c) Attainment: AS Maths



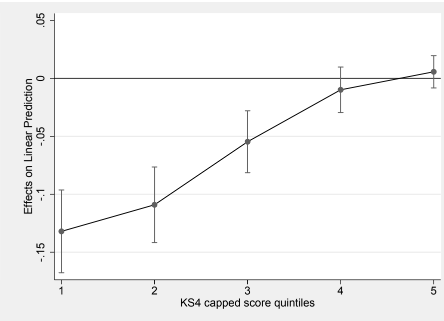
Notes. Sample of pupils selected from the National Pupil Database. These are full-time students, high Maths achievers attending non-special schools. The sample selection is discussed in more detail in 3.3.1.

Figure 1.3: Uptake and attainment of Maths by ability group

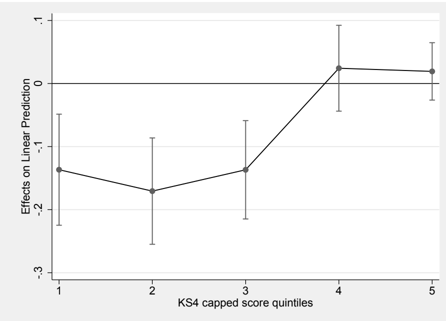
(a) AS uptake



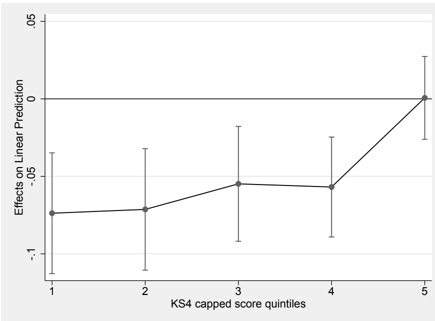
(b) AS passes



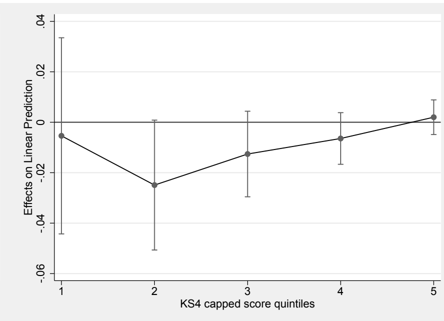
(c) AS grades



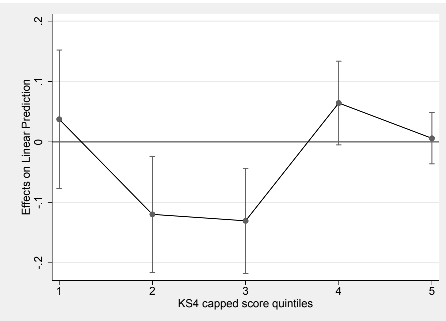
(d) A-level|AS uptake



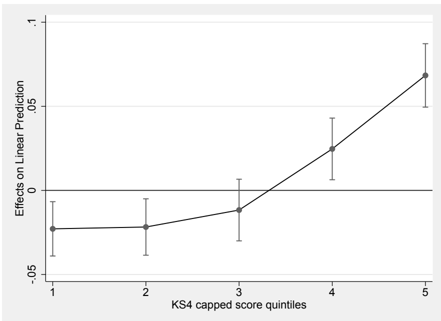
(e) A-level passes



(f) A-level grades



(g) A-level uptake



Notes. AME of *Post* across academic ability (i.e. KS4 capped score) quintiles. The lowest ability quintile is denoted by 1, the middle ability quintile by 3, and the highest ability quintile by 5. RHS variables: post, trend and their interaction; gender, months of birth, ethnicity, English first language, FSM eligibility, SEN status, type of KS4 school, independent school dummy, IDACI rank. KS5 school FE. Standard errors are clustered by KS4 school. 95% confidence interval.

Table 1.1: English educational system

Key Stage (school year)	**Age**	**Duration**	**Qualification acquired**
Compulsory education			
KS1 (1-2)	6-7	2 years	KS1 SATS, Phonics and Reading Check
KS2 (3-6)	8-11	4 years	SATS Tests, eleven plus exam (for Grammar school entry)
KS3 (7-9)	12-14	3 years	/
KS4 (10-11)	15-16	2 years	General Certificate of Secondary Education (GCSEs)
Post-compulsory education			
KS5 (12-13)	17-18	2 years or more	AS and A-level (NVQs and National Diplomas in vocational routes)
Higher Education	19+	3+	Degree

Notes. Description of the English educational system divided by Key Stages which correspond to different school years. At each of these stages a qualification is acquired, except for KS3.

Table 1.2: Summary statistics

Variable	Pre mean	Post mean	Post-Pre diff	s.e.	p-value
Female	0.515	0.522	0.006	0.002	0.000
Ethnicity:					
White	0.659	0.670	0.011	0.003	0.000
Indian	0.034	0.034	0.000	0.001	0.442
Pakistani	0.014	0.016	0.002	0.000	0.000
Bangladeshi	0.006	0.007	0.002	0.000	0.000
Other white	0.023	0.024	0.001	0.001	0.231
African	0.008	0.013	0.004	0.000	0.000
Caribbean	0.005	0.006	0.001	0.000	0.000
Chinese	0.007	0.008	0.001	0.000	0.001
Gypsy/traveller	0.000	0.000	0.000	0.000	0.000
other Asian	0.004	0.009	0.006	0.000	0.000
Other African	0.003	0.002	-0.001	0.000	0.000
Other ethnicity	0.012	0.008	-0.004	0.000	0.000
White & Asian	0.002	0.005	0.003	0.000	0.000
White & black African	0.001	0.002	0.001	0.000	0.000
White & black Caribbean	0.001	0.004	0.002	0.000	0.000
Mixed other	0.003	0.007	0.004	0.000	0.000
Unknown	0.217	0.184	-0.033	0.003	0.000
English is the first language:					
Yes	0.739	0.751	0.011	0.003	0.000
No	0.076	0.086	0.010	0.001	0.000
Unknown	0.185	0.163	-0.022	0.003	0.000
Special Educational Need (SEN):					
Yes	0.010	0.024	0.013	0.000	0.000
No	0.401	0.814	0.413	0.003	0.000
Unknown	0.589	0.162	-0.427	0.003	0.000
Free School Meal (FSM):					
Yes	0.034	0.038	0.004	0.001	0.000
No	0.781	0.800	0.019	0.003	0.000
Unknown	0.185	0.162	-0.023	0.003	0.000
Type of KS4 school:					
Community	0.256	0.246	-0.010	0.003	0.001
Voluntary aided	0.115	0.122	0.007	0.002	0.000
Voluntary controlled	0.033	0.030	-0.003	0.002	0.099
Foundation	0.143	0.167	0.025	0.003	0.000
Independent	0.162	0.135	-0.026	0.003	0.000
Further Ed.	0.289	0.298	0.009	0.003	0.004
Academy	0.000	0.000	0.000	0.000	0.155
Sixth form	0.002	0.001	-0.001	0.001	0.095

Notes. This table reports several values of the main variables that we use as covariates in our analysis on the whole sample of pupils (N=969,862). In the first column we have the mean value of each variable for the KS4 cohorts not affected by the MCR (2002-03) and in the second column for those KS4 cohorts affected by the MCR (2004-07). We then have the difference between the two means, followed by the standard errors, and the p-value of a t-test implemented with clustering at KS5 school level.

Table 1.3: AS uptake: different specifications

	AS uptake			
	1	2	3	4
Specification I				
2004	-0.002	0.011**	0.010**	0.010**
	(0.002)	(0.002)	(0.002)	(0.002)
2005	0.011**	0.021**	0.019**	0.019**
	(0.001)	(0.002)	(0.002)	(0.002)
2006	0.025**	0.032**	0.031**	0.031**
	(0.001)	(0.002)	(0.002)	(0.002)
2007	0.037**	0.046**	0.045**	0.045**
	(0.001)	(0.002)	(0.002)	(0.002)
Specification II				
Post	0.018**	0.028**	0.026**	0.026**
	(0.001)	(0.001)	(0.001)	(0.002)
Specification III				
Post	-0.014**	-0.003	-0.003+	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Trend	0.010**	0.011**	0.011**	0.011**
	(0.001)	(0.000)	(0.000)	(0.001)
Specification IV				
Post	-0.066**	-0.032**	-0.035**	-0.035**
	(0.004)	(0.006)	(0.006)	(0.008)
Trend	-0.017**	-0.003	-0.005+	-0.005
	(0.002)	(0.003)	(0.003)	(0.004)
Post*Trend	0.030**	0.015**	0.017**	0.017**
	(0.002)	(0.003)	(0.003)	(0.004)
AME Post	0.041**	0.022**	0.025**	0.025**
	(0.004)	(0.006)	(0.005)	(0.007)
Obs.	969,862	969,862	969,862	969,862
Control variables	✗	✓	✓	✓
KS5 school FE	✗	✗	✓	✓
Cluster s.e. by KS4 school	✗	✗	✗	✓

Notes. Control variables: female, months of birth, ethnicity, English first language, FSM eligibility, SEN status, type of KS4 school, independent school dummy, IDACI rank dummies, and ability quintiles. “AME Post” shows the overall effect of the MCR by taking into account both the changes in levels and the trends in specification 4 - at page 18 we describe how this average marginal effect is derived by the combination of the estimated coefficients of $Trend$ and $Post*Trend$. Significance at 1%, 5%, and 10%-level are indicated by **, *, and +.

Table 1.4: Effect of the MCR on uptake and attainment

	AS			A-level|AS uptake			A-level
	Uptake	Passes	Grades	Uptake	Passes	Grades	Uptake
	1	2	3	4	5	6	7
Post	-0.035**	0.074**	0.084**	0.075**	0.018**	0.039+	0.001
	(0.008)	(0.009)	(0.024)	(0.014)	(0.004)	(0.023)	(0.007)
Trend	-0.005	0.030**	0.042**	0.026**	0.004*	0.016	0.005
	(0.004)	(0.004)	(0.012)	(0.006)	(0.002)	(0.011)	(0.004)
Post*Trend	0.017**	-0.030**	-0.037**	-0.031**	-0.004*	-0.014	0.001
	(0.004)	(0.004)	(0.012)	(0.007)	(0.002)	(0.012)	(0.004)
AME Post	0.025**	-0.037**	-0.053*	-0.039**	0.002	-0.012	0.006
	(0.007)	(0.008)	(0.023)	(0.012)	(0.004)	(0.022)	(0.006)
y	0.380	0.858	3.563	0.676	0.967	3.837	0.257
Obs.	969,862	368,438	314,635	368,438	249,130	240,806	969,862

Notes. RHS variables not shown in the table: female, months of birth, ethnicity, English first language, FSM eligibility, SEN status, type of KS4 school, independent school dummy, IDACI rank dummies, and ability quintiles. KS5 school FE included. Standard errors are clustered by KS4 school. Significance at 1%, 5%, and 10%-level are indicated by **, *, and +.

Table 1.5: Ability composition in Maths classrooms

	AS uptake				A-level uptake			
Outcomes	Mean	Median	Mode	M.D.	Mean	Median	Mode	M.D.
Post	-0.034	-0.092	-0.166	0.056	-0.043	-0.073	-0.230*	0.045
	(0.052)	(0.072)	(0.102)	(0.036)	(0.060)	(0.077)	(0.102)	(0.042)
Trend	-0.021	-0.058	-0.093+	0.030+	-0.033	-0.059	-0.084+	0.019
	(0.026)	(0.036)	(0.050)	(0.018)	(0.030)	(0.038)	(0.050)	(0.021)
Post*Trend	0.019	0.054	0.092+	-0.032+	0.027	0.047	0.092+	-0.023
	(0.026)	(0.036)	(0.051)	(0.018)	(0.030)	(0.039)	(0.051)	(0.021)
AME Post	0.033	0.098	0.157+	-0.057+	0.052	0.092	0.094	-0.035
	(0.044)	(0.061)	(0.090)	(0.030)	(0.051)	(0.067)	(0.091)	(0.035)
Obs.	14,452	14,452	11,857	14,452	13,777	13,777	10,866	13,777

Notes. Outcomes: mean, median, mode, and mean deviation (M.D.). For the mode outcome we only consider those cases in which only one mode exists. RHS variables are aggregated at school/cohort-level: female, month of birth, ethnic group, English first language, FSM eligibility, SEN status, IDACI rank, ability quintiles, and type of KS4 school. We also condition on total number of students within school/cohort and include KS5 school FE. Standard errors are clustered by KS5 school and KS4 cohort. Obs. reports the total number of KS5 school observed. Significance at 1%, 5%, and 10%-level are indicated by **, *, and +.

Table 1.6: School heterogeneity

	AS			A-level|AS uptake			A-level
	Uptake	Passes	Grades	Uptake	Passes	Grades	Uptake
	1	2	3	4	5	6	7
I Private vs. non-private							
Post*Trend*Private	0.021	0.047*	0.057	0.071**	0.007	-0.042	0.040**
	(0.016)	(0.020)	(0.052)	(0.023)	(0.012)	(0.068)	(0.014)
Obs.	969,862	368,438	314,635	368,438	249,130	240,806	969,862
II Maths propensity							
Post*Trend*MP 14-20%	-0.011	0.027+	0.023	0.001	0.017	0.045	-0.004
	(0.007)	(0.014)	(0.032)	(0.015)	(0.011)	(0.041)	(0.005)
Post*Trend*MP 20/25%	0.000	0.041**	0.074*	0.021	0.020+	0.062	0.011*
	(0.007)	(0.014)	(0.031)	(0.014)	(0.010)	(0.039)	(0.005)
Post*Trend*MP 25/32%	-0.007	0.053**	0.067*	0.015	0.021*	0.104**	0.004
	(0.007)	(0.014)	(0.030)	(0.014)	(0.010)	(0.039)	(0.005)
Post*Trend*MP 32/89%	-0.003	0.072**	0.104**	0.047**	0.020*	0.136**	0.022**
	(0.008)	(0.013)	(0.030)	(0.014)	(0.010)	(0.038)	(0.006)
Obs.	969,862	368,438	314,635	368,438	249,130	240,806	969,862
III Share of female classmates							
Post*Trend*Share	0.008	-0.003	0.020	-0.018	0.002	-0.011	-0.001
	(0.009)	(0.011)	(0.028)	(0.016)	(0.005)	(0.027)	(0.009)
Obs.	969,862	368,438	314,635	368,438	249,130	240,806	969,862
IV Single- vs. mixed-sex school							
Post*Trend*Single-sex	0.029**	0.018*	0.049*	0.029*	-0.006	-0.027	0.033**
	(0.007)	(0.008)	(0.020)	(0.012)	(0.003)	(0.019)	(0.006)
Obs.	969,862	368,438	314,635	368,438	249,130	240,806	969,862
V Boys/Girls-only vs. mixed							
Post*Trend*Boys-only	0.041**	0.021*	0.065*	0.032+	-0.004	-0.008	0.049**
	(0.011)	(0.010)	(0.029)	(0.018)	(0.004)	(0.026)	(0.013)
Obs.	465,766	219,633	184,868	219,633	151,672	145,945	465,766
Post*Trend*Girls-only	0.017*	0.012	0.026	0.031*	-0.007	-0.033	0.023**
	(0.009)	(0.012)	(0.028)	(0.015)	(0.005)	(0.027)	(0.007)
Obs.	504,096	148,805	129,767	148,805	97,458	94,861	504,096

Notes. RHS variables not shown in the table: variable of interest (private/MP, i.e. Maths Propensity/share of female/single-sex school), post, trend and their interactions; female, months of birth, type of KS4 school, ethnicity, ability quintiles, number of students within KS5 school and KS4 cohort, whether the school is a single-sex school, share of students by each ability quintile. In all panels, except for I (not available information for private schools), we also include: English first language, FSM eligibility, SEN status, private school dummy, IDACI rank dummies, share of students by ethnic group, by FSM eligibility, and by SEN status. KS5 school FE included. Standard errors are clustered by KS4 school. Significance at 1%, 5%, and 10%-level are indicated by **, *, and +.

Table 1.7: Gender heterogeneity

	AS			A-level|AS uptake			A-level
	Uptake	Passes	Grades	Uptake	Passes	Grades	Uptake
	1	2	3	4	5	6	7
A Conditioning on general academic ability							
Post*Trend*Female	0.010**	0.012*	0.029*	0.007	0.002	-0.017	0.010**
	(0.004)	(0.005)	(0.013)	(0.006)	(0.003)	(0.013)	(0.003)
Q1	-0.350**	-0.370**	-1.592**	-0.395**	-0.124**	-1.640**	-0.390**
	(0.003)	(0.004)	(0.010)	(0.004)	(0.003)	(0.012)	(0.003)
Q2	-0.318**	-0.204**	-1.363**	-0.254**	-0.065**	-1.377**	-0.326**
	(0.002)	(0.003)	(0.006)	(0.004)	(0.002)	(0.008)	(0.003)
Q3	-0.245**	-0.091**	-1.013**	-0.153**	-0.025**	-0.989**	-0.249**
	(0.002)	(0.002)	(0.006)	(0.003)	(0.001)	(0.006)	(0.002)
Q4	-0.148**	-0.026**	-0.572**	-0.077**	-0.006**	-0.522**	-0.152**
	(0.002)	(0.001)	(0.005)	(0.003)	(0.001)	(0.005)	(0.002)
AME Post Boys	0.015+	-0.050**	-0.094**	-0.048**	0.002	-0.007	-0.004
	(0.008)	(0.009)	(0.026)	(0.013)	(0.005)	(0.026)	(0.008)
AME Post Girls	0.033**	-0.016	0.009	-0.025+	0.001	-0.022	0.015*
	(0.008)	(0.010)	(0.028)	(0.014)	(0.006)	(0.027)	(0.007)
Obs.	969,862	368,438	314,635	368,438	249,130	240,806	969,862
B Conditioning on general and Maths-specific ability							
Post*Trend*Female	0.009*	0.012**	0.033**	0.008	0.002	-0.014	0.009**
	(0.004)	(0.005)	(0.012)	(0.006)	(0.003)	(0.013)	(0.003)
Q1	-0.466**	-0.337**	-1.563**	-0.385**	-0.112**	-1.564**	-0.449**
	(0.006)	(0.005)	(0.017)	(0.007)	(0.003)	(0.019)	(0.006)
Q2	-0.304**	-0.172**	-1.302**	-0.228**	-0.055**	-1.294**	-0.292**
	(0.004)	(0.004)	(0.010)	(0.005)	(0.002)	(0.011)	(0.004)
Q3	-0.203**	-0.069**	-0.965**	-0.134**	-0.018**	-0.928**	-0.199**
	(0.003)	(0.002)	(0.008)	(0.004)	(0.001)	(0.009)	(0.003)
Q4	-0.111**	-0.013**	-0.537**	-0.064**	-0.002**	-0.486**	-0.113**
	(0.002)	(0.001)	(0.006)	(0.003)	(0.001)	(0.006)	(0.003)
Maths relative ability	1.422**	0.141**	0.938**	0.414**	0.015**	0.618**	1.068**
	(0.017)	(0.009)	(0.033)	(0.013)	(0.005)	(0.036)	(0.015)
Maths dispersion	0.025**	0.012**	0.043**	0.017**	0.003**	0.042**	0.026**
	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
AME Post Boys	0.004	-0.044**	-0.088**	-0.043**	0.004	0.006	-0.007
	(0.008)	(0.009)	(0.025)	(0.013)	(0.005)	(0.025)	(0.007)
AME Post Girls	0.031**	-0.008	0.026	-0.017	0.004	-0.000	0.019**
	(0.007)	(0.010)	(0.028)	(0.014)	(0.005)	(0.027)	(0.006)
Obs.	969,862	368,438	314,635	368,438	249,130	240,806	969,862

Notes. RHS variables not shown in the table: post, trend, female, and their interactions; months of birth, ethnicity, English first language, FSM eligibility, SEN status, type of KS4 school, independent school dummy, and IDACI rank dummies. Q1-Q4 denotes the ability quintiles (Q5, the highest ability quintile is the omitted category). KS5 school FE included. Standard errors are clustered by KS5 school. Significance at 1%, 5%, and 10%-level are indicated by **, *, and +.

Table 1.8: AS Maths uptake by gender: KS4-school FE model

A.	Girls	Boys
Post	-0.071**	-0.071**
	(0.011)	(0.013)
Trend	-0.008	-0.005
	(0.005)	(0.006)
Post*Trend	0.028**	0.024**
	(0.005)	(0.006)
AME Post	0.031**	0.014
	(0.009)	(0.010)
$\overline{y}$	0.294	0.471
Obs.	489,566	451,054

B.	Girls		Boys	
	Mixed-sex	Single-sex	Mixed-sex	Single-sex
Post	-0.105**	-0.037*	-0.073**	-0.074**
	(0.015)	(0.016)	(0.015)	(0.026)
Trend	-0.019**	0.001	-0.002	-0.016
	(0.007)	(0.008)	(0.007)	(0.011)
Post*Trend	0.043**	0.014+	0.023**	0.031*
	(0.007)	(0.008)	(0.007)	(0.012)
AME Post	0.050**	0.013	0.009	0.034+
	(0.013)	(0.015)	(0.012)	(0.020)
$\overline{y}$	0.281	0.331	0.471	0.475
Obs.	367,079	122,487	386,452	64,602

C.	Girls	Boys
Post*Trend*Single-sex	-0.027**	0.007
	(0.007)	(0.008)
Obs.	489,566	451,054

Notes. RHS variables not shown in the table: female, months of birth, ethnicity, English first language, FSM eligibility, SEN status, type of KS4 school, independent school dummy, IDACI rank dummies, ability quintiles, Maths relative ability, Maths dispersion. In panel C we also include an indicator of whether KS4 is single/mixed-sex and its interactions with the variables capturing the effect of the reform. KS4 school FE included. Standard errors are clustered by KS4 school. Significance at 1%, 5%, and 10%-level are indicated by **, *, and +.

Table 1.9: AS Maths uptake: mixed/single-sex schools switching endogenous regression

	Girls	**Boys**
I. Outcome eq.: mixed-sex school		
Post	-0.025	-0.069**
	(0.018)	(0.017)
Trend	0.007	-0.013
	(0.009)	(0.009)
Post*Trend	0.009	0.026**
	(0.009)	(0.009)
II. Outcome eq.: single-sex school		
Post	-0.044**	-0.064+
	(0.021)	(0.030)
Trend	-0.009	-0.009
	(0.010)	(0.014)
Post*Trend	0.022**	0.024**
	(0.011)	(0.014)
III. Selection eq.		
Density	4.902**	3.922**
	(0.536)	(0.645)
Observations	439,132	399,381
Selection Test		
$\rho_0 = \sigma_{u0}/\sigma_0$	-0.116**	-0.065*
	(0.017)	(0.031)
$\rho_1 = \sigma_{u1}/\sigma_1$	-0.083**	0.028
	(0.015)	(0.026)
Wald test of indep. eqns.		
$Prob > chi2$	0.000	0.050

Notes. Covariates included in both the selection and outcome equations: female, months of birth, ethnicity, English first language, FSM eligibility, SEN status, independent school dummy, IDACI rank dummies. In the outcome equation we also include: ability quintiles, Maths relative ability, Maths dispersion, and type of KS4 school. In the selection equation we also include a linear time trend and the standardized grades in KS2 Maths, English, and Science exams at individual and school/cohort level. Standard errors are clustered by KS4 school. Significance at 1%, 5%, and 10%-level are indicated by **, *, and +. ρ_0 and ρ_1 indicate the error correlation between outcome and selection equation. The last row reports the Wald test for the independence of the equations.

Table 1.10: AS Maths uptake: gender heterogeneity by share of female classmates

AME Post	Girls	Boys
FS=20%	0.009	0.010
	(0.027)	(0.026)
FS=40%	0.039**	0.020
	(0.014)	(0.013)
FS=60%	0.069**	0.030
	(0.017)	(0.019)
FS=80%	0.098**	0.041
	(0.033)	(0.035)
Obs.	375,576	396,959

Notes. Sample restricted to pupils who are observed in mixed-sex KS4 schools only. FS stands for classmates' female share. RHS variables not shown in the table: post, trend, female, share of female classmates and their interactions; months of birth, ethnicity, English first language, FSM eligibility, SEN status, type of KS4 school, independent school dummy, IDACI rank dummies, ability quintiles, Maths relative ability, Maths dispersion. KS4 school FE included. Standard errors are clustered by KS4 school. Significance at 1%, 5%, and 10%-level are indicated by **, *, and +.

Appendix

A1 The Maths courses

There are several options for studying Maths at KS5. Table A1 describes them. Our Maths variable is defined by pooling together the following courses: Maths, Maths (Applied), Maths (Decision), Maths (Mechanics), Maths (Pure), and Maths (Statistics). In our data, Maths (Applied), Maths (Decision), and Maths (Mechanics) existed only as an AS and not an A-level qualification. These AS qualifications lead to an A-level qualification in Maths if students decided to pursue studying the A-level Maths course. However, since the introduction of the MCR the distinction in Applied, Decision, and Mechanics has been discarded to avoid having too many different combinations constituting a Maths A-level.

The course "Use of Maths" is an applied course, targeted to students who want to acquire Maths skills for the job market; it is not meant to be for students who want to enter into HE. It was introduced in year 2006 as an AS qualification.[43] Across all the cohorts considered only about 5,000 pupils choose to study AS Use of Maths and the amount of students choosing the pilot A-level is more or less non existent in our cohorts.

The course "Further Maths" is instead an advanced course in Maths for those

[43]The introduction of an A-level in this course in 2011 was not well received by practitioners. Based on the observations of the AS and pilot A-level they argued that this course was not at A-level standard and would have been mainly chosen by students in low performing schools promoting the wrong believe that this would have been considered by universities to be equivalent to a Maths A-level. `http://news.bbc.co.uk/2/hi/uk_news/education/8143060.stm` Nowadays while the Pilot A-level Maths is still running, it is meant to be finally scrapped and this course will remain an AS qualification only. `http://www.aqa.org.uk/subjects/Maths/as-and-a-level/pilot-use-of-Maths-9360`

Table A1: List of Maths courses in the NPD

	AS	A-level
Maths	✓	✓
Maths (Applied)*	✓	✓
Maths (Decision)*	✓	X
Maths (Mechanics)*	✓	X
Maths (Pure)*	✓	X
Maths (Statistics)*	✓	✓
Use of Maths	✓	X
Additional Maths	✓	✓
Further Maths	✓	✓

Notes: Break-down of all AS and A-level in Maths in the NPD. * indicates that these labels were used only for KS5 years 2004 and 2005.

pupils who study the standard course in Maths and who want to achieve a deeper knowledge of the subject to access courses with demanding Maths content at university. In fact, an A-level in this subject is usually required to enter into undergraduate programmes such as Engineering and Physics. Before the academic year 2003/4 (not included), students could study AS Further Maths only after having taken AS Maths. Since 2003/4, Further Maths has acquired an AS and A-level status like all other subjects such that AS Further Maths has been made accessible in parallel to AS Maths from the first KS5 year.

"Additional Maths" is a course that is taken by those pupils who study Further Maths and want to study it even more deeply. There are very few pupils taking this course because, similarly to Further Maths, the provision of it is not always guarantee by schools which need to have a trained teacher to teach these advanced courses.

A2 Sample selection and other adjustments to the original data

The NPD data is provided in two different files. One contains the KS5 results of all students who obtained their KS4 qualification in the academic years 2001/2-2006/7. The other file is based on the school census and hence contains all pieces of information on the socio-economic and demographic characteristics of the pupils who obtained their KS4 qualification in the academic years 2001/2-2006/7, as well as their prior educational achievements at KS4. Table A2 shows the sample selections and restrictions before and after merging these two files.

Table A2: Sample selection and restrictions

	N
KS5 Results	
Original sample	2,012,682
At least one GCE qualification	1,659,548
Keep only first two years observed being in KS5	1,659,548
Keep only first attempt if exam is re-seated	1,659,548
Non-special KS5 schools only	1,649,375
KS4 Census	
Original sample	3,815,333
Full-time KS4 students only	3,814,053
Non-special KS4 schools only	3,783,480
Merge KS4 Census with KS5 Results	
Initial sample	1,648,316
Keep if year of birth 1985/1991	1,648,312
Keep if KS5 year is one/two/three years after KS4 year	1,647,992
Intermediate sample	1,647,992
With KS4 Maths A*-B	990,689
Keep schools observed across all cohorts	969,862
Final sample	969,862

In the KS5 Result file for part of the sample we observe that some students have an A-level in a subject but not AS (for example for A-level Maths this is true for about 5% of pupils in the final sample). For these cases we impute an AS in the same subject, e.g. we consider that the student has passed an AS in that subject with a grade which is equal to the A-level grade.

A3 Available statistics on A-level entries

Figure A1 shows the number of entries in England by KS5 exam year reported by three different sources. While the trend is the same across the different sources, the number of entries slightly differs across them. This is due to the way in which the entries are counted by each one of these sources.

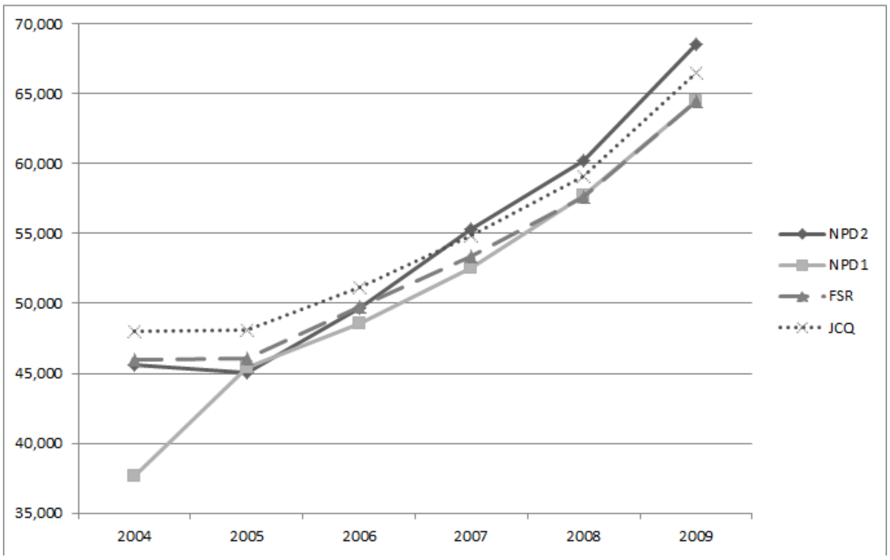
The first source is the Joint Council Qualification (JCQ). This is a membership organization comprising of the seven largest providers of qualifications (GCSEs, A levels, Scottish Highers as well as vocational qualifications) in the UK which are AQA (AQA Education Ltd), CCEA (Northern Ireland Council for Curriculum, Examinations and Assessment), City Guilds, OCR (Oxford Cambridge and RSA Examinations), Pearson, SQA (Scottish Qualifications Authority), and WJEC. They publish yearly statistics on A-level entries in the UK and in England each August as National Provisional A-Level GCE Results.[44]

The second source of information on A-level entries is the time series on GCE AS and A-level entries in England collected by the Department of Education and published yearly as reports under the name of the First Statistical Released (FSR). As specified in the yearly reports of the First Release on GCE/VCE A/AS examination results for young people in England[45]: "The coverage of this Statistical First Release is 16 to 18 year old students at the end of their second (and final) year of post-16 study. However, as the year group is not collected, a set of proxy criteria has been established. The criteria are that students must be 16, 17 or 18 (age at the start of the academic year) and they must have been entered for a GCE/VCE A level, a VCE Double Award or a Level 3 qualification equivalent in size to at least one GCE/VCE A Level in Summer [...]". In the FSR time series the subject of Maths is composed of Maths, Pure Maths, Use of Maths, Mechanics and Statistics. Alongside the statistics on Maths, the time series reports separately the entries in Further Maths since 1996.

[44] Available on-line at: `http://www.jcq.org.uk/examination-results/a-levels`

[45] Archive of the Reports available at: `http://webarchive.nationalarchives.gov.uk/20110907100731/education.gov.uk/rsgateway/db/sfr/`

Figure A1: A-level Maths uptake by different data sources



Finally, the figure reports the entries for A-level Maths from our NPD data before implementing any sample selection and restriction. The way the data is provided by the Department for Education is by KS4 cohort, i.e. the sample is composed of all students who obtained their KS4 qualification in England from the year 2002 to the year 2007 inclusive, and that are observed acquiring a qualification in post-compulsory schooling (KS5). The line NPD1 represents all entries reported in the "KS5 Results" file (see section A2). Notice that this line overlaps with the FSR line for all KS5 years except 2004. This is because this year coincides with the first cohort in the NPD. The data is provided by KS4 cohort and this results in a censoring of those KS4 cohorts previous to 2002 which obtained a KS5 qualification after the year 2003. Since our sample is composed of pupils who finished their KS4 between years 2002/7, we define our cohorts and their exposition to the MCR by KS4 year. This is represented by the line NPD2 (this requires merging the "KS5 Results" file with the "KS4 Census" file, again see A2). In Figure A1 I associate all students from the KS4 cohort 2002 to KS5 exam year 2004 and so on until students from KS4 cohort 2007 to KS5 exam year 2009. As a result, this line slightly underestimates entries for the first two years and then slightly overestimates them afterwards.

The highest number of entries is reported by the JCQ followed by the FSR (and NPD1 for 2005-2007) which reports approximately 2,000 unit less each year. The way we consider students in our paper is by KS4 cohort because this gives us a clear identification of the cohorts who have been affected by the MCR and those that were not, independently of when they obtained their KS5 qualification. Despite the differences in level, the trend shown by the different sources are the same.

A4 The MCR in detail

Table A3 summarizes the main changes in the Maths curriculum introduced by the MCR by school year (the first year of post-secondary school is *year 12* and the second year is *year 13*). In the system before the MCR, students had three compulsory modules to study: P1 in year 12 and P2 and P3 in year 13. These constitute the common core courses in Pure Maths that any student had to study for an A-level in Maths. To these courses, students had to add other 3 modules (either two in year 12 and one in year 13 or one in year 12 and two in year 13) by choosing between Pure, Mechanics, Statistics, and Discrete Maths. After the MCR, the content of three compulsory modules was spread over four different units called C1, C2, C3, and C4. C1 and C2 constitute the two compulsory core modules in Pure Maths to be studied in year 12; C3 and C4 the core compulsory modules in Pure Maths to be studied in year 13. To these core modules students could add either another module in year 12 and one in year 13 or other two modules in year 12 in the other Maths disciplines. In the last rows of the table we describe the possible two combinations that pupils could have chosen in both regimes. The underlined Pure Maths modules (called "P" before the MCR and "C" after the MCR) are compulsory, while the "O" modules are the optionals, i.e. Applied Maths modules chosen by students. It is evident that while in the pre-MCR period pupils had to study 3 Applied Maths modules, in the post-MCR period the Applied modules are only 2 - because the content of Pure Maths is now spread into 4 modules instead of 3. Furthermore, since the study of the compulsory modules in Pure Maths requires more time in the post-MCR period, the possible combinations of modules that students can choose changed. While the combination of three modules in year 12 plus three modules in year 13 is available in both periods, in the post-MCR period another option available is four modules in year 12 plus two modules in year 13, which is less demanding compared to the second option available in the pre-MCR period of two modules in year 12 plus four modules in year 13. All these changes made the study of Maths less challenging for pupils in post-MCR cohorts.

Table A3: Changes in Maths curriculum

	Pre-MCR		Post-MCR	
	Year 12	Year 13	Year 12	Year 13
Pure	$\underline{\text{P1}}$	$\underline{\text{P2}}$ $\underline{\text{P3}}$ P4 P5 P6	$\underline{\text{C1}}$ $\underline{\text{C2}}$	$\underline{\text{C3}}$ $\underline{\text{C4}}$
Mechanics	M1	M2 M3 M4	M1	M2 M3 M4
Statistics	S1	S2 S3 S4	S1	S2 S3 S4
Discrete	D1	D2	D1	D2
Possible combinations	Either 3+3 or 2+4		Either 3+3 or 4+2	
combination 1	$\underline{\text{P1}}$+O1+O2	$\underline{\text{P2}}$+$\underline{\text{P3}}$+O3	$\underline{\text{C1}}$+$\underline{\text{C2}}$+O1	$\underline{\text{C3}}$+$\underline{\text{C4}}$+O2
combination 2	$\underline{\text{P1}}$+O1	$\underline{\text{P2}}$+$\underline{\text{P3}}$+O2+O3	$\underline{\text{C1}}$+$\underline{\text{C2}}$+O1+O2	$\underline{\text{C3}}$+$\underline{\text{C4}}$

Source: Robinson, Harrison, and Lee 2005.
Notes: Underlined units are compulsory while the others must be chosen by students to form one of the two combinations specified in the last rows. When displaying the possible combinations in the last two rows "O" stands for optional module and it could be any of the non-Pure ones, i.e. Mechanics, Statistics, and Discrete.

Table A4: Robustness checks

	AS			A-level|AS uptake			A-level
	Uptake	Passes	Grades	Uptake	Passes	Grades	Uptake
	1	2	3	4	5	6	7
A Conditioning on whether the KS4 school attended offered Triple Science							
AME Post	0.024**	-0.037**	-0.057*	-0.039**	0.002	-0.014	0.006
	(0.007)	(0.008)	(0.023)	(0.012)	(0.004)	(0.022)	(0.006)
Obs.	969,862	368,438	314,635	368,438	249,130	240,806	969,862
B Conditioning on general and Maths-specific ability							
AME Post	0.018**	-0.030**	-0.043+	-0.033**	0.004	0.004	0.006
	(0.007)	(0.008)	(0.023)	(0.012)	(0.004)	(0.022)	(0.006)
Obs.	969,862	368,438	314,635	368,438	249,130	240,806	969,862

Notes. RHS variables not shown in the table: post, trend and their interaction, female, months of birth, ethnicity, English first language, FSM eligibility, SEN status, type of KS4 school, independent school dummy, IDACI rank dummies, ability quintiles. In panel i. we also condition on whether the KS4 attended by students offered the option of studying Triple Science. In panel ii. we instead additionally condition on Maths relative ability and Maths dispersion. KS5 school FE included. Standard errors are clustered by KS4 school. Significance at 1%, 5%, and 10%-level are indicated by **, *, and +.

Table A5: Gender heterogeneity: attainment

	AS		A-level	
	Passes	Grades	Passes	Grades
	1	2	3	4
i. Conditioning on N of AS/A-level				
Post*Trend*Female	0.012**	0.032**	0.002	-0.017
	(0.005)	(0.012)	(0.003)	(0.013)
AME Post Male	-0.043**	0.005	-0.090**	0.012
	(0.009)	(0.005)	(0.025)	(0.025)
AME Post Female	-0.007	0.004	0.022	0.002
	(0.010)	(0.005)	(0.028)	(0.027)
Obs.	368,438	249,130	314,635	240,806
ii. Conditioning on N of AS/A-level and subj. uptake				
Post*Trend*Female	0.011*	0.031**	0.002	-0.018
	(0.005)	(0.012)	(0.003)	(0.013)
AME Post Male	-0.043**	0.004	-0.101**	-0.008
	(0.009)	(0.005)	(0.024)	(0.025)
AME Post Female	-0.009	0.003	0.006	-0.021
	(0.010)	(0.005)	(0.027)	(0.026)
Obs.	368,438	249,130	314,635	240,806

Notes. RHS variables not shown in the table: post, trend, female, and their interactions; months of birth, ethnicity, English first language, FSM eligibility, SEN status, type of KS4 school, independent school dummy, IDACI rank dummies, ability quintiles, Maths relative ability, Maths dispersion, and total number of AS (A-level) studied for AS (A-level) outcomes. In Panel ii. we additionally include indicators on whether the student studied AS (A-level) Biology, Chemistry, Physics, and Further Maths for AS (A-level) outcomes. KS5 school FE included. Standard errors are clustered by KS5 school. Significance at 1%, 5%, and 10%-level are indicated by **, *, and +.

Table A6: Heterogeneity effect of the MCR across different socio-economic and demographic groups

	AS			A-level|AS uptake			A-level
	Uptake	Passes	Grades	Uptake	Passes	Grades	Uptake
	1	2	3	4	5	6	7
I Ethnicity							
Non-white	0.031	-0.118*	-0.071*	0.018	-0.059	0.024	-0.048
	(0.029)	(0.046)	(0.033)	(0.025)	(0.113)	(0.141)	(0.048)
White	0.034	-0.084+	-0.044	0.009	-0.072	0.079	-0.080+
	(0.027)	(0.044)	(0.033)	(0.023)	(0.109)	(0.136)	(0.045)
Obs.	781,678	295,789	195,071	781,678	247,397	187,680	295,789
II English first language							
No	0.048+	-0.117**	-0.074*	0.021	-0.063	0.134	-0.062
	(0.028)	(0.042)	(0.029)	(0.026)	(0.098)	(0.137)	(0.043)
Yes	0.024	-0.073+	-0.028	-0.002	-0.060	0.150	-0.084*
	(0.024)	(0.039)	(0.027)	(0.021)	(0.089)	(0.130)	(0.039)
Obs.	805,149	304,375	200,712	805,149	254,519	193,085	304,375
III Free school meal eligible							
No	0.026	-0.069+	-0.032	0.003	-0.049	0.151	-0.073+
	(0.023)	(0.039)	(0.028)	(0.022)	(0.089)	(0.130)	(0.039)
Yes	0.008	-0.103*	-0.095**	-0.014	-0.221+	0.163	-0.086+
	(0.032)	(0.050)	(0.035)	(0.028)	(0.117)	(0.156)	(0.051)
Obs.	805,777	304,623	200,868	805,777	254,718	193,235	304,623

Notes. RHS variables not shown in the table: post, trend, and their interactions; female, months of birth, ethnicity, English first language, FSM eligibility, SEN status, type of KS4 school, IDACI rank dummies, and ability quintiles. KS5 school FE included. Standard errors are clustered by KS5 school. Significance at 1%, 5%, and 10%-level are indicated by **, *, and +. Information on ethnicity, language and FSM is available for students who did not attend a private institution. Furthermore, even within the group of students with no missing values on these characteristics, there are some unknown cases. This explains the variation in the total amount of observations between the different panels in the table.

A5 Subject choice, signal of own ability and gender

The choices made at each level of education are important because, through the revelation of one's own ability, they determine the set of choices that can be made in the next stages. In a standard additive model of human capital accumulation individuals maximize their human capital y at each time $t \in 1, 2, ..., T$, where t=T is the absorbing state in which students exit education. Individuals make a choice in the following choice space $j \in J$ to maximize their expected lifetime utility. In our case j is the field of study in which students decide to specialize. Individuals have the following additively separable inter-temporal utility function:

$$U_t = u(y_t, j_t) + \sum_{\tau=t+1}^{T} \beta^{\tau-t} u(y_\tau, j_\tau) \tag{1.7}$$

where $u(y_t, j_t)$ is the instantaneous utility function and the discount factor $\beta \in [0, 1]$. From Equation 1.7 we can derive the value function at the time of choice:

$$V(y_t) = max_{j_t \in J}[u(y_t, j_t) + \beta \int [V(y_{t+1}) p(y_{t+1}|y_t, j_t) dY_{t+1}] \tag{1.8}$$

Equation 1.8 introduces subjective expectations as determinants in the process of subject choice. For each choice an instantaneous utility is associated plus the expected utility given current choice and human capital. Given uncertainty, the function $p(.)$ represents the subjective expectations that individuals have about the future states given their current choices. Agents are rational and adapt their believes on their experiences as per Bayes' law. As econometricians we do not know individuals' expectations but we observe the choices made as a revelation of latent subjective expectations.

Let's denote D^*_{ij} the net benefit of studying subject j. This is not observed. D_{ij} represents the realization of the decision, i.e. the choice that we observe.

$$D_{ij} = 1 \text{ if } D^*_{ij} > 0,$$
$$D_{ij} = 0 \text{ otherwise.} \quad (1.9)$$

Let's now assume that students make their choices based on the available information about their own ability with respect to subject j. However, the *true* ability is unknown both to individuals themselves and econometricians. We instead observe the realization of this ability in the form of students' academic achievements. This information is a signal which is a function of the true ability with some noise, e.g. $s_i = a_i + \mu$ where: $a_{ij} \sim N(\overline{a_j}, \sigma^2_{a_j})$; $\mu \sim N(0, \sigma^2_{\mu_j})$; and $cov(a_{ij}, \mu_j) = 0$.

We can now incorporate the decision conditional on own ability signal as:

$$Prob(D_{ij} = 1|s_{ij}) = Prob(D^*_{ij} > 0|s_{ij}) \quad (1.10)$$

Let's now define D^*_{ij} as linear combination of the benefit and cost of i with respect to the study of subject j:

$$D^*_{ij} = \pi_{ij}(a_{ij}, e_{ij}) - c_{ij}(e_{ij}) \quad (1.11)$$

π_{ij} denotes the payoff of studying subject j, or its performance. e_{ij} denotes effort, i.e. the cost of studying subject j. We assume that: $\frac{\partial \pi_{ij}(.)}{\partial a_{ij}} > 0$; $\frac{\partial^2 \pi_{ij}(.)}{\partial a^2_{ij}} < 0$; $\frac{\partial \pi_{ij}(.)}{\partial e_{ij}} > 0$; $\frac{\partial^2 \pi_{ij}(.)}{\partial e^2_{ij}} < 0$; $\frac{\partial^2 \pi_{ij}(.)}{\partial a_{ij} \partial e_{ij}} > 0$, i.e. ability and effort are complements in performance; $\frac{\partial c_{ij}(.)}{\partial e_{ij}} > 0$, where $c'(0) = c(0) = 0$; and $\frac{\partial^2 c_{ij}(.)}{\partial e^2_{ij}} > 0$. In this way, the cost function depends on ability and effort and the performance function depends on ability. Effort is as costly for low as for high achievers in subject j.[46]

[46]The framework we use here is an adaptation of what was proposed in Ertac (2005) on how information about one's own ability affects effort of the agent in their subsequent tasks and, consequently, their performances in those tasks. The theoretical framework adapted to different principal-multiple agent models in uncertainty is tested experimentally. However, we are not the first in adopting this model to predict outcomes in real life circumstances. Azmat and

We can then re-write the subject choice problem as:

$$Prob(D_{ij} = 1|s_{ij}) = E[D_{ij}|s_{ij}] = E[\pi_{ij}(a_{ij}, e_{ij}) - c_{ij}(e_{ij})|s_{ij}] = E[a_{ij}|s_{ij}]e_{ij} - c(e_{ij}). \tag{1.12}$$

Hence, based on the signal received in the previous period, a student decides the effort e_{ij} so that the first order condition in the maximization problem is: $E[a_{ij}|s_{ij}] - c'(e_{ij}) = 0$.

By externally decreasing the expected effort of studying subject j we would expect that for those students at the margins, there is an increase in uptake. In other words, we would expect some heterogeneity in the response to the incentive across different s_{ij}. However, if individuals with same s_{ij} respond differently to this incentive, we hypothesise that their response to the signal is different by a weighting parameter $\theta > 0$, so that $E[a_{ij}|\theta_{ij} * s_{ij}]$. This parameter shapes the preferences towards subject j by altering the "true" value of the signal of ability in j. A way in which this parameter could be formed is by giving different importance to different types of source from which individuals derive their own ability signal. For example, as we investigate in the second part of this paper, the signal can be weighted differently based on the type of the reference group (e.g. characteristics of peers) which individuals compare to in order to get their signals of ability.

Iriberri (2010) and Megalokonomou and Goulas (2015) adopted the theoretical model in different educational settings in Spain and Greece to investigate the mechanisms underlying investment in effort after receiving relative ability signals with respect to peers' ability as opposed to absolute or other different relative signals. Notice that, differing from these studies, we are interested in a dichotomous outcome, i.e. whether to study a subject, so that the latent effort variable is assumed to be continuous and we observe that the decision on whether studying j is made only when effort overtakes a certain threshold.

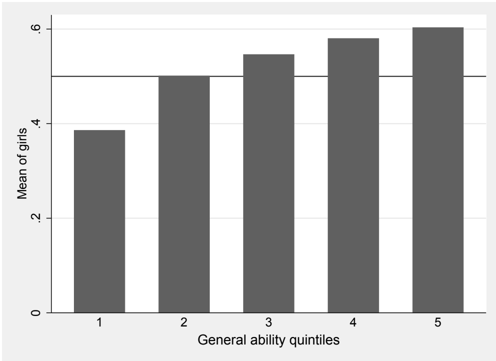
Table A7: Signals of academic ability by type of school and gender

	Girls		Boys	
	Mixed-sex	Single-sex	Mixed-sex	Single-sex
I KS4 capped score				
mean	2.990	3.510	2.622	3.204
sd	1.346	1.338	1.383	1.436
II Maths ability				
mean	1.032	1.016	1.095	1.073
sd	0.114	0.104	0.132	0.121
III Maths dispersion				
mean	3.815	1.551	3.753	1.585
sd	3.546	2.371	3.720	2.558
Obs.	375,576	128,520	396,959	68,807

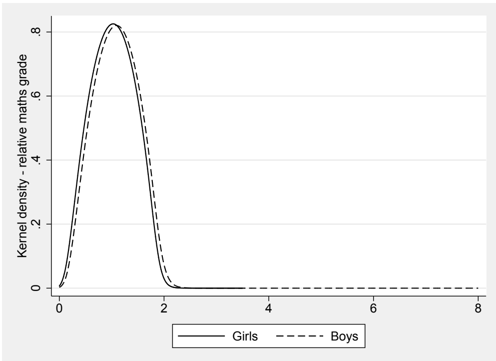
Notes. Mean and standard deviation of ability quintiles, Maths relative ability, and Maths dispersion by gender and single-sex and mixed-sex schools, separately.

Figure A2: Gender differences in academic attainment

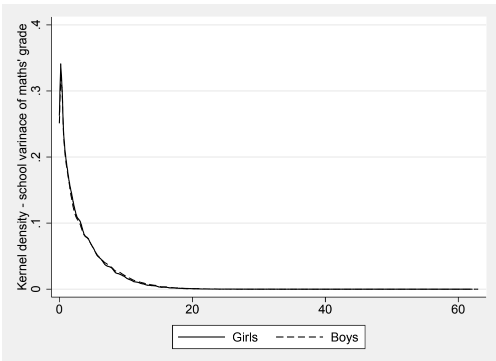
(a) KS4 capped score quintiles



(b) Maths relative ability



(c) Maths-school variance



Notes. Share of female within each of the ability quintile (a); distribution of Maths relative ability and Maths dispersion by gender at KS4 cohort/school level (b and c, respectively).

Chapter 2

For some, luck matters more: the impact of the Great Recession on early careers of graduates from different socio-economic backgrounds

2.1 Introduction

Socio-economic background plays an important role in several aspects of life. The endowment of human and social capital helps to achieve a desirable status, while lack or scarcity of financial resources negatively affects the chances that one has in life. Education is one of the channels through which family background affects the level of well-being of new generations. Differences in opportunities emerge early. Sometimes they are already clearly evident in the pre-school and school years. As a result, education has an important role in trying to smooth the inter-generational transmission of (dis-)advantages and to promote social mobility. What is unclear is whether equalizing educational outcomes is enough to guarantee that people from different socio-economic backgrounds have the same labour market opportunities later on in life. Human capital theory mainly focuses on the socio-economic-status (SES) gradient on educational outcomes in the early years (Cunha & Heckman, 2010). The direct impact of family background on adult outcomes when conditioning on prior educational achievement is a topic much less explored (see Blanden, Gregg, and Macmillan 2007 for an exception).

In this paper we analyse the relationship between family SES and the early labour market outcomes of several cohorts of students graduating from English universities. The first job plays a crucial role in one's life because it affects one's overall employment prospects (Gibbons & Waldman, 2004). Indeed, it has been found that the state of the business cycle at the time of graduation matters for early and long-term graduate careers (Kahn, 2010; Oreopoulos, von Wachter, & Heisz, 2012). Here we focus on the way in which SES background interacts with labour demand conditions at entry to determine the initial labour market destinations of new graduates. We exploit the change in labour demand due to the Great Recession to investigate whether graduates from different socio-economic backgrounds have been affected in different ways by the economic downturn. In other words, if luck matters - because those entering into the labour market in a recession are disadvantaged for no reason other than bad timing - does this affect graduates with different socio-economic opportunities in the same way?

In answering this question we want to understand the main reason why family SES is associated with the labour market outcomes of Higher Education graduates. One possible explanation is that more advantaged families have higher endowments of financial resources and can therefore support their children through a more expensive job searching process, by, for example, favouring wider geographical mobility. Another factor frequently cited in the literature on social mobility is that higher SES individuals have access to wider and more effective social and professional networks, which facilitate the process of finding a job match. A period of high unemployment is expected to have negative consequences both in terms of financial resources and networks effectiveness. By studying how geographical mobility and social network effectiveness of students from different SES backgrounds are affected by higher unemployment at graduation, we provide new evidence on whether financial or social capital is the main factor driving the relationship between SES and adult outcomes.

Our empirical analysis is based on the UK Destination of Leavers from Higher Education (DLHE) survey. This survey contains a rich set of socio-demographic and labour market characteristics of students graduating from UK Higher Education Institutions between 2002/3 and 2011/2, and who were interviewed 6 months after graduation. We match this dataset with graduate unemployment rates (defined by field of study) in order to investigate the influence of the business cycle on early graduate careers. Our main focus is on labour market outcomes 6 months after graduation.

We show that middle SES and low SES graduates are always more disadvantaged as they suffer higher rates of unemployment compared to high SES graduates, and that this gap increases during the downturn. Graduates respond to graduating in bad times by staying longer in Higher Education, although individuals from more advantaged backgrounds choose academic courses, while graduates from more disadvantaged backgrounds choose professional courses that have more immediate returns in the labour market. High SES gradates also have an additional safety net when graduating in bad times: they fall back more on non-paid jobs/internships. These findings are robust when controlling for several observable individual characteristics - such as demographic composition, degree class, institutional time-invariant characteristics, and business cycle conditions at the time of enrolment. We further show that even among graduates who are in employment 6 months after graduation there are stark SES differences according to access to full-time positions, professional occupations, graduate jobs, and salary; these differences become more pronounced during the recession. When looking at sub-groups, we find a significant degree of heterogeneity across subject studied.

The recession has particularly increased the SES gradient among graduates in STEM subjects (i.e. Science, Technology, Engineering, and Mathematics).

The DLHE survey also offers information about the main channel graduates have used in order to find their job (internet search, university career service, personal and social contact, etc.) and their geographical mobility, as we have access to identifiers for area of residence before attending university and the postcode of the current employer. We exploit this information to analyse whether SES groups differ in the effectiveness of their networks, and in the degree of geographical mobility, and whether the economic downturn has accentuated these gaps. We find evidence that, during periods of higher unemployment, middle and low SES graduates are less likely to find a job through family and social contacts than their high SES counterparts. Among students who had no effective social networks, those disadvantaged found a job farther away from their original domicile than advantaged students. We interpret this as evidence that social capital is a key factor in understanding SES inequalities in graduate outcomes.

We finally provide evidence on the longer-term effect of graduating in bad times and on the persistence of the SES gradient over time by looking at labour market outcomes at 3.5 years after graduation. There is also suggestive evidence on these negative outcomes affecting the well-being dimension through sentiments such as dissatisfaction of one's own career and regret for past choices. We find evidence of an SES gradient in these outcomes too.

Our paper is related to two broad areas of research. The first area is one which examines the effect of initial labour market conditions on the long term labour outcomes of college graduates. This literature finds that graduating when unemployment rates are high is very disruptive for college students' long-term careers. In some cases the effects are found to be very persistent (Kahn, 2010). Other evidence shows that an initial negative shock has long-term consequences but that these eventually fade out due to an increase in job mobility (Oreopoulos et al., 2012). A more recent study by Altonji, Kahn, and Speer (2016) further indicates that the effects on earnings is partly explained by a reduction in hours worked (part-time vs. full-time) and that the Great Recession had a stronger negative impact on US graduates than previous downturns. Studies in European countries are also in line with this evidence. For example, Liu, Salvanes, and Sørensen (2016) find a 3% rise in the unemployment rate at regional level implies a 30% increase in the probability of a job mismatch, defined in terms of field of study and industry worked, for college students in Norway. Cockx and Ghirelli (2016) find that a typical recession in Belgium implies wages and earnings penalties for high educated individuals. These penalties increase with experience, reaching a maximum ten years after labour market entry.

The second body of literature that we relate to is the literature on social mobility. A large part of intergenerational mobility studies focuses on the effect of socio-economic inequalities on educational outcomes, particularly early academic attainment. Only a few studies, mostly focused on the UK, have explored the existence of SES differences in labour market outcomes when conditioning on having a high level of education. Machin, Murphy, and Soobedar (2009) look at differences in education attainment and labour market outcomes of graduates by gender, parental SES, state/private school status, ethnicity, and disability. They consider students graduating in 2002/3 at 6 months and 3.5 years after graduation. They find that after 6 months, graduates from managerial/professional backgrounds are most likely to be in full-time employment and that all groups earn significantly more than those with parents classified as unskilled workers. Private school students earn significantly more than any other student, and this gap increases after 3.5 years for both men and women (from 3.8% to 8.3% for males and from 7.3% to 12.1% for females). More recently Macmillan, Tyler, and Vignoles (2015) investigate the socio-economic gradient with respect to accessing to top occupations. They consider UK first degree graduates leaving Higher Education in the year 2006/7. Even after controlling for a comprehensive set of variables representing human capital at graduation, they find that private school graduates are still 2.5 percentage points more likely to access top occupations 3.5 years after graduation.

None of the studies looking at the effect of "graduating at a bad time" considers whether the business cycle has a different impact on college students' outcomes according to family SES. At the same time, all the evidence about the association between SES and graduate labour market outcomes is based on a single cohort, and cannot take into account the impact of labour demand. In our analysis we focus on the socio-economic background of university students and on how this interacts with the macroeconomic conditions at graduation to determine labour market outcomes at entry. Our idea is that changes in labour demand translate into changes in the social and financial capital of individual students and their families. By exploiting variation in the graduate SES gap over the business cycle we will thus try to understand the relative importance of social and financial capital in determining socio-economic differences in labour market outcomes after conditioning on human capital attainment.

The rest of the chapter is organized as follows. Section 2.2 explains the English educational system. Section 2.3 shows the empirical strategy and Section 2.4 presents the data and the main variables of interest. Section 2.5 goes through the main results. We then analyse the possible mechanisms underlying our findings in Section 2.6 and we conduct several robustness checks in Section 2.7. Finally, we look at some longer-term outcomes in Section 2.8, and Section 2.9 concludes.

2.2 Institutional settings

Our analysis focuses on England. The rigidity of the educational system in this country makes it an ideal setting to investigate the role of the business cycle on graduate labour market outcomes. In England students typically enrol at university when they are 18 years old. To enrol in UK university, students who choose an academic track (leading to A-level qualifications) must formally apply through the Universities and Colleges Admissions Service (UCAS). The deadline for applying is usually in mid-January of the academic year before enrolment. In these applications, alongside their personal details and statement, students specify their ordered preferences for undergraduate courses and universities.

The choice of subject degree is conditional on the subjects and marks that students studied in the previous stage of education, called Key Stage 5 (KS5), when they are 16-18 years old. For example, for programmes with an important scientific content having studied maths is a necessary requirement, and it is also usually required to have achieved a particular mark, although this might differ across universities. For humanities subjects, having studied English language is often a must. In order to study particular subjects at Key Stage 5, students need to have achieved certain results in relevant subjects in the previous stage of education, called Key Stage 4 (KS4).[1] For example, to study maths at KS5, most schools require students to have achieved the highest two marks in maths at KS4 (A*/A).

In other words, specialization into different subject areas occurs quite early on. Furthermore, at university, students enrol straight away into a specific programme: they do not decide what to study after having taken exams in the first year, unlike in other countries, such as in Scotland or the US. Switching course of study is costly, and not common in this system, and transfers between institutions are very rare (fewer than 3 percent switch institutions, Vignoles and Powdthavee 2009). On the other hand, dropouts from Higher Education is much less of a problem than in other countries.[2] Finally, a bachelor degree usually lasts for three years, and its duration is fixed because students cannot choose to give exams when they want, unlike in other European countries such as Italy.

[1] At Key Stage 4 students obtain a General Certificate of Secondary Education (GCSE) for each subject studied. Students have to study maths, English and science (although for this last subject they can choose several options) and then usually choose another 5/7 additional subjects.

[2] Vignoles and Powdthavee (2009) cites several statistics: the cohorts who started university in 2004/5, 91.6 percent of full-time students continued into their second year and "[...] HESA data indicate that the UK noncontinuation rate from the first year of study to the second for young, full-time entrants was 7.2 percent in 2004–2005. In the data for England, the figure is very similar (just over 6 percent)."

The rigidity of the educational system makes England very appealing for studying our topic. This is because students do not have much, if any, scope to manipulate the choices made in Higher Education as a result of the state of the current business cycle.[3] The choice of degree studied is in most cases pre-determined several years before its actual realization, and changes between subjects and Higher Education institutions, as well as dropout rates, are negligible.

2.3 Empirical strategy

Our aim is to investigate whether graduating when macroeconomic conditions are bad has any effects on the labour market outcomes of graduates and whether the impact differs by socio-economic background. While the effect of graduating in bad times has already been investigated in other countries and periods, our focus on the variation by SES is novel. We use an identification strategy that is common to the papers cited towards the end of Section 2.1.

Our unit of analysis is a graduate i who obtained a degree in field of study f, from a Higher Education Institution (HEI) h and is observed at time t, i.e. 6 months after graduation. Our proxy of socio-economic background, SES, is a categorical variable indicating whether students are from a high, middle, or low SES. Our principal interest is to establish whether there is any impact of unemployment rates ($U_{f,t-1}$) on graduate destinations and whether this effect is heterogeneous across the socio-economic backgrounds of graduates. To capture this heterogeneity, we include an interaction term between graduate SES and the log of the unemployment rate at year of graduation.[4] Hence, δ is our parameter of interest in equation (2.1):

[3] Blom, Cadena, and Keys (2015) show how the business cycle affects degree choice in the US, where the higher educational system allows ample margins of discretion. On the other hand, Cockx and Ghirelli (2016) find no evidence of the impact of the Great Recession on duration of the degree in Belgium.

[4] The use of the log allows us to take into account that different SES groups experience different average rates of the outcome of interest.

$$
\begin{aligned}
Y_{ifhdt} = \alpha + \beta ln(U_{f,t-1}) + \gamma SES_{ifhdt} + \delta ln(U_{f,t-1}) * SES_{ifhdt} \\
+\lambda ln(U_{d,t-3}) + \sigma ln(U_{d,t-3}) * SES_{ifhdt} + \theta X_{ifhdt} + \omega_{ifhdt},
\end{aligned}
\tag{2.1}
$$

The outcome variable, Y, represents the activity status of a graduate student 6 months after graduation, or the characteristics of his or her job when employed. The main variation we exploit comes from changes in unemployment over time. How we define the unemployment rate is an important issue because this must represent the labour demand conditions that individuals face at the time of their transition from Higher Education to the labour market. First, we use the unemployment rate at the time of graduation to capture the relevant labour economic conditions. This is what is likely to best capture the job market faced by each individual at time of graduation (Cockx & Ghirelli, 2016; Kahn, 2010; Liu et al., 2016; Oreopoulos et al., 2012). Second, instead of looking at the total unemployment rate we focus on the unemployment rate of the sector related to the degree studied by students. As to our knowledge, only Altonji et al. (2016) has used unemployment rate by field of study in their analysis. Thus, we proxy labour demand conditions using *field* or subject-specific graduate unemployment rates as we assume that what really matters for graduate labour market outcomes is the labour demand within their sector. Graduates in fields highly sensitive to the business cycle - such as business studies - might experience a higher penalty in making the transition to the labour market during a recession than graduates in fields where long-term demographic trends matter more - such as medicine or education.[5] Notice that the unemployment rate by field of study is demeaned so that we can interpret the non-interacted estimated coefficients of the SES indicator ($\hat{\gamma}$) as if there was no interaction with the unemployment rate.

In Section 2.2 we explained that the educational system is rather rigid and

[5]All our regressions cluster the standard errors by field-specific time trend to take into account possible correlation of individual outcomes within subjects over time. We hence have 120 clusters (12 fields of study over 10 cohorts).

that it is unlikely that students can respond by adjusting their choices to the business cycle. This makes our estimates more likely to have a causal interpretation. However, one possible concern with this empirical strategy is that business cycle variables affect the decision to enrol in HE, and therefore the composition of the cohort. We condition on several socio-demographic and academic characteristics of graduates, X: gender, cohort (defined by student's year and month of birth), ethnicity, disability status, and degree classification. We also consider distance in Km between the domicile at the time of the university application and the university attended, as a proxy for the propensity to be geographically mobile.

Furthermore, we condition on the unemployment rate at time of enrolment. This is because the business cycle might have played a role in the decision to enrol in HE and on the choice of the degree.[6] Ignoring this aspect would bias our results since the unemployment rate is a serially correlated variable. To best capture labour market conditions at time of enrolment we use the unemployment rate at the Local Authority District (LAD) level.[7] We consider that this is the relevant proxy of the labour market circumstances affecting students before university enrolment. The LAD unemployment rate is measured at time of enrolment, i.e. $t-3$,[8] and is attributed to each student using the area where the student was

[6]The latter, however, appears to be a less important issue for the UK context, where specialization into different subjects starts during secondary school and is almost complete by age 16. D. Clark (2011) looks at the labour market effects on enrolment in post-compulsory education in England by using variation in youth unemployment rates across regions and over time (1976-2005). His analysis is performed at the aggregate (regional) level. He finds that youth unemployment rates have an important and positive effect on enrolment as well as some measure of expectations of future labour market success at national level. In another recent study, Barr and Turner (2015), find a positive impact of the Great Recession on post-secondary enrolment outcomes in US by using variation in local labour market conditions as well as state-specific variation in Unemployment Insurance (UI) programs and their duration. M. P. Taylor (2013), investigates the effect of leaving education at age 16 when unemployment is high for both men and women in Britain. He finds the negative effect of an increase in unemployment rates for men. Other papers in the UK suggest that aspiration and attitudes towards education are influenced by the economic climate, and this varies across different groups in the population, with particularly important differences across SES (Meschi, Swaffield, and Vignoles 2011, Tumino and Taylor 2015, Rampino and Taylor 2012).

[7]Local authority districts is a generic term to describe the district level of local government in the United Kingdom. It includes non-metropolitan districts, metropolitan districts, unitary authorities and London boroughs in England; Welsh unitary authorities; Scottish council areas; and Northern Irish district council areas. The areas are made up of whole electoral wards/divisions. http://data.gov.uk/dataset/local-authority-districts-uk-2012-names-and-codes

[8]From the data we know when students enrolled. The majority of our sample enrolled 3

domiciled before going to university (U_d). We also consider the interaction of U_d with the SES categories, to allow for different effects for different subgroups of the population.

The composite error term of equation (2.1) includes linear time trend (t), SES time trend ($\zeta_i * t$), field of study dummies (μ_f), HEI dummies (ρ_h), and LAD dummies (τ_d) as shown in equation (2.2a). In this manner we compare students within university and field of study and take into account overall macroeconomic shocks and changes in SES student composition over time. However, this specification does not take into account that different fields of study might have experienced different trends with respect to the outcome considered because they associate with different sectors in the economy. This heterogeneity could confound with the unemployment rate by field of study. We hence implement a specification where we also include a field-specific time trend, $\mu_f * t$, as in equation (2.2b). Finally, in a third specification we condition on year dummies, ν_t, instead of a linear time trend (2.2c). In this way we take into account any cohort-specific shocks that could otherwise confound the effect of the yearly changes in the unemployment rate.

$$\omega^a_{ifhdt} = t + \zeta_i * t + \mu_f + \rho_h + \tau_d + \phi_{ifhdt}, \tag{2.2a}$$

$$\omega^b_{ifhdt} = t + \zeta_i * t + \mu_f * t + \rho_h + \tau_d + \phi_{ifhdt}, \tag{2.2b}$$

$$\omega^c_{ifhdt} = \nu_t + \zeta_i * t + \mu_f * t + \rho_h + \tau_d + \phi_{ifhdt}. \tag{2.2c}$$

years before graduation. Time from enrolment to graduation is very stable over time and does not vary with unemployment. To address this concern we will only select full-time students.

2.4 Data and descriptive statistics

2.4.1 Data

The Destination of Leavers from Higher Education (DLHE) is a very rich survey that is carried out 6 months after graduation on the whole population of graduates from UK Higher Education Institutions. The survey is conducted by the Higher Education Statistical Agency (HESA). This survey replaced the First Destination Survey in Autumn 2003, and it contains a larger amount of information on graduate labor market outcomes, including main activity status, occupation, salary and type of contract, among others. The dataset is linked to the Universities and Colleges Admissions Service (UCAS) student applications, which contains student demographic characteristics (e.g. their nationality, their ethnicity, and their parents' social class grouping derived from their occupational status), and information about their education before attending university (type of school attended, overall grades obtained in A level examinations at KS5). There is also information on degree class, subjects studied, and the HEI attended. The DLHE started in the academic year 2002/3 and in this paper we use information up to year of graduation 2011/2.

The DLHE allows us to investigate the activity status of students and the type of job that they are doing 6 months after graduation. We present all our results separately for (i) activity status, and (ii) type of job held. This is to highlight the fact that in the second group of outcomes we consider only students in full-time or part-time employment at the time of the survey. In our empirical specification we do not however model this selection. All outcomes are dummy variables (=0/1) except for the salary. More specifically the definition of our main outcomes is as follows:

- *Activity status*:

  1. Whether studying in a HE programme (higher degree by research, higher degree by taught course) vs. all other activity statuses;

2. Whether studying in a professional programme (postgraduate diploma or certificate, first degree, other diploma or certificate, professional qualification, other qualification) vs. all other activity statuses;
3. Whether working full-time vs. all other activity statuses;
4. Whether working part-time vs. all other activity statuses;
5. Whether unemployed vs. all other activity statuses;
6. Whether doing something else (e.g. voluntary jobs, non-paid internships, other not specified) vs. all mentioned activity statuses.

- *Type of job for those working either part-time or full-time*:

7. Part-time vs. full-time jobs;
8. Managerial/professional occupation vs. all other socio-occupational categories (built on the Social Occupation Classification);
9. Graduate vs. non-graduate job (students are asked whether their degree was required for the job);
10. Fixed-term contract for less than 12 months vs. all other types of contract;
11. Natural log of self-reported annual gross salary (for full-time employed only).

2.4.2 Sample selection

Since our main interest is the transition from Higher Education to work, we start by selecting a sample of full-time non-mature first degree students (2,082,080), which comes to about 45% of the initial sample of graduates. The biggest drop occurs when keeping only first degree students. This group represent 61% of the original sample (14% graduated from foundation degrees, HE diplomas and certificates, while 25% graduated from postgraduate research or taught programmes).

We restrict our analysis to UK nationals ($> 90\%$). This is because our main interest is to see how graduates of different SES groups are affected by the business cycle, and it would not make sense to compare SES across different countries.[9] As one of the variables defining SES is based on the neighbourhood where students lived before going to university, we include only mainland areas in the UK (dropping 5,164 observations). We further restrict our analysis to English universities because comparisons with the other UK countries would be difficult due to institutional differences (in tuition fees, in maintenance grants regime, and duration of study). Our intermediate sample consists of 1,492,289 observations.

Next, we operate the following restrictions. First of all, we look at information on the subject studied. Some students appear in the records as studying a combination of subjects. As the percentage of time spent on each subject is recorded in the data, we assign a field by taking the course attended for more than 50% of the time. In some cases, however, the field is undefined (8,665) or there is no field which is studied for at least 50% of the time (6,440). Another small number of observations (15,651) is dropped because the field of study does not find an equivalent in the Labour Force Survey, which is our source of information on field-specific unemployment rates.

Secondly, we drop observations for which we cannot derive an indicator for SES. This means we exclude records with missing information on: domicile before attending university (6,859); type of school attended (private vs. state) or participation in Higher Education at the area level (152,709). Finally, we drop all students included in the issued sample but who did not reply to the survey (247,095). The latter is probably the most controversial selection, so we will check that response rates do not vary by SES and unemployment (see Section 2.7). Our final sample consists of 1,054,863 records, about 71% of our intermediate sample. Table B1 in the Appendix summarizes the restrictions that we implement in the sample selection.

[9] Information on SES is missing for a large proportion of non-UK nationals.

2.4.3 The SES index

The three main pieces of information that we use to derive an indicator of family SES[10] are derived from UCAS applications. The first variable we consider is the Low Participation Neighbourhood marker (LPN), which summarizes the Higher Education participation in the neighbourhood of residence at the time of application to university. This is expressed in quintiles.[11]

The second variable indicates the type of secondary school attended, codified as state vs. private. This is clearly an indicator of SES, since those from wealthier families are more likely to go to private schools (Artess, McCulloch, and Mok 2014). Finally, we know the postcode sector of the residence of students before university. We match to this the corresponding value of the Index of Multiple Deprivation (IMD).[12] Figure 2.1 (a, b, and c), shows the distribution of these proxies of SES across the period we observe. We can clearly see that the distribution has been quite stable over time, with no sharp change in the composition of graduates by SES. If anything, we can see a small monotonic increase in graduates coming from a low SES background.

We next construct an overall SES index. The three different characteristics (LPN, type of school, and IMD) capture family SES in a different way, so that, by pooling these variables together, we hope to better capture the socio-economic

[10] There is more information on SES in the data but we cannot use it because this is available only from year of graduation 2005/6 and has a large amount of missing values. This consists of variables such as (i) the socio-economic classification of the parent who earns the most, defined by the 8 social class categories, and (ii) an indicator on whether parents have a degree.

[11] More precisely, this variable is based on the HE participation rates of people who were aged 18 between 2005 and 2009 and entered a HE course in a UK Higher Education institution or an English or Scottish further education college, aged 18 or 19, between academic years 2005-06 and 2010-11.

[12] The Index of Multiple Deprivation is derived by combining several domains of deprivation (e.g. income, employment, crime and education) of a delimited geographical area (for example in England and Wales the IMD is based on local super output areas, LSOA, which are areas with at least 1000 inhabitants and the mean population is composed of 1500 inhabitants). We use the 2010 IMD for students residing in England and Northern Ireland, the 2009 one for students residing in Scotland, and the 2011 one for students residing in Wales. The way in which the IMD is constructed differs slightly by country. To limit this concern, we transform the continuous variable in quintiles. When the same postcode is associated with different values of the IMD, because for example it is part of several LSOAs, we compute a weighted average of the corresponding IMD values depending on the extension of the postcode in the areas in which the IMD is calculated.

background of the students. To create the SES index, we use principal component analysis (PCA).[13] We consider the last cohort of graduates (the one with the smallest amount of missing information on SES variables) and we take the values (or weight) attributed by the first principal component to each category within each SES variable. For all our cohorts, we then create a score that is equal to the sum of the actual value of the variable multiplied by the values obtained using the PCA.

Table 2.1 shows how each of the SES measures relates to the composite SES index. In panel A we first show the Polychoric correlation matrix showing that all these SES measures are positively correlated among themselves although with different intensity (notice that the higher the value of LN and IMD, the higher is the SES). We choose the principal component with the highest eigenvalue (the rule of thumb is to choose an eigenvalue greater than 1), which explains about 60% of the variance in our data (panel B of Table 2.1). From this we obtain the scoring coefficients exposed in panel C. These coefficients weight each category in the SES measure and we use them to create the SES index. The SES index is the sum of the products of the scoring coefficients with the value of each SES variable.

In this way we build a composite SES continuous variable which defines individuals' socio-economic background in a consistent way across time. This allows us to take into account any changes in the SES composition of students across the ten years considered. We then split this score into quintiles. Figure 2.1.d shows that the percentage of students in the highest three quintiles slightly falls over time. The share of the lowest quintile (Q5), those students with the lowest SES, rises over time, suggesting that there has been a widening of the participation of low SES students in Higher Education (as previous studies suggest: see discussion in Chowdry, Crawford, Dearden, Goodman, and Vignoles 2013). For the sake of exposition, we group the three middle quintiles in a unique category (middle SES; 55% of observations), and we retain the highest (25% of observations) and the low-

[13]Given the discrete nature of the variable used, we implement PCA by using the polychoric correlations.

est quintiles (20% of observations) to represent high and low SES, respectively. Our analysis focuses on this three-category SES index.

This SES index takes into account changes in the SES composition of undergraduate students over time. Notice that in the period that we consider, there have been changes in the way that Higher Education has been financed.[14] However, Figure 2.1 shows that the composition of graduates by SES changed smoothly over time, reflecting long-term trends rather than any particular change of policy.

2.4.4 How do students with different SES differ?

Table 2.2 shows the characteristics of graduates broken down by SES category. We can see interesting differences between graduates of different SES groups. The highest proportion of non-white studenst is found in the low SES category; 90% of high SES graduates are white, but this percentage falls to 84% and to 70% for middle and low SES students, respectively. There are also differences in the non-white composition of the population; Indians and Pakistani represent 6% of low SES students, but only 2% and 1% of the middle and high SES groups, respectively. This suggests the importance of controlling for ethnicity to avoid confounding SES and ethnicity.

In terms of educational achievement, there is evidence that those in the highest SES perform better. While 71% of high SES students exit university with a first or higher second class degree, this percentage falls to 67% and 59% for middle

[14]From the academic year 2002/3 to 2005/6 students had to pay up-front tuition fees of a total of approximately £1,000 p/y. In 2006/7 the tuition fees increased to £3,000 p/y repayable after graduation for all students. At the same time, maintenance grants were also increased. If these changes in the HE financial system had an effect on the socio-economic composition of those going to university this would be a cause for concern. Our data consists in the population of graduate students, and it is possible that the changes that occurred after 2006/7 affected participation and drop-out rates. Dearden, Fitzsimons, and Wyness (2011) found that tuition fees have had, on average, a significant negative effect on participation (a £1,000 increase in fees resulting in a decrease in participation of 3.9 percentage points), while maintenance grants have had a positive effect (a £1,000 increase in grants resulting in a 2.6 percentage point increase in participation), with a very small change in overall participation. In a related study, Crawford (2012) shows that the increase in tuition fees and student support (and other relevant policies implemented over the same period) may have in fact reduced the socio-economic gap in HE participation rates, but this effect is almost negligible.

and low SES groups, respectively.[15] If students from different SESs differ also in their preferences and information about the financial returns of education, then we may expect them to differ also in the choices of degree subject. There is no SES difference in the proportion of graduates studying STEM subjects compared to non-STEM (39% of graduates in each SES group graduated in a STEM subject)[16] but, within these categories, some differences arise; most notably, high SES students are more likely to graduate in Architecture & Engineering among STEM subjects and in Humanities and Languages in non-STEM subjects than middle or low SES graduates; high SES students are less likely to graduate in Mathematics & Computing (STEM) and Communication (non-STEM) degrees.

But one of the most striking differences is the type of university attended. While in the empirical analysis we consider each university singularly, here we group them by their "prestige" following standard classifications.[17] As we can see, 29% of high SES graduates attended a Russell group university and 9% of them attended a Golden Triangle university, the most prestigious groups. These percentages are much lower for low SES graduates: 14% and 4% (20% and 7% for middle SES), respectively. Conversely, the gap remains but changes direction when we look at the least prestigious groups of universities. Finally, we see that there is a clear SES gradient in the propensity of students to move geographically when going to university. The highest average distance between the domicile prior going to university and the location of the HEI attended is found for high SES graduates (129 km), followed by middle SES (111 km) and low SES (77 km).

Figures 2.2 and 2.3 show the distribution of labour market outcomes across the ten years of graduation that we consider (2003-12). The vertical line at 2008

[15]These differences in the academic performances are also evident if we consider the tariff score of students (information collected at the point in which students apply to enrol at HEIs and that summarizes how well the individual has done at secondary school). However, this information is not available for all cohorts of graduates in our sample, but in the robustness checks we will implement some specifications in which we condition on this information by restricting the sample of graduates to those for whom this information is provided.

[16]STEM subjects are: Medicine & related subjects, Biological science, Physical science, Maths & Computing, and Architecture & Engineering. Non-STEM subjects are: Social studies, Business studies, Communication, Languages, Arts, Humanities, Education.

[17]For a description of the various groups see Appendix B1.

shows the beginning of the recession in the UK. From these figures we can establish three different things. First, for all outcomes there is a visible SES gradient. High SES graduates perform better (in terms of studying for a post-graduate HE programme, Figure 2.2.a, or holding a full-time job, Figure 2.2.c), followed by middle, and then by low SES graduates. Second, when the recession hits we can see that there is a change in the trend, and this is true for all SES groups. Third, for most outcomes the differences between SES groups widens in the period post-2008. For example, the percentage of low SES graduates who report being unemployed (Figure 2.2.e) in the period pre-2008 is on average 7%, while this is 5.7% for high SES graduates. In 2008 there is a parallel jump in unemployment for all three groups, but at the height of the recession in 2011 the percentage of low SES graduates in unemployment is above 11% while for those in the high SES group this is about 7.8%. What was a high-low SES gap of about 1 percentage point before the recession more than doubled a few years later. Another example is given by the part-time versus full-time job gap that we can see in Figure 2.3.a. While in 2003 the high-low SES gap was about 5 percentage points, in 2012 this is doubled.

2.4.5 Measuring labour demand

In order to capture variation in the business cycle we use field or subject-specific unemployment rates of graduate workers. These are derived from the Annual Population Survey/Labor Force Survey (APS/LFS), which is the only large dataset that contains information on activity, level of education, and field of study.[18]

Figure 2.4 describes the variation in unemployment rates by demographic groups (active population, graduates, and non-graduates within the same age group of graduates) over the period 2000-12. Graduate unemployment rates, as

[18]The yearly unemployment rate is calculated as an average of the quarterly unemployment rate within a year. This means that we consider the unemployment rate by field of study six months prior graduation and six months after graduation. The latter corresponds to the month in which the student in surveyed. So if a student graduated in June 2005, we consider the unemployment rate from January 2005 to December 2005.

expected, are low compared to the unemployment rate of non-graduates. This is true across the whole period, the Great Recession included, where the graduate unemployment rate rose from 2.5% in 2003 to 3.1% in 2009 and to 3.2% in 2012. However, these averages disguise important variations across fields. Figure 2.5 shows that the variation in graduate unemployment rate over the years of graduation considered in the paper. Interestingly, there is important heterogeneity across all fields of study even within the STEM (Medicine & related subjects, Biological Sciences, Physical Sciences, Mathematics and Computing, and Architecture & Engineering) and non-STEM (Social Studies, Business & Financial studies, Communication, Languages, Arts, Humanities, and Education) categorization. For example, within STEM subjects, Medicine & related subjects exhibit a low and relatively constant level of unemployment of around 1%-2%. Instead, for graduates in Architecture & Engineering unemployment goes from 2% in the pre-recession years up to 4% in 2012, most likely a consequence of the drop in activity in the construction sector. The same can also be seen in the non-STEM group where the unemployment rate of graduates in Education (another sector not particularly affected by the business cycle) has been stable at around 2% across all years considered, while graduates in Business studies experienced an increase of two percentage points with the recession. We expect to see these differences across fields of study. They are determined by the fact that the recession affected different sectors in different ways, and this is what we want to exploit in our analysis. On average in the UK between 2008 and 2012 there has been a decrease in the workforce in industries such as wholesale & retail trade, manufacturing, construction, administrative & support service activities, and arts, entertainment & recreation. On the other hand, sectors like human health & social work activities saw a rise in workforce jobs (ONS, 2011).

We think that the unemployment rate measured by field of study is the most relevant one to capture the actual labour market conditions faced by graduates. This is because this unemployment rate captures possible changes across sectors that might occur when the economic situation is bad. This is possible because we measure the labour market condition by the labour market situation of workers who graduated in the same field of study.[19] If we used another unemployment rate, for example by industry, we would assume that the occupational destination of graduates were fixed and would not have any margins of adjustment.

To capture the local labour market conditions at time of enrolment we use unemployment rates at LAD level derived from the Claimant Count statistics.[20] We associate a level of unemployment to each graduate depending on the postcode where s/he was living before going to university. Figure 2.6 shows that the average unemployment rate at enrolment measured at LAD level followed a U-shape, with relatively high levels for the first and the last cohorts when compared to the middle cohorts. On average this measure of unemployment ranges from a minimum of 2% to a maximum of 3%, although much more variation is found across different LADs, with values between 0.5% to almost 8%.

2.5 Results

2.5.1 The consequences of graduating in bad times

Graduating during a recession could have different consequences on initial labour market outcomes. First, the literature on human capital investment suggests that the trade off between continuing to study and entering the labour market depends on whether the labour market is tight (D. Clark, 2011; M. P. Taylor, 2013). In our case, we would expect that graduates who finished their undergraduate studies in the recession to be more willing to continue their studies given the relative low returns of entering the labour market at that time. We would also expect that those induced to stay in education by the bad economic climate would choose less academic and more professional oriented programmes. This is because the reces-

[19]Notice that results are robust to changes in the age of the graduates that we consider in order to construct the unemployment rate by field.

[20]This data is made available by the Office for National Statistics at `https://www.nomisweb.co.uk/`.

sion brings less "academic" individuals to stay in education. These individuals delay their entry in the labour market by acquiring further education that will be useful in the labour market. However, staying in education is financially costly because of the living and fees expenses, and the lack of income. So we would expect that, while students from an advantaged background have the resources for staying in education, this is less the case for low SES students.

Furthermore, during recessions, firms adjust in the following ways: by decreasing the number of vacancies, by decreasing the numbers of hours offered, or by decreasing the salaries offered. We hence expect to see an increase of activity statuses such as unemployment and part-time jobs versus all other possible states. If students from disadvantaged SES are not able to stay in education or to get into alternative activities, such as unpaid internships, they will be more affected by the worse economic climate than high SES students. If this is true, we should also see that among the pool of employed students only, those from disadvantaged backgrounds are less likely to work in high quality jobs.

Table 2.3 shows the results of our analysis for the activity status of students 6 months after graduation. We have six definitions of activity, and three different specifications for each of them. All specifications control for the demographic characteristics of the students, such as gender, ethnicity, and disability status. We also take into account academic outcomes by using degree class dummies, field of study dummies, and HEI dummies, and for the economic condition at time of enrolment by using the unemployment rate at LAD level and its interaction with SES. We further condition on a linear time trend. In addition to these, in specification 2 we include field-specific trends, and in specification 3 we consider dummies for year of graduation instead of a linear time trend to take into account possible changes in survey coverage that have affected all groups equally and to consider general time shocks. As we can see, the results are not very sensitive to these different specifications. Therefore, we focus on specification 2 because it allows us to fully exploit the yearly variation of the unemployment rate by conditioning on a linear time trend instead of year of graduation dummies.

It is clear that there are statistically significant interactions between SES and unemployment rates. An increase in the unemployment rate at the time of graduation by field of study results in low SES students being less likely to be enrolled in HE programmes and more likely to be unemployed. Both low and middle SES students are more likely to be enrolled in professional programmes and to be in part-time jobs. They are less likely to be in full-time jobs and in alternative activity statuses (outcome "Other"). The non-interacted coefficient on the middle and low SES coefficients shows *ceteris paribus* the differential in the outcome between high, middle and low SES students.[21]

From these results we can conclude that when the unemployment rate is high students are more likely to stay in education. However, while high SES students are more likely to enrol in HE programmes, disadvantaged students are more likely to enrol in professional programmes. Disadvantaged SES students are also less likely to be in full-time jobs but are more likely to be in part-time jobs or to be unemployed. On the other hand, advantaged students are more likely to be in gap years, and employed in non-paid internships and voluntary jobs. We thus find evidence that both advantaged and disadvantaged students postpone their labour market entry when the unemployment rate is high. However, it seems that disadvantaged students are more likely to invest in courses which promise quicker and safer returns in the labour market compared to those courses that are more academic. We find that disadvantaged students choose to switch to new subjects (e.g. diplomas) that plausibly promise relatively high returns in the labour market, or to specialize in a profession that is not very sensitive to

[21]Notice that these coefficients are affected by the other interactions between the SES variables and other terms. For example, with respect to the HE programme outcome, low and middle SES coefficients are 0.002 and 0.004 (although they are not statistically significant). However, the SES-specific trends (not shown in Table 2.3) for middle and low SES graduates are indeed negative and statistically significant (-0.001, statistically significant at 10% for middle SES and at 1% for low SES graduates). As another example, the coefficient indicating middle and low SES students are negative with respect to the part-time job variable (-0.002 and -0.003 not statistically significant), although their SES-specific time trends are positive (0.001 and 0.002, respectively) and statistically significant at the 1% level.

the business cycle (e.g. teaching).[22] Another way of escaping the bad economic conditions and increase one's own human capital is to participate in internships and other activities that will help to build a portfolio that is valuable in the labour market. These activities, however, are often not remunerated, so only those with financial support have access to them. We hence interpret our results in terms of high SES students falling back more than disadvantaged SES on these alternative ways to traditional jobs when the unemployment rate is high.

Table 2.4 shows the effects of unemployment on the *quality* of the job. Notice that this set of outcomes is only observed for those students who are either in a part-time or full-time job six months after graduation. Consistent with our previous results, higher unemployment rates lead to a deterioration in the quality of the jobs held by low and middle SES graduates. Specifically, a higher rate of unemployment increases the probability that a graduate from a more disadvantaged family background will hold a part-time vs. a full-time job, and it reduces the probability that s/he occupies a professional position and that s/he finds a job for which a degree is actually required. Salary is also negatively affected; a one percent increase in the unemployment rate decreases the yearly salary of full-time employed graduates by 0.01 and 0.02 percent on an average salary of £20,600. We do not find any statistically significant effects of unemployment rate on type of contract, however.

Table 2.5 shows how much of the SES gap can be explained by the increase in the unemployment rate for the cohorts who graduate before the recession (2003-07) compared to those who graduated just after (2008-12). In this manner we can quantify how much of the spread in the SES gap in labour market outcomes is explained by the increase in unemployment rates during the Great Recession. First, we compute the differential of the gap between high and low SES before/after the recession (columns 1-3). Second, in column 5 we multiply the estimated coefficient of the interaction between the unemployment rate and the low SES dummy

[22] This is consistent with what has been found in Blom et al. (2015), i.e. when the labour market is tight, students enrol in those courses with higher returns.

(column 4) with the percent change of unemployment.[23] We finally divide this product by the differential of the SES gap across the two periods to obtain the contribution of the recession to the increase in this gap (column 6). Our model can explain about 20% of the actual increase in the gap between low and high SES graduates in terms of enrolment in HE programmes. The implication is that the remaining difference is explained by general trends as well as changes in the composition of graduate students. The total increase in the unemployment SES gap is explained by the observed changes in demand. In relation to the baseline gap, the opening up of the SES gap as a result of the Great Recession is sizeable from an economic point of view especially with respect to the outcomes indicating the quality of the job. For example, the SES gap in part-time vs. full-time jobs increased for the cohorts who graduated after the Great Recession by 3.5 percentage points in the row data, equivalent to a 60% rise. From our estimates, almost two fifths of the rise in the SES gap is explained by the bad economic situation. The SES gap in the professional occupation outcome has instead increased by 2.5 percentage points (equivalent to a 34% rise). Almost two thirds of the opening of the gap can be explained by the Great Recession. We can hence conclude that the recession has had a heterogeneous and relevant impact in widening the SES gap across the different outcomes considered.

2.5.2 Heterogeneity: gender, STEM field, and quality of university

We are interested next in establishing whether graduating in bad times affects the SES gap of certain groups more than others. There are three types of characteristics that we focus on. The first one is gender. Within the same sector, e.g. the health sector, there could be gender differences in terms of the specific role in which graduates are employed. Some of these might be affected more than others

[23] The average unemployment rate between the two periods increased from 2.9 to 3.9 percent (about 35%).

by the recession (because they require differences in hours worked or salary). Furthermore, with the expansion of HE, the quality of the university attended might be considered an important signal of quality by employers. This signal may be of particular relevance when the labour demand is low. Finally, we will specifically look at STEM vs. non-STEM degrees. It has been found that having a STEM degree in past recessions has mediated the negative effects of graduating in bad times. This has been less the case in the latest recession, given the financial nature of the downturn (Altonji et al., 2016). Within these categories, the SES status of students can interact differently with the recession. For example, students from a low SES status might not be particularly affected if they graduate from a top university or in a degree that was not particularly affected by the recession.

We interact the main coefficients of interest (SES, unemployment rate by field, and their interaction) with the following characteristics of the students: gender, whether s/he graduated from a top ranked university (i.e. Golden Triangle group), and whether the student graduated in a STEM field. Table 2.6 shows the results for activity status outcomes and Table 2.7 shows the results for the quality of job outcomes.

Interestingly, we do not find relevant differences in the SES gradient across gender or across type of university attended. The most relevant results concern the type of degree obtained. Disadvantaged graduates in STEM degrees are less likely to be studying in postgraduate programmes, and are less likely to be in full-time jobs than high SES students. Furthermore, the former are more likely to be in a part-time job and are less likely to be working in non-paid jobs. When employed, the quality of jobs of disadvantaged students in STEM subjects is statistically significantly lower compared to advantaged students. Finally, disadvantaged graduates in STEM degrees are more likely to work for a period of twelve months or less.

These results suggest that the recession has increased the SES gradient for students who graduated in STEM subjects compared to non-STEM subjects. This can be explained by the fact that the recession has affected STEM sectors more than others. These findings are consistent with those found by Altonji et al. (2016) in the U.S.

2.6 Possible mechanisms

SES gaps in the labour market might arise because of differences in human capital, financial resources, or access to social and professional networks.[24] We rule out explanations in terms of human capital since we consider a population of first-degree full-time graduates, we look at their situation 6 months after graduation, and we condition on university attended and degree class. This leaves us to consider social and financial capital as possible reasons for the existence of an SES gradient.

The previous results show that, during a period of higher unemployment, the graduate SES gap in labour market outcomes - measured in terms of activity or quality of jobs - widens significantly. A higher level of unemployment would have negative effects on both the effectiveness of social networks - as individuals in these networks are likely to become unemployed themselves - and the amount of financial resources individuals can rely upon. In both cases these effects should be more severe for more disadvantaged families. This is because: (i) their social networks are more likely to be made up of lower-skilled individuals whose jobs are more vulnerable in a recession, and (ii) their families have lower levels of wealth or savings that can be used to counteract reductions in income due to unemployment or lower earnings. Due to this, our results cannot reveal yet whether social or financial resources drive SES inequalities in the labour market.

To go one step further, we analyse more closely the process which leads some graduate students to find a job after leaving university. First, we look at whether the student indicates that s/he has found a job through family or social networks as opposed to employer adverts, web searches, etc. We call this the degree of

[24] There is of course the possibility of discrimination, but we do not consider it here.

effectiveness of social networks. Second, we consider the degree of geographical mobility associated with finding a job, the idea being that a higher degree of geographical mobility is related to a higher availability of financial resources. Notice that in all of our regressions we control for the distance (in Km) between the domicile before enrolment into university and the location of the HEI attended, as a proxy for the propensity of being geographically mobile (on the basis of preferences, for example).

We start by examining the impact of the recession on the effectiveness of social networks.[25] Figure 2.7.a shows that there is a remarkable fall in the effectiveness of social networks during the recession period for all SES groups. This job search method then becomes particularly successful again in the period after the recession where, however, the SES gap grows. As seen in column 1 of Table 2.8, the regression results clearly show that higher levels of unemployment make it less likely that low and middle SES students will find a job through family and social contacts.

The geographical mobility outcome may help to understand how financial resources of graduates and their families determine their labour market outcomes. Being able to find or take a job requires, at least initially, extra expenditure in travel and accommodation. Consider, for example, the travel and accommodation on the day of an interview. If capital markets are imperfect and students are financially constrained, the only way to meet these costs is by drawing on family resources. If the recession had a stronger impact on the resources of low SES families (as compared to the high SES families), the area of job search for low SES students would be smaller than for high SES students. We should therefore expect that during the recession disadvantaged graduates are more likely to find a job closer to their original domicile compared to advantaged students.

On the other hand, the economic opportunities in the domicile area could deteriorate more rapidly for low SES than high SES students during periods of rising

[25] Figure B1 shows the trends across the period considered for each of the successful channels to find a job.

unemployment. We could hence expect that during the recession disadvantaged graduates are less likely to find a job closer to their original domicile compared to advantaged students. However, our regressions include LAD fixed effects and LAD-specific unemployment rates at the time of high school. As a result, this channel should be controlled for. So, if (a lack of) financial resources were an important mechanism driving the first destinations of graduates we would expect that during a recession graduate students from low SES families would find jobs closer to their domicile.

Figure 2.7 shows that low SES students are on average more likely to find a job closer to home than middle or high SES students. This is compatible with the idea that coming from a more disadvantaged family restricts the area of geographical job mobility. The figure also shows that the degree of mobility of low SES students decreases over the observed period, but there is not a visible discontinuity before/after the start of the recession. There is instead a long-term trend which could be attributed to many different factors. Once we take the data to our regression model (column 2 of Table 2.8) we see that in fact the effects of unemployment are quite surprising. Controlling for SES-specific trends, as well as for initial propensity to move (distance from domicile to HE), higher unemployment rates push low SES students to find a job further away from their domicile. This result would suggest that the deterioration of family financial resources during a recession is not the main mechanism explaining the destination of young graduates.

In order to investigate this effect further, we consider an alternative channel. We see that in our data graduates who found their job through social networks work closer to their original domicile than when the job has been found through other channels.[26] We could hence expect that during the recession disadvantaged graduates were less likely to find a job closer to their original domicile compared to advantaged students because their social networks were less effective. Although

[26] The average distance between domicile and workplace is 65 (54) Km when the job has been found through social networks (other channels).

we control in our regression for the local labour market conditions of the family domicile, it is possible that this does not completely remove the possibility that low-SES individuals have to move further away from their initial area of residence because of fewer job opportunities.

In columns 3 and 4 of Table 2.8 we look at the geographical mobility separately by whether the job was found through networks or through any other channel. We find that the group who drives the previous result is the group of graduates who found a job through other channels. In other words, during the recession among students who had no effective social networks, those disadvantaged found a job farther away from their original domicile than advantaged students. These findings strengthen the importance of the social network as a safety net when the labour market is tight.

2.7 Robustness checks

In this section we address three specific concerns. First, it is possible that we do not control well enough for academic achievement given that degree class is a very broad indicator (half of our students gain an upper second class degree). Second, we have a large number of missing values for our salary variable. Indeed this is only available for students in full-time jobs. Third, response rates to the survey might be a function of SES and unemployment rates.

Early academic achievements are particularly important in determining later academic outcomes.[27] We therefore include in our specification the tariff score. The tariff score summarizes the grades achieved in post-secondary academic exam results ("A levels") - which are usually a pre-requisite for university enrolment in the UK, and other vocational qualifications obtained post-16. Tariff scores are

[27] Several papers have highlighted how in the UK SES is particularly important in determining university entry, drop-out and academic attainment (Chowdry et al. 2013, Johnes and McNabb 2004, McNabb, Pal, and Sloane 2002, J. P. Smith and Naylor 2001, Vignoles and Powdthavee 2009). Chowdry et al. (2013) recognize that, while participation rates at high status universities by SES has decreased over time (they observe the period 2004-2007) the gap still persists and it is mostly attributed to poor achievement in secondary school.

available only from graduation year 2004/5 however, and there are year-on-year differences in the range. As a result, we use quintiles.

Tables 2.9 and 2.10 show that the inclusion of the tariff score does not importantly affect the magnitude and the statistical significance of the coefficients of interest. This might be because of the important positive correlation between the tariff scores and the degree classification. As a result, having the latter already in our model is sufficient to take into account differences in human capital. However, when there are differences compared to the baseline specification, the coefficients are greater (e.g. full-time job, professional qualification, and professional job) and are of statistical significance (e.g. graduate job, fix contract), making our previous findings even stronger.

The salary is reported with a large number of missing values (only 308,765 replied to this question out of the 575,869 graduates in a full-time job).[28] Given this issue and the fact that the salary is self-reported we imputed the salary using the Annual Population Survey (APS). We did this by matching the DLHE with the APS on six dimensions: region, full-/part-time, number of employees in workplace, permanent vs. fixed and temporary contracts, industry sector, occupation code.[29]

Table 2.11 shows our estimates of interest when using this imputed salary as the dependent variable for the salary at 6 and 42 months after graduation. For the salary at six months after graduation we also report the estimates for the population of full-time employees to obtain a better comparison with the results that we obtained with the self-reported salary (which was only asked to full-time employees). The sign and the magnitude of the coefficient of interest for full-time workers in columns 1 and 3 is very close to what we obtain when using self-reported salaries in Table 2.4. Furthermore, the estimates in column 2 suggests that the SES gradient increases over time.

[28]Notice that we exclude those reporting a null salary and we trim the highest and the lowest 1 percent of the distribution to exclude extreme values. Results are not sensitive to this restriction, however.

[29]We used only four of these dimensions when industry sector or number of employees was not available.

One of the concerns related to the use of the DLHE is that there is a relatively high non-response rate (about 16.72% non-respondents and 2.27% explicit refusals). If this differs by SES according to levels of unemployment, it could introduce a source of bias. We run a linear regression on whether graduates replied to the survey to see whether in periods of high unemployment the probability of response varies by SES. Table 2.12 shows the results. In periods of a high unemployment rate, we do not find any evidence of different behaviour across the SES groups on the likelihood of responding to the questionnaire. The coefficients of the interaction term of SES and unemployment are not statistically significant.

2.8 Is graduating in bad times having longer-lasting consequences?

Our main outcomes are measured at 6 months after graduation. While looking at graduate destinations is interesting, it might not be a good proxy for longer-term labour market outcomes and future careers of those affected. It has however been shown (and we discussed this in section 2.1) that graduating during recessions has long-lasting negative consequences for the career progression of those affected. As a result, we expect to see a strong association between short- and longer-term outcomes. If there is a perpetuating effect of economic conditions from short to longer-term outcomes and we see that individuals from different SES respond differently to the economic conditions at graduation, this can have important implications with respect to the perpetuation of socio-economic inequality and reinforcement of barriers to social mobility in the longer term.

We now investigate how the outcomes at 6 months are related to those at 3.5 years after graduation and if this relationship changes for the cohorts who graduated in the period pre/post-recession. To do this we use the DLHE questionnaire collected at 3.5 years after graduation. Notice that this questionnaire is run only for certain cohorts of graduates and only a subsample of students within each cohort is contacted. Hence, in our data we have the opportunity to observe four cohorts of students for which we know their outcomes at both 6 months and 3.5 years after graduation. These are the cohorts who graduated in 2003, 2005, 2007, and 2009. Because only a representative group of the population of graduates is contacted for each cohort, we use the weights provided by HESA in our analysis. Also notice that the number of students contacted for the longitudinal survey has increased over time.

Table 2.13 shows the coefficients associated with the activity statuses at 6 months after graduation. The omitted one is full-time employment. It is clear that there is an important and statistically significant relationship between the outcomes at 6 and 42 months after graduation for both pre and post recession groups of graduates, and that this goes in the expected direction. The 2009 cohort exhibits a higher degree of correlation between the outcomes at 6 and 42 months after graduation (even after accounting for the difference in the average value of the outcome before/after the recession) for outcomes such as full-time job, part-time job, and study. Overall, the highest correlation is found among the same activity statuses. We hence conclude that there is strong evidence that the activity status at entry in the labour market is a good indicator of future career prospects.

We next look at the interaction of SES with the unemployment rate at 6 months after graduation to see whether there is any evidence of the SES gradient also at 3.5 years after graduation. More specifically, we focus on the activity status as well as on whether graduates work in a professional occupation, achieved a qualification as high as a master or higher, and on the salary earned. Results are shown in Table 2.14. The signs of the coefficients indicate that low SES graduates are less likely to be in a full-time job, to be studying, to be working and studying, to be employed in a professional occupation and to hold a postgraduate degree. They are instead more likely to be in a part-time job, to be in other jobs, and to be unemployed. However, only the negative effect on wages is statistically significant.

Finally, given the importance that work has in our lives, we would expect that the recession, through the negative impact on the activity status and job quality of individuals, has affected other dimensions of life such as well-being. Furthermore, if graduating during a recession has negatively affected the possibility that individuals have the jobs that they probably expected when they invested in their Higher Education studies, this might generate sentiments of frustration and regret. If different SES groups have been differently affected (as we have already shown) we would also expect that these levels of dissatisfaction or regret differ across these groups. In other words, if low SES students have been affected by the recession more severely than others, we would expect that the low unexpected returns of the degree qualification would affect the well-being, broadly speaking, of disadvantaged graduates in particular.

The DLHE longitudinal survey asks graduates whether they are satisfied with their career and their likelihood of choosing to study a different subject, to study in a different institution, and to study a different qualification with respect to the choices made 3.5 years earlier. These variables are scaled from 1 to 4. For the satisfaction variable, category one corresponds to "not at all satisfied" , category three to "not very satisfied", two to "fairly satisfied" and three to "very satisfied". For the likelihood of making different choices the values one to four correspond to "very likely", "likely", "not very likely", and "not likely at all", respectively.

Table 2.15 shows that a higher unemployment rate is associated with disadvantaged graduates being more likely to state that they would change qualification (i.e. they would not obtain an undergraduate degree) and subject studied if they could go back in time by 3.5 years. Low SES graduates would, however, not change the university in which they studied. Nevertheless, only the finding on the likelihood of change of the field of study (subject) is statistically significant for low SES. Disadvantaged graduates who graduated in bad times are unsatisfied with their professional career. This is true especially for low SES graduates for which a worsening of the economic conditions at graduation is equivalent to a decrease in career satisfaction, which is statistically significant at the 5% level. We hence provide evidence that graduating in bad times differently affects individuals from different backgrounds on several outcomes in the sphere of well-being 42 months later.

2.9 Conclusion

In this paper we address two important questions. We first ask whether achieving a higher level of education is enough to ensure that an economic downturn will not increase socio-economic inequalities in the labour market. We then go on to analyse whether the SES disadvantage in securing a job and in finding a good match during "bad times" is due to the deterioration of financial or social capital endowments.

We use data from the Destination of Leavers from Higher Education Survey, a repeated cross-sectional survey of graduates leaving UK universities after completing their qualification. We observe successive cohorts of graduates over the period 2002/3 to 2011/2 and match this dataset with information on graduate labour demand using field-specific unemployment rates derived from the Labour Force Survey. This allows us to use variation over time and across field of study to identify the effect of the Great Recession on entry-level graduate labour market outcomes.

Our results show that the sharp increase in unemployment experienced by the UK - as well as many other countries - between 2009 and 2011 translated into wider SES gaps across a range of labour market outcomes measured 6 months after graduation, including employment, salary and access to professional or graduate occupations. This is so after taking into account the effects of compositional changes in the population of graduates, university fixed effects, field- and SES-specific time trends, and economic conditions at the time of enrolment.

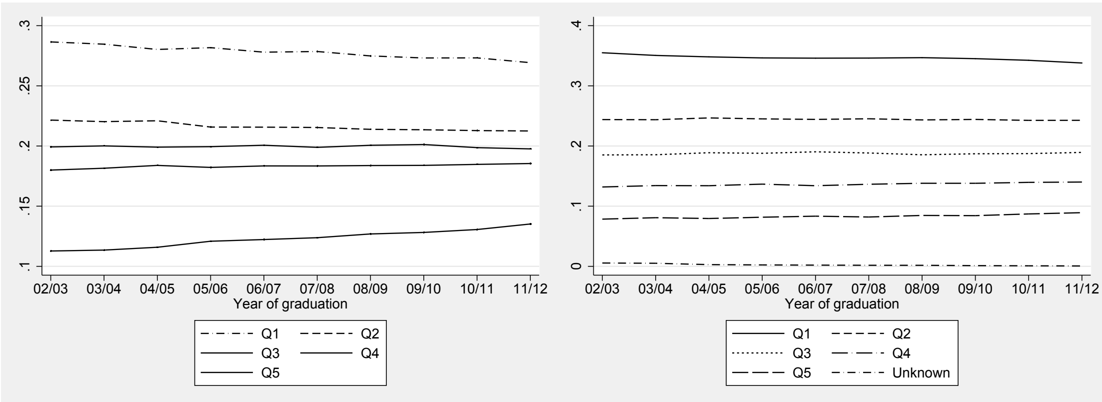
Next, we analyse the possible mechanisms that explain our findings and we provide evidence of the importance of social capital. The recession impacted negatively on the effectiveness of social networks as a channel to find employment, and this was more so for students from disadvantaged families.

Finally, we provide evidence of the persistence of the SES gradient over time. This might explain the higher level of career dissatisfaction and regret about the subject studied that we found among disadvantaged graduates at 42 months after graduation.

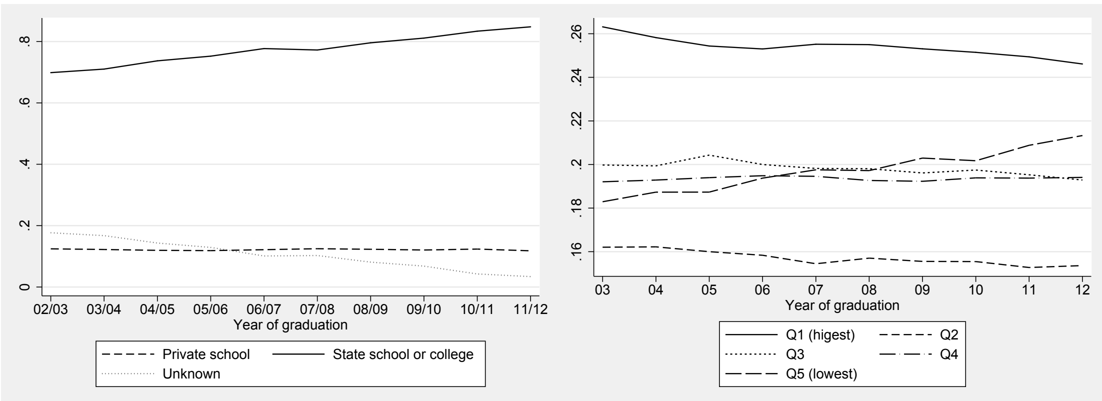
Overall, our findings show that the recession has reduced social mobility even among the most educated stratum of the population since the negative effects of the recession on labour market outcomes have longer-lasting effects on graduates' careers.

Figure 2.1: SES indicators

(a) Index of Multiple Deprivation (IMD) (b) Low Participation Neighbourhood (LPN)



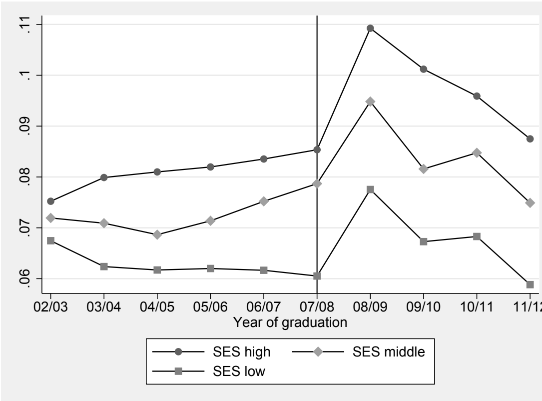
(c) Type of school (d) SES Index



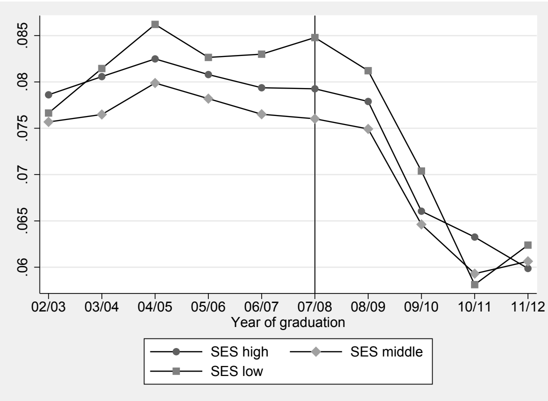
Notes. DLHE data on the selected sample described in section 2.4.2. The variables used to construct the SES index are described in Section 2.4.3.

Figure 2.2: Labour market outcomes - Activity status

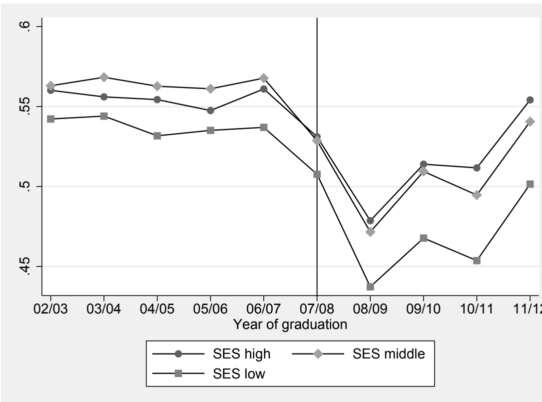
(a) Studying in HE programme



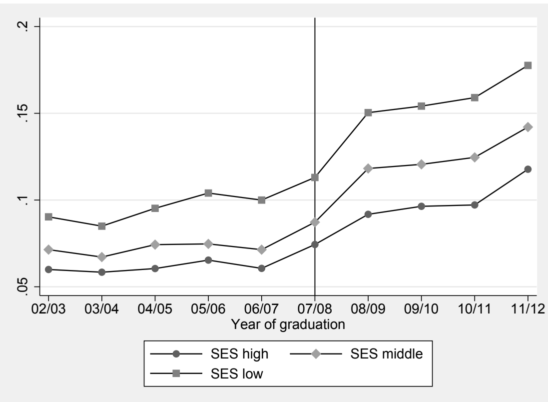
(b) Studying in professional programme



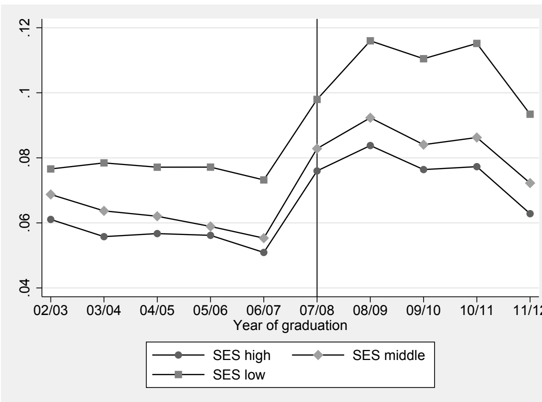
(c) Full-time work



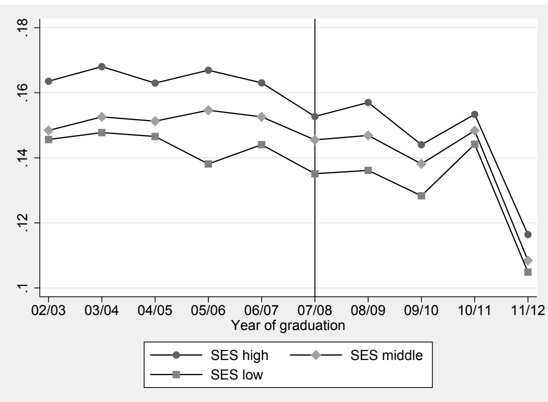
(d) Part-time work



(e) Unemployed



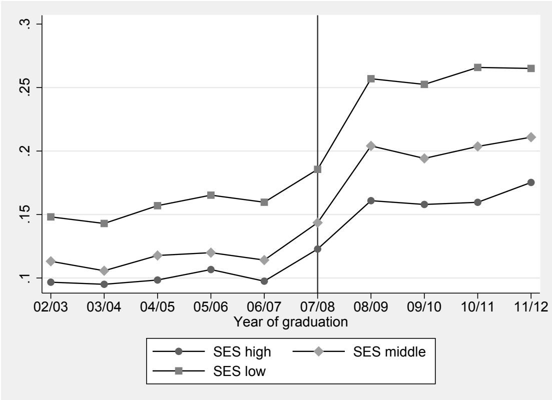
(f) Other activity status



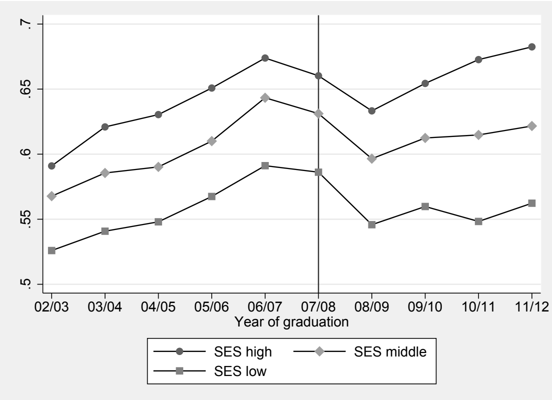
Notes. DLHE data on the selected sample described in Section 2.4.2. The variables are described in Section 2.4.4.

Figure 2.3: Labour market outcomes - Employed graduates only

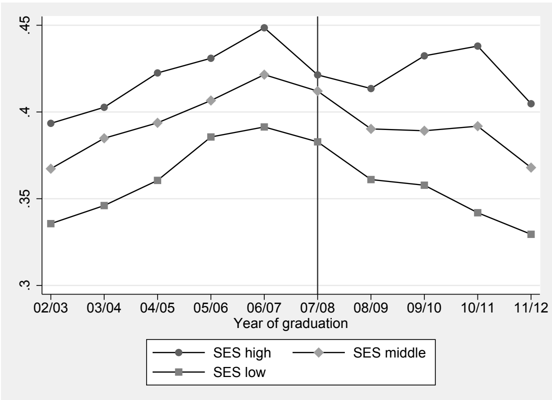
(a) Part-time vs. full-time job



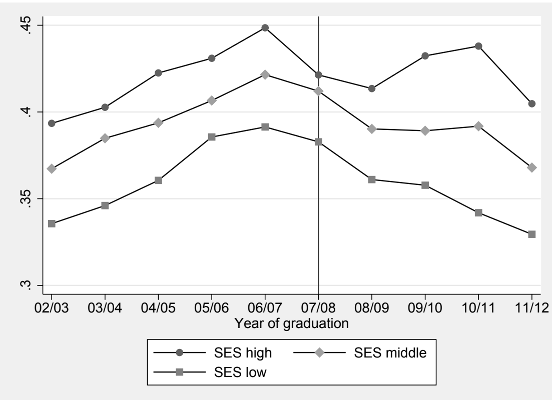
(b) Professional job



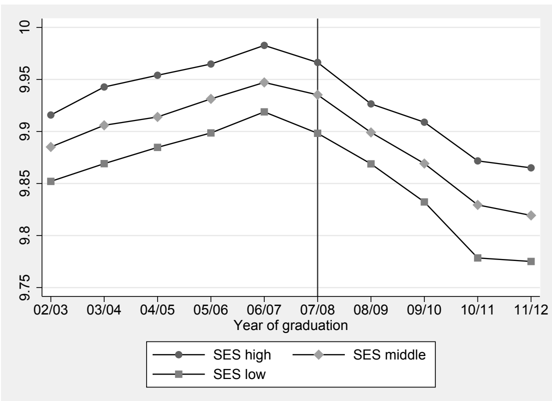
(c) Graduate job



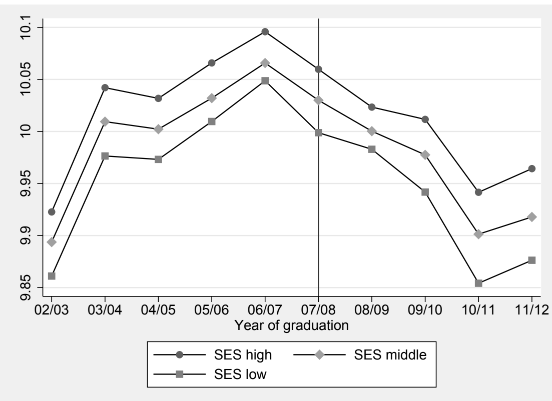
(d) Fixed-term (<12 months)



(e) Salary (ln)

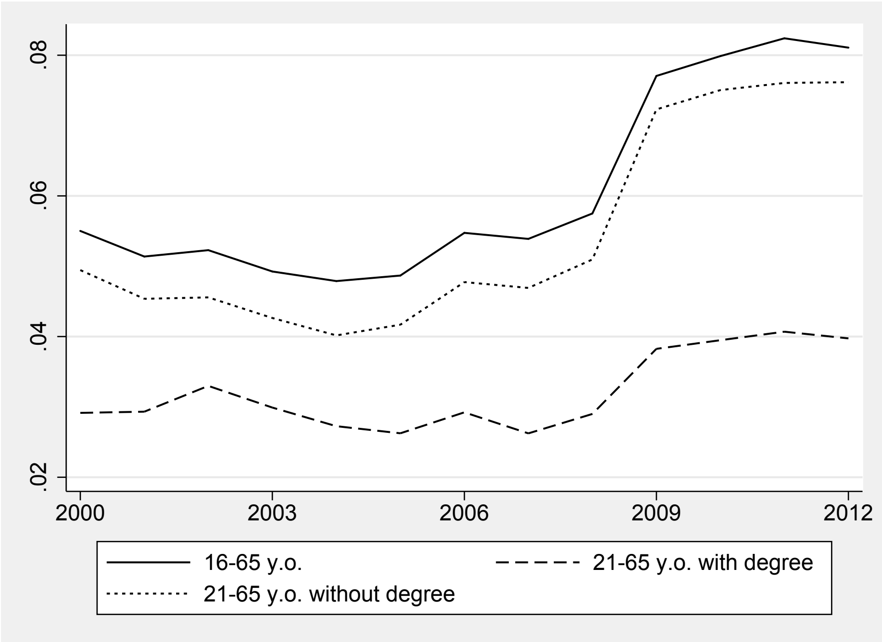


(f) Salary (ln) imputed



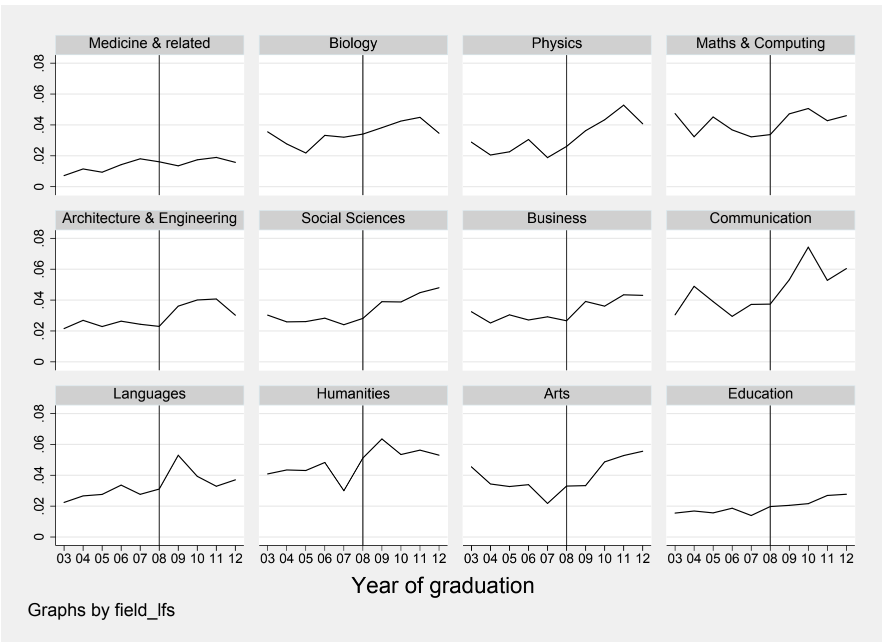
Notes. DLHE data on the selected sample described in Section 2.4.2. The variables are described in Section 2.4.4.

Figure 2.4: Unemployment rate by graduate/non-graduate population



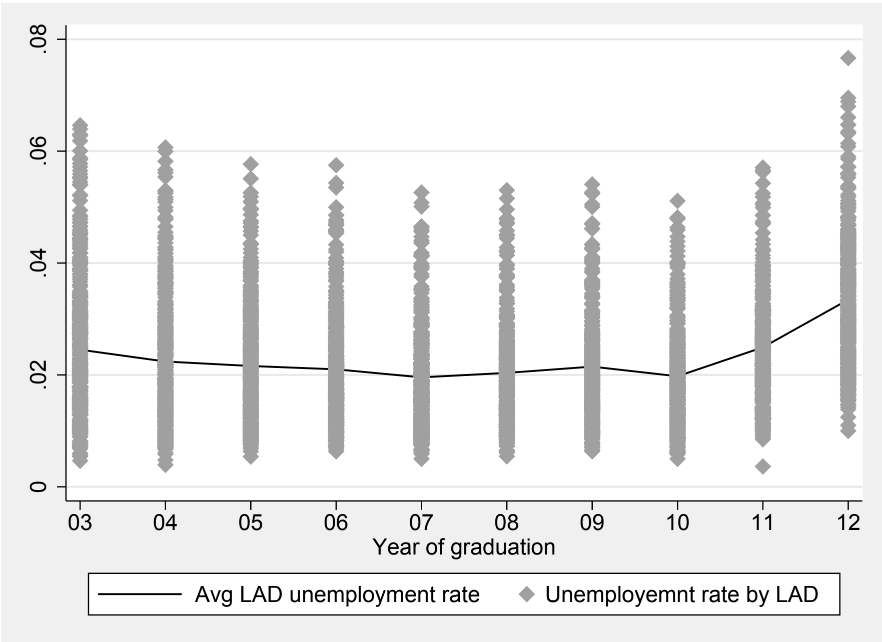
Notes. Derived from the Annual Population Survey/Labour Force Survey.

Figure 2.5: Graduate unemployment rate by field of study



Notes. Derived from the Annual Population Survey/Labour Force Survey.

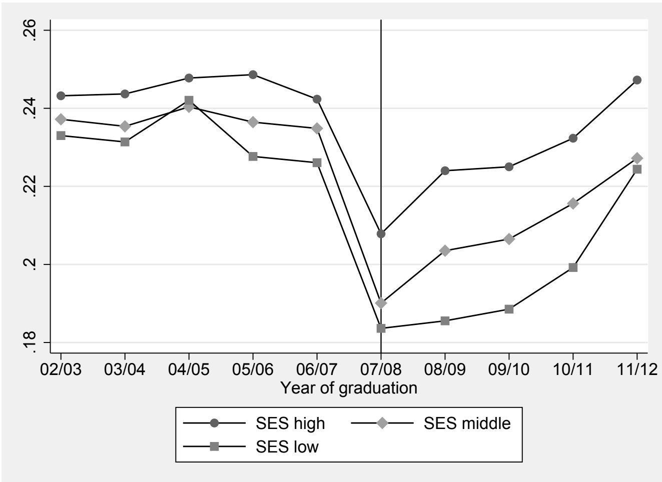
Figure 2.6: Unemployment rate between and within LAD



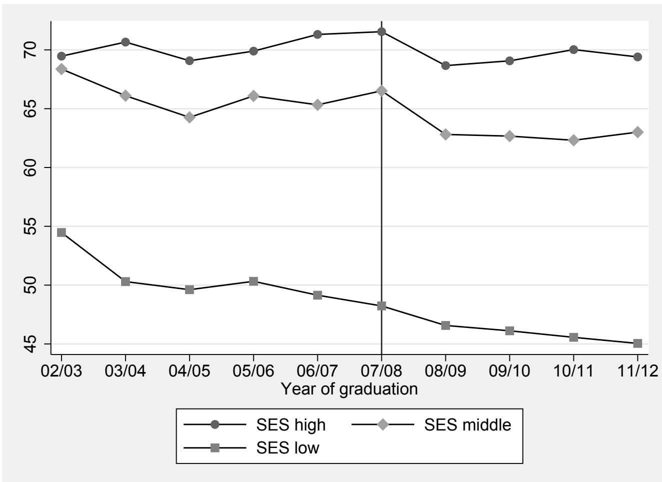
Notes. The unemployment rate by LAD is derived from the Claimant Count.

Figure 2.7: Mechanisms

(a) Job found through social network



(b) Distance work-home (Km)



Notes. DLHE data on the selected sample described in Section 2.4.2. The variables are described in Section 2.6.

Table 2.1: SES index

	A Polychoric correlation matrix		
	IMD	School	LPN
IMD	1		
School	.242	1	
LPN	.560	.380	1
	B Principal componenets		
PC	Eigenvalues	Proportion explained	Cum. Explained
1	1.803	0.601	0.601
2	0.780	0.260	0.861
3	0.417	0.139	1.000
	C Scoring coefficients of PC1		
IMD	1	-0.740	
	2	-0.210	
	3	0.094	
	4	0.398	
	5	0.893	
School	0	-0.812	
	1	0.107	
LPN	1	-0.716	
	2	-0.103	
	3	0.242	
	4	0.560	
	5	1.056	

Notes. Panel A shows the correlation between the three variables of interest. Panel B shows the three principal components obtained by the principal component analysis ("polychoricpca" command in Stata). Panel C shows the scoring coefficient of the first principal component for each variable and value.

Table 2.2: Summary statistics of main explanatory variables

	High SES		Middle SES		Low SES	
	Mean	*sd*	*Mean*	*sd*	*Mean*	*sd*
Female	0.531	0.499	0.554	0.497	0.579	0.494
Ethnicity						
White	0.900	0.301	0.837	0.369	0.700	0.458
Caribbean	0.002	0.042	0.008	0.089	0.022	0.146
African	0.003	0.050	0.009	0.093	0.031	0.173
Other Black	0.001	0.023	0.002	0.040	0.004	0.064
Indian	0.032	0.176	0.059	0.235	0.073	0.260
Pakistani	0.007	0.081	0.017	0.130	0.062	0.242
Bangladeshi	0.002	0.042	0.005	0.072	0.028	0.165
Chinese	0.007	0.086	0.010	0.101	0.016	0.124
Other Asian	0.007	0.084	0.010	0.098	0.011	0.105
Other (incl. mixed)	0.026	0.158	0.030	0.171	0.039	0.195
Unknown	0.015	0.122	0.014	0.116	0.013	0.113
Any disability	0.096	0.295	0.084	0.277	0.075	0.263
Classification degree						
First class honour	0.153	0.360	0.141	0.348	0.112	0.315
Upper second	0.552	0.497	0.525	0.499	0.478	0.500
Lower second	0.228	0.419	0.266	0.442	0.328	0.469
Third/Pass	0.031	0.173	0.040	0.195	0.057	0.232
Unclassified	0.036	0.187	0.029	0.168	0.026	0.158
Field of study						
Medicine & related	0.081	0.272	0.078	0.269	0.081	0.272
Biology	0.104	0.306	0.113	0.317	0.118	0.323
Physics	0.061	0.239	0.057	0.232	0.046	0.210
Maths & Computing	0.060	0.237	0.071	0.257	0.088	0.283
Architecture & Engineering	0.080	0.271	0.072	0.259	0.061	0.239
Social Sciences	0.152	0.359	0.143	0.351	0.151	0.358
Business	0.113	0.317	0.117	0.322	0.127	0.333
Communication	0.032	0.177	0.037	0.189	0.041	0.199
Languages	0.098	0.297	0.083	0.276	0.067	0.250
Humanities	0.074	0.261	0.061	0.240	0.046	0.209
Arts	0.116	0.321	0.126	0.332	0.124	0.330
Education	0.029	0.169	0.041	0.197	0.050	0.217
HEI group						
Non-grouped	0.286	0.452	0.298	0.458	0.254	0.435
Russell	0.285	0.451	0.201	0.401	0.139	0.346
Golden	0.093	0.291	0.066	0.248	0.036	0.186
Ex-polytechnics	0.055	0.228	0.077	0.266	0.114	0.317
Alliance	0.201	0.400	0.238	0.426	0.303	0.459
Million Plus	0.039	0.194	0.067	0.251	0.108	0.310
Guild	0.041	0.199	0.052	0.222	0.047	0.212
Distance domicile-HEI (Km)	128.975	98.805	111.429	98.129	77.283	89.076
N	267,184		577,989		209,690	

Notes. Summary statistics of graduates' characteristics in the sample described in Section 2.4.2.

Table 2.3: The effect of graduating in bad times by SES - Activity status

A.	HE programme			Professional programme		
	1	2	3	1	2	3
Middle SES	0.003	0.002	0.002	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Low SES	0.005+	0.004	0.003	0.009*	0.010**	0.010**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
ln(U field) * Middle SES	-0.002	-0.002	-0.002	0.009**	0.009**	0.009**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)
ln(U field) * Low SES	-0.007*	-0.007*	-0.007*	0.023**	0.024**	0.024**
	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)	(0.005)
ln(U field)	0.009+	0.009*	0.005	-0.014*	-0.011*	-0.009+
	(0.005)	(0.004)	(0.003)	(0.006)	(0.005)	(0.004)
$\overline{y}$		0.078			0.073	
B.	Full-time job			Part-time job		
	1	2	3	1	2	3
Middle SES	0.015**	0.015**	0.015**	-0.003	-0.002	-0.002
	(0.004)	(0.004)	(0.004)	(0.002)	(0.002)	(0.002)
Low SES	0.007	0.008	0.010	-0.004	-0.003	-0.003
	(0.008)	(0.008)	(0.008)	(0.003)	(0.003)	(0.003)
ln(U field) * Middle SES	-0.009+	-0.009+	-0.009*	0.010**	0.009**	0.009**
	(0.005)	(0.005)	(0.005)	(0.002)	(0.002)	(0.002)
ln(U field) * Low SES	-0.029**	-0.028**	-0.028**	0.019**	0.018**	0.018**
	(0.010)	(0.010)	(0.010)	(0.004)	(0.004)	(0.004)
ln(U field)	-0.030+	-0.042**	-0.013	0.010	0.013*	0.005
	(0.015)	(0.012)	(0.012)	(0.007)	(0.006)	(0.007)
$\overline{y}$		0.527			0.101	
C.	Unemployed			Other		
	1	2	3	1	2	3
Middle SES	0.000	0.000	0.000	-0.015**	-0.015**	-0.015**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Low SES	0.001	0.001	0.001	-0.020**	-0.020**	-0.021**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
ln(U field) * Middle SES	0.002	0.002	0.002	-0.009**	-0.009**	-0.009**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
ln(U field) * Low SES	0.011**	0.011**	0.011**	-0.017**	-0.018**	-0.018**
	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)
ln(U field)	0.011*	0.014**	0.001	0.014*	0.016**	0.010*
	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)	(0.005)
$\overline{y}$		0.076			0.144	
Obs.			1,054,863			
Individual characteristics	x	x	x	x	x	x
HEI FE	x	x	x	x	x	x
Classification degree	x	x	x	x	x	x
Field of study	x	x	x	x	x	x
ln(U enrolment)	x	x	x	x	x	x
ln(U enrolment)*SES	x	x	x	x	x	x
SES-specific time trends	x	x	x	x	x	x
Time trend	x	x		x	x	
Field specific-time trend		x	x		x	x
Year of graduation dummy			x			x

Notes. Individual characteristics: cohort, gender, ethnicity, any disability, distance home-HEI, distance home-HEI squared, LAD dummies. Robust standard errors are clustered by field of study and year of graduation in parentheses. Significance at 1%, 5%, and 10%- level are indicated by **, *, and +.

Table 2.4: The effect of graduating in bad times by SES - Job quality

	Part-time vs full-time job	Professional occupation	Graduate job	Fixed term contract	(ln) Salary
Middle SES	-0.005	-0.014*	0.001	-0.011**	-0.007+
	(0.003)	(0.005)	(0.005)	(0.004)	(0.004)
Low SES	-0.002	-0.031**	-0.010	-0.019**	-0.014*
	(0.006)	(0.009)	(0.008)	(0.005)	(0.006)
ln(U field) * Middle SES	0.015**	-0.023**	-0.010+	-0.004	-0.007+
	(0.004)	(0.005)	(0.005)	(0.003)	(0.004)
ln(U field) * Low SES	0.037**	-0.045**	-0.016+	-0.005	-0.018**
	(0.007)	(0.009)	(0.009)	(0.004)	(0.006)
ln(U field)	0.025**	-0.037**	-0.040**	0.005	-0.049**
	(0.009)	(0.010)	(0.010)	(0.006)	(0.009)
$\overline{y}$	0.160	0.611	0.394	0.101	9.889
Obs.	662,081	661,210	555,265	579,816	291,991

Notes. RHS variables not included in the table: (ln) U at enrolment, interaction between SES categories and (ln) U at enrolment, cohort, gender, ethnicity, any disability, degree classification, distance home-HEI, distance home-HEI squared, HEI dummies, LAD dummies, field of study dummies, linear time trend, SES-specific time trends, and field-specific time trends. Robust standard errors are clustered by field of study and year of graduation in parentheses. Significance at 1%, 5%, and 10%- level are indicated by **, *, and +.

Table 2.5: Quantifying the contribution of the recession to the SES gap

	$\overline{y^{2003-07}}$	$\overline{y^{2008-12}}$	Δ *SES gap*	$\hat{\delta}$	*Contrib*	*% contrib*
HE programme						
High SES	0.0804	0.0957				
Low SES	0.0629	0.0663				
	0.0175	0.0294	0.0120			
				-0.0070	0.0025	20%
Unemployment						
High SES	0.0509	0.0838				
Low SES	0.0732	0.1160				
	-0.0223	-0.0322	0.0099			
				-0.0280	0.0098	99%
Part-time vs. full-time job						
High SES	0.0975	0.1609				
Low SES	0.1570	0.2559				
	-0.0595	-0.0950	0.0355			
				0.0370	0.0130	36%
Professional occupation						
High SES	0.6346	0.6624				
Low SES	0.5597	0.5624				
	0.0749	0.1000	0.0252			
				-0.0450	0.0158	63%

Notes. The first two columns report the SES gap with respect to the outcome of reference (HE programme, unemployment, working part-time vs. full-time, and working in a professional occupation) for the cohorts who graduated before and after the Great Recession, respectively. The third column reports the difference in the SES gap before/after the Great Recession. $\hat{\delta}$ is the estimated coefficient of the interaction of the low SES dummy with the (ln) of the unemployment rate at graduation. *Contrib* indicates the change in the SES gap across the period before/after the Great Recession (i.e. $(\hat{\delta}/100) * 35$). *% contrib* is the equivalent of *Contrib* / Δ *SES gap*, i.e. how much of the change in the SES gap can be explained in our model by the increase in the unemployment rate.

Table 2.6: Heterogeneity: activity status

	Full-time job	Part-time job	HE programme	Professional programme	Unemployed	Other
A Gender						
ln(U field) * Middle SES * Female	0.005	0.006+	-0.008	0.006+	-0.002	-0.008
	(0.003)	(0.003)	(0.007)	(0.004)	(0.003)	(0.005)
ln(U field) * Low SES * Female	0.008+	0.004	-0.000	0.005	-0.011*	-0.006
	(0.005)	(0.005)	(0.008)	(0.004)	(0.004)	(0.005)
B HEI quality (Golden Triangle)						
ln(U field) * Middle SES * Best HEI	0.010	0.005	-0.008	-0.005	0.001	-0.003
	(0.007)	(0.006)	(0.007)	(0.004)	(0.004)	(0.005)
ln(U field) * Low SES * Best HEI	0.008	0.031**	-0.014	-0.012+	-0.008	-0.005
	(0.011)	(0.011)	(0.011)	(0.006)	(0.007)	(0.009)
C Field of study (whether STEM)						
ln(U field) * Middle SES * STEM	0.006	0.017**	-0.019**	0.009	0.002	-0.014**
	(0.004)	(0.005)	(0.007)	(0.005)	(0.003)	(0.005)
ln(U field) * Low SES * STEM	0.011+	0.022**	-0.045**	0.017**	0.006	-0.011+
	(0.006)	(0.007)	(0.013)	(0.007)	(0.005)	(0.006)
Obs.			1,054,863			

Notes. RHS variables not included in the table: (ln) U at graduation, SES index dummies and their interactions with the variable of interest (female/best HEI/STEM), (ln) U at enrolment, interaction between SES categories and (ln) U at enrolment, cohort, gender, ethnicity, any disability, degree classification, distance home-HEI, distance home-HEI squared, HEI dummies, LAD dummies, field of study dummies, linear time trend, SES-specific time trends, and field-specific time trends. Robust standard errors are clustered by field of study and year of graduation in parentheses. Significance at 1%, 5%, and 10%- level are indicated by **, *, and +.

Table 2.7: Heterogeneity: job quality

	Part-time vs full-time job	Professional occupation	Graduate job	Fixed term contract	(ln) Salary
A Gender					
ln(U field) * Middle SES * Female	0.009+	-0.015*	-0.011	-0.002	-0.007
	(0.005)	(0.007)	(0.007)	(0.005)	(0.006)
ln(U field) * Low SES * Female	0.005	0.008	0.010	-0.006	-0.017*
	(0.006)	(0.010)	(0.011)	(0.007)	(0.008)
B HEI quality (Golden Triangle)					
ln(U field) * Middle SES * Best HEI	-0.003	0.003	0.008	-0.003	-0.009
	(0.006)	(0.009)	(0.010)	(0.011)	(0.009)
ln(U field) * Low SES * Best HEI	-0.011	-0.001	0.018	0.020	-0.005
	(0.010)	(0.015)	(0.017)	(0.020)	(0.014)
C Field of study (whether STEM)					
ln(U field) * Middle SES * STEM	0.016+	-0.009	0.013	0.011+	0.004
	(0.008)	(0.009)	(0.010)	(0.006)	(0.008)
ln(U field) * Low SES * STEM	0.032**	-0.030*	-0.028+	0.030**	0.001
	(0.012)	(0.014)	(0.014)	(0.008)	(0.012)
Obs.	662,081	661,210	555,265	579,816	291,991

Notes. RHS variables not included in the table: (ln) U at graduation, SES index dummies and their interactions with the variable of interest (female/best HEI/STEM), (ln) U at enrolment, interaction between SES categories and (ln) U at enrolment, cohort, gender, ethnicity, any disability, degree classification, distance home-HEI, distance home-HEI squared, HEI dummies, LAD dummies, field of study dummies, linear time trend, SES-specific time trends, and field-specific time trends. Robust standard errors are clustered by field of study and year of graduation in parentheses. Significance at 1%, 5%, and 10%- level are indicated by **, *, and +.

Table 2.8: The effect of graduating in bad times by SES - Mechanisms

	I Social network (0/1)	II Distance work-home (Km)		
	whole sample	whole sample	network=1	network=0
Middle SES	-0.006	1.407	1.495	2.026+
	(0.004)	(1.041)	(1.700)	(1.129)
Low SES	-0.019**	2.023	0.213	1.842
	(0.006)	(1.491)	(2.132)	(1.542)
ln(U field) * Middle SES	-0.010*	3.557**	2.891	2.744**
	(0.004)	(0.734)	(1.830)	(0.933)
ln(U field) * Low SES	-0.034**	7.808**	3.410	6.310**
	(0.005)	(1.100)	(2.183)	(1.378)
ln(U field)	0.010	-6.027**	-3.343	-4.135**
	(0.008)	(1.062)	(2.309)	(1.173)
$\overline{y}$	0.223	63.165	53.929	64.498
Obs.	536,926	621,682	111,476	395,007

Notes. RHS variables not included in the table: (ln) U at enrolment, interaction between SES categories and (ln) U at enrolment, cohort, gender, ethnicity, any disability, degree classification, distance home-HEI, distance home-HEI squared, HEI dummies, LAD dummies, field of study dummies, linear time trend, SES-specific time trends, and field-specific time trends. Robust standard errors are clustered by field of study and year of graduation in parentheses. Significance at 1%, 5%, and 10%- level are indicated by **, *, and +. The first two columns consider the whole sample of graduates, while column 3 and 4 restrict the population of graduates to those who found their job through social network and through any other channels, respectively.

Table 2.9: Conditioning on pre-university academic attainment: activity status

	Full-time job	Part-time job	HE programme	Professional programme	Unemployed	Other
Q1	0.007**	-0.016*	-0.011	0.021**	0.017**	-0.019**
	(0.002)	(0.006)	(0.007)	(0.002)	(0.002)	(0.003)
Q2	0.001	-0.018**	0.010*	0.013**	0.010**	-0.016**
	(0.002)	(0.005)	(0.005)	(0.002)	(0.001)	(0.002)
Q3	-0.004+	-0.015**	0.015**	0.011**	0.006**	-0.013**
	(0.002)	(0.004)	(0.004)	(0.002)	(0.001)	(0.002)
Q4	-0.010**	-0.008**	0.016**	0.006**	0.004**	-0.007**
	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)
Middle SES	-0.003	0.002	0.024**	-0.005	-0.003	-0.014**
	(0.004)	(0.004)	(0.006)	(0.003)	(0.003)	(0.003)
Low SES	-0.004	0.019**	0.012	-0.001	0.002	-0.028**
	(0.005)	(0.006)	(0.013)	(0.005)	(0.004)	(0.005)
ln(U field) * Middle SES	-0.005	0.011*	-0.010+	0.010**	0.001	-0.006*
	(0.003)	(0.005)	(0.006)	(0.003)	(0.002)	(0.003)
ln(U field) * Low SES	-0.010+	0.032**	-0.038**	0.020**	0.013**	-0.018**
	(0.005)	(0.006)	(0.013)	(0.004)	(0.003)	(0.004)
ln(U field)	0.016**	-0.014+	-0.054**	0.011*	0.018**	0.023**
	(0.006)	(0.007)	(0.013)	(0.005)	(0.005)	(0.006)
Obs.	687,635	687,635	687,635	687,635	687,635	687,635

Notes. Q1-Q4 are the first four quintiles in which we divided the tariff score (Q5, which group graduates with the highest attainment, is the omitted category). RHS variables not included in the table: (ln) U at enrolment, interaction between SES categories and (ln) U at enrolment, cohort, gender, ethnicity, any disability, degree classification, distance home-HEI, distance home-HEI squared, HEI dummies, LAD dummies, field of study dummies, linear time trend, SES-specific time trends, and field-specific time trends. Robust standard errors are clustered by field of study and year of graduation in parentheses. Significance at 1%, 5%, and 10%- level are indicated by **, *, and +.

Table 2.10: Conditioning on pre-university academic attainment: job quality

	Part-time vs full-time job	Professional occupation	Graduate job	Fixed term contract	(ln) Salary
Q1	0.030**	-0.067**	-0.059**	-0.005+	-0.036**
	(0.004)	(0.007)	(0.008)	(0.003)	(0.005)
Q2	0.016**	-0.041**	-0.039**	-0.006**	-0.019**
	(0.003)	(0.005)	(0.005)	(0.002)	(0.004)
Q3	0.012**	-0.026**	-0.030**	-0.003	-0.018**
	(0.003)	(0.004)	(0.004)	(0.002)	(0.003)
Q4	0.005*	-0.012**	-0.021**	0.002	-0.011**
	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)
Middle SES	-0.011*	-0.017*	0.001	0.002	-0.007
	(0.005)	(0.009)	(0.010)	(0.005)	(0.006)
Low SES	0.003	-0.041**	-0.018	-0.009	-0.011
	(0.009)	(0.014)	(0.013)	(0.006)	(0.009)
ln(U field) * Middle SES	0.017**	-0.029**	-0.014*	-0.005	-0.007
	(0.004)	(0.005)	(0.006)	(0.004)	(0.005)
ln(U field) * Low SES	0.044**	-0.053**	-0.027**	-0.008*	-0.019**
	(0.008)	(0.010)	(0.010)	(0.004)	(0.006)
ln(U field)	0.029**	-0.025*	-0.027+	0.020**	-0.041**
	(0.009)	(0.012)	(0.014)	(0.007)	(0.011)
Obs.	420,477	419,969	358,060	373,408	189,620

Notes. Q1-Q4 are the first four quintiles in which we divided the tariff score (Q5, which group graduates with the highest attainment, is the omitted category). RHS variables not included in the table: (ln) U at enrolment, interaction between SES categories and (ln) U at enrolment, cohort, gender, ethnicity, any disability, degree classification, distance home-HEI, distance home-HEI squared, HEI dummies, LAD dummies, field of study dummies, linear time trend, SES-specific time trends, and field-specific time trends. Robust standard errors are clustered by field of study and year of graduation in parentheses. Significance at 1%, 5%, and 10%- level are indicated by **, *, and +.

Table 2.11: Imputed (ln) salary

	6 months	42 months	6 months FT only
Middle SES	-0.006+	-0.014	-0.006+
	(0.004)	(0.017)	(0.004)
Low SES	-0.012+	-0.024	-0.012+
	(0.007)	(0.023)	(0.007)
ln(U field) * Middle SES	-0.007+	-0.022	-0.007+
	(0.004)	(0.022)	(0.004)
ln(U field) * Low SES	-0.017**	-0.061*	-0.017**
	(0.006)	(0.030)	(0.006)
ln(U field)	-0.076**	0.018	-0.076**
	(0.017)	(0.029)	(0.017)
Obs.	606,448	40,081	467,066

Notes. RHS variables not included in the table: (ln) U at enrolment, interaction between SES categories and (ln) U at enrolment, cohort, gender, ethnicity, any disability, degree classification, distance home-HEI, distance home-HEI squared, HEI dummies, LAD dummies, field of study dummies, linear time trend, SES-specific time trends, and field-specific time trends. Robust standard errors are clustered by field of study and year of graduation in parentheses. Significance at 1%, 5%, and 10%- level are indicated by **, *, and +.

Table 2.12: Non-response

	Non-response
Middle SES	-0.012**
	(0.002)
Low SES	-0.029**
	(0.003)
ln(U field) * Middle SES	0.002
	(0.002)
ln(U field) * Low SES	0.001
	(0.004)
ln(U field)	0.018**
	(0.006)
Obs.	1,301,958

Notes. RHS variables not included in the table: (ln) U at enrolment, interaction between SES categories and (ln) U at enrolment, cohort, gender, ethnicity, any disability, degree classification, distance home-HEI, distance home-HEI squared, HEI dummies, LAD dummies, field of study dummies, linear time trend, SES-specific time trends, and field-specific time trends. Robust standard errors are clustered by field of study and year of graduation in parentheses. Significance at 1%, 5%, and 10%-level are indicated by **, *, and +.

Table 2.13: Are the 6 months outcomes good indicators of the 3.5 years outcomes?

	Full-time job (42m)		Part-time job (42m)		Unemployed (42m)	
	Pre	Post	Pre	Post	Pre	Post
Part-time work (6m)	-0.091**	-0.130**	0.053**	0.074**	0.023**	0.032**
	(0.018)	(0.019)	(0.009)	(0.009)	(0.008)	(0.009)
Studying (6m)	-0.113**	-0.177**	0.013**	0.020**	0.106**	0.126**
	(0.025)	(0.032)	(0.003)	(0.005)	(0.023)	(0.032)
Unemployed (6m)	-0.104**	-0.137**	0.044**	0.046**	0.012+	0.016+
	(0.014)	(0.015)	(0.008)	(0.006)	(0.006)	(0.007)
Working & Studying (6m)	-0.082**	-0.094**	0.014**	0.025	0.012+	0.020*
	(0.012)	(0.021)	(0.005)	(0.018)	(0.006)	(0.008)
Other (6m)	-0.107**	-0.152**	0.026**	0.063**	0.021**	0.028*
	(0.013)	(0.022)	(0.007)	(0.010)	(0.007)	(0.013)
$\overline{y}$	0.761	0.737	0.040	0.053	0.084	0.104
Obs.	28,772	20,261	28,772	20,261	28,772	20,261

	Studying (42m)		Working & Studying (42m)		Other (42m)	
	Pre	Post	Pre	Post	Pre	Post
Part-time work (6m)	-0.012*	-0.002	0.021*	0.016*	0.007+	0.008
	(0.005)	(0.010)	(0.008)	(0.007)	(0.004)	(0.005)
Studying (6m)	-0.015+	0.004	0.010*	0.021**	0.001	0.005
	(0.008)	(0.006)	(0.004)	(0.004)	(0.003)	(0.004)
Unemployed (6m)	-0.009	-0.010+	0.051**	0.073**	0.006	0.012*
	(0.006)	(0.005)	(0.007)	(0.009)	(0.005)	(0.005)
Working & Studying (6m)	0.054**	0.043**	0.001	0.005	0.000	-0.000
	(0.009)	(0.008)	(0.004)	(0.004)	(0.004)	(0.003)
Other (6m)	0.012	-0.000	0.026**	0.026**	0.020**	0.033**
	(0.010)	(0.010)	(0.006)	(0.008)	(0.006)	(0.007)
$\overline{y}$	0.061	0.049	0.031	0.030	0.023	0.028
Obs.	28,772	20,261	28,772	20,261	28,772	20,261

Notes. RHS variables not included in the table: SES categories, (ln) U at graduation, interaction between SES categories and (ln) U at graduation, (ln) U at enrolment, interaction between SES categories and (ln) U at enrolment, cohort, gender, ethnicity, any disability, degree classification, distance home-HEI, distance home-HEI squared, HEI dummies, LAD dummies, and field of study dummies. Robust standard errors are clustered by field of study and year of graduation in parentheses. Significance at 1%, 5%, and 10%- level are indicated by **, *, and +. The sample is split into students who graduated in the years pre (2003, 2005, and 2007) and post the recession (2009).

Table 2.14: Outcomes at 3.5 years after graduation

	FT job	PT job	Working & studying	Studying	Unemployed	Other	Prof. job	Master	(ln)Salary
Middle SES	-0.007	0.004	0.000	0.003	-0.001	-0.001	-0.011	-0.007	-0.030*
	(0.008)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.011)	(0.013)	(0.012)
Low SES	-0.013	0.009+	0.005	-0.001	-0.003	0.001	-0.019	-0.018	-0.051**
	(0.009)	(0.005)	(0.005)	(0.005)	(0.004)	(0.003)	(0.014)	(0.018)	(0.015)
ln(U field) * Middle SES	0.010	-0.005	-0.004	-0.008	0.006	-0.001	-0.008	0.025+	-0.014
	(0.015)	(0.008)	(0.011)	(0.007)	(0.006)	(0.005)	(0.014)	(0.015)	(0.019)
ln(U field) * Low SES	-0.008	0.004	0.000	-0.009	0.009	0.003	-0.030	0.005	-0.071**
	(0.018)	(0.007)	(0.008)	(0.010)	(0.008)	(0.006)	(0.019)	(0.027)	(0.023)
ln(U field)	-0.000	0.000	-0.009	0.017	-0.006	-0.001	-0.003	0.034+	-0.073**
	(0.021)	(0.008)	(0.010)	(0.013)	(0.007)	(0.006)	(0.027)	(0.018)	(0.021)
$\overline{y}$	0.504	0.801	0.934	0.176	0.827	0.634	0.361	0.295	9.907
Obs.	49,033	49,033	49,033	49,033	49,033	49,033	33,994	21,255	18,168

Notes. RHS variables not included in the table: (ln) U at enrolment, interaction between SES categories and (ln) U at enrolment, cohort, gender, ethnicity, any disability, degree classification, distance home-HEI, distance home-HEI squared, HEI dummies, LAD dummies, and field of study dummies. Robust standard errors are clustered by field of study and year of graduation in parentheses. Significance at 1%, 5%, and 10%- level are indicated by **, *, and +.

Table 2.15: Regret and career satisfaction at 3.5 years after graduation

	Change subject	Change institution
Middle SES	0.002	-0.017
	(0.021)	(0.015)
Low SES	0.003	-0.058**
	(0.024)	(0.020)
ln(U field) * Middle SES	0.035	-0.003
	(0.042)	(0.022)
ln(U field) * Low SES	0.080*	-0.046
	(0.038)	(0.030)
ln(U field)	0.007	0.028
	(0.054)	(0.039)
Obs.	47,951	47,173
	Change qualification	Career satisfaction
Middle SES	0.026+	-0.021
	(0.015)	(0.015)
Low SES	0.033	-0.074**
	(0.020)	(0.018)
ln(U field) * Middle SES	-0.010	-0.026
	(0.032)	(0.029)
ln(U field) * Low SES	0.015	-0.065*
	(0.036)	(0.030)
ln(U field)	0.011	0.041
	(0.052)	(0.040)
Obs.	47,639	48,364

Notes. RHS variables not included in the table: (ln) U at enrolment, interaction between SES categories and (ln) U at enrolment, cohort, gender, ethnicity, any disability, degree classification, distance home-HEI, distance home-HEI squared, HEI dummies, LAD dummies, and field of study dummies. Robust standard errors are clustered by field of study and year of graduation in parentheses. Significance at 1%, 5%, and 10%- level are indicated by **, *, and +.

Appendix

Table B1: Sample selection

Overall number of observations for DLHE years 2002/3-2011/2
N=4,680,237
Keep if first degree graduates (-1,810,741)
Keep if studied full-time (-303,859)
Keep 21-24 years old in June (-483,557)
Initial sample
N=2,082,080
Keep UK nationals (-296,177)
Keep if not from Isle of Man, Guernsey, Jersey (-5,164)
Keep only English universities (-288,450)
Intermediate sample
N=1,492,289
Drop if subject studied is undefined (-8,665)
Drop if there is no subject studied at least 50% (-6,440)
Drop if the subject has no correspondent in the LFS (-15,651)
Drop if postcode of domicile unknown (-6,865)
Drop if LPN and/or school type missing (-152,709)
Drop if non-respondent (-247,095)
Drop if gender other than male or female (-1)
Final sample
N=1,054,863

B1 University groups

- *Golden Triangle Group*: elite universities located in the southern English cities of Cambridge, London and Oxford. These universities belong to the Russell Group as well but we do not include them in that group in our analysis to avoid overlapping definitions.
  The University of Cambridge, The University of Oxford, University College London, Imperial College London, King's College London, London School of Economics and Political Science.

- *Russell Group*: prestigious British public research universities.
  The University of Birmingham, The University of Bristol, University of Durham, The University of Exeter, The University of Leeds, The University of Liverpool, Queen Mary and Westfield College, The University of Newcastle-upon-Tyne, The University of Nottingham, The University of Sheffield , The University of Southampton, The University of Warwick, The University of York, The University of Manchester.

- *Ex-Polytechnics*: tertiary education teaching institutions turned into independent universities with the Further and Higher Education Act 1992. Most of these universities also belong to the groups below (University Alliance, Million Plus, and Guild HE), but we have grouped them there only to avoid overlapping definitions.
  The University of Brighton, The University of Central Lancashire, Leeds Metropolitan University, De Montfort University, London South Bank University, The University of Westminster, The University of Wolverhampton.

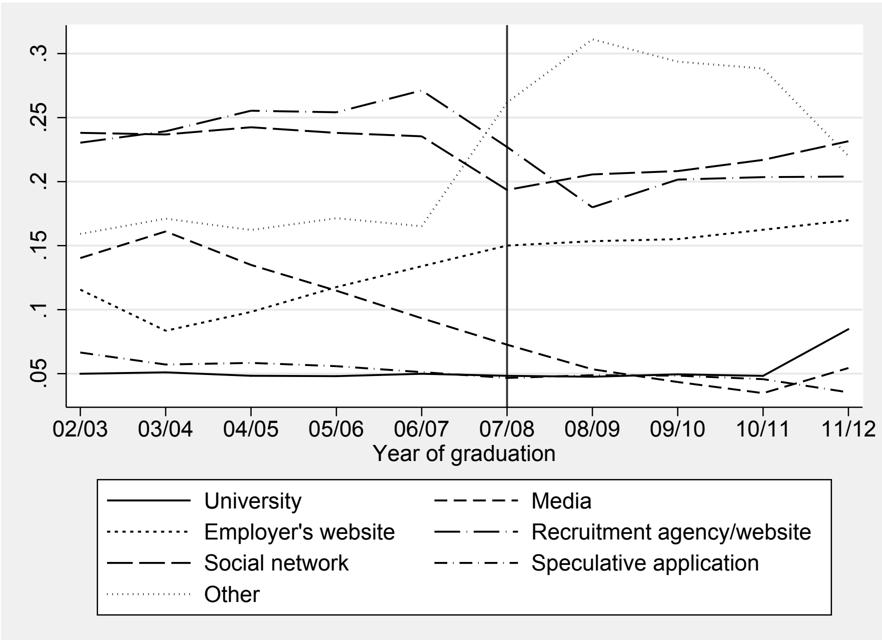
- *University Alliance*: group of 'business engaged' universities that claim to drive innovation and enterprise growth through research and teaching.
  Bournemouth University, Coventry University, The University of Greenwich, University of Hertfordshire, The University of Huddersfield, The University of Lincoln, Kingston University, Liverpool John Moores University,

The Manchester Metropolitan University, The University of Northumbria at Newcastle, The Nottingham Trent University, Oxford Brookes University, The University of Plymouth, The University of Portsmouth, Sheffield Hallam University, Teesside University, University of the West of England Bristol, The University of Bradford, The University of Salford.

- *Million Plus*: group of universities (mainly ex-polytechnics and university colleges) forming a think-tank, seeking to solve complex problems in the Higher Education sector.
  Canterbury Christ Church University, University of Bedfordshire, University of Cumbria, Anglia Ruskin University, Bath Spa University, The University of Bolton, Birmingham City University, The University of East London, Middlesex University, Staffordshire University, The University of Sunderland, The University of West London, London Metropolitan University.

- *Guild HE*: some of the most recently designated universities and university colleges, specialist colleges and other bodies providing Higher Education programs.
  York St John University, University College Plymouth St Mark and St John, University College Falmouth, The University of Winchester, Southampton Solent University, St Mary's University College Twickenham, Leeds Trinity University College, The University of Worcester, The University of Chichester, Writtle College, Royal Agricultural College, University College Birmingham, University for the Creative Arts, The Liverpool Institute for Performing.

Figure B1: Job found through...



Notes. Different methods through which graduates found their job by cohort.

Chapter 3

On the comparability of ethnic minorities in inter-ethnic and co-ethnic partnerships

3.1 Introduction

Labour market penalties of ethnic minority groups with respect to the white majority group are observed in different dimensions and concern different ethnic groups in various ways. In the UK, ethnic minorities have higher rates of non-employment (unemployment and inactivity) than the majority group (Blackaby, Leslie, Murphy, & O'Leary, 1999; Nandi & Platt, 2010). When employed, members of ethnic minority groups seem to be segregated in certain occupations (Brynin & Güveli, 2012; Elliott & Lindley, 2008), to be over-represented in self-employment (K. Clark & Drinkwater, 2010), to suffer from wage penalties (K. Clark & Drinkwater, 2009; Longhi, Nicoletti, & Platt, 2013) and to be over-qualified (Lindley, 2009). All these disadvantages are important to explain phenomena such as poverty and deprivation, which particularly affect many ethnic minority groups (Nandi & Platt, 2010; Platt, 2007).

Discrimination and lack of integration into society both play an important role in generating such labour market disadvantages (Heath & Cheung, 2007). In this paper we will focus on the social integration dimension. More specifically, we will explore the validity of a new empirical strategy in the UK context. This strategy compares ethnic minority individuals in a partnership with a person of the white majority population (inter-ethnic partnership) to those ethnic minority individuals in a partnership with a person of the same ethnic minority group (co-ethnic partnership) to infer the role of integration of ethnic minorities on labour market outcomes.

All the cited papers above compare ethnic minorities with the white majority group in a regression type analysis. However, this comparison could lead to misleading estimates of ethnic minority penalties if the two groups differ substantially in their observable and unobservable characteristics. Furthermore, lack of comparability could be more or less severe depending on the migrant generation which ethnic minorities belong to. In this paper we establish if, by only conditioning on their observable characteristics, ethnic minorities in co- and inter-ethnic partnerships are actually comparable. If they are, we explore whether the difference in their labour market outcomes could tell us something about how important integration is for the labour market opportunities of ethnic minorities in the UK.

The literature that compares co- and inter-ethnic partnerships approximates social integration of ethnic minorities with their partners' ethnicity (Furtado & Trejo, 2013). This is because having a white majority partner can improve the integration of ethnic minorities in several ways. Having a white majority partner might influence the integration of an ethnic minority person into society as well as his or her labour market opportunities due to the attainment of English language proficiency. Lack of language proficiency or language fluency indeed constitute an obstacle for ethnic minorities in the labour market (K. Clark & Drinkwater, 2008; Dustmann & Fabbri, 2003; Lindley, 2002; Miranda & Zhu, 2013; Shields & Price, 2004). Furthermore, a white majority partner could also help in understanding cultural and institutional aspects. It has in fact been found that ethnic penalties suffered by ethnic minority groups decline over generations (K. Clark & Lindley, 2006; Dustmann, Frattini, & Theodoropoulos, 2011; Heath & Cheung, 2007; Modood et al., 1997). This is because second and further generation migrants are born and brought up in the UK, so they are familiar and acquainted with British institutional, social, and cultural norms and values. Another aspect by which having a white majority partner could affect social integration and, consequently, labour market opportunities of ethnic minorities is the possibility of reaching networks which are mainly composed of other majority individuals. Network composition and its diversification is a relevant issue for labour market opportunities since it has been found that characteristics of network members are of particular importance for labour market opportunities.[1] Ethnic minorities tend to live in highly concentrated areas of co-ethnic and other minority groups, and this also influences the composition of their social network, which is a very important channel for getting jobs.[2]

The literature comparing co- and inter-ethnic partnerships is relatively recent because the phenomenon of inter-ethnic partnerships is rather new, although it is now increasing. In 1991 in the UK these partnerships made up 1.3% of all unions (Berrington, 1996) and Census data of 2001 and 2011 show that this has increased to 7% and 9% of all unions, with the large majority of these partnerships involving a white majority person (ONS, 2014; Simpson, 2012). In defining what an inter-ethnic partnership is, some papers focus on unions among immigrants and natives, while others focus on unions between a member of an ethnic minority group and a member of the majority population. This choice is driven by the institutional

[1] For example, networks with high numbers of employed people are associated with a higher probability of employment (Blau & Robins, 1990; Calvó-Armengol & Zenou, 2005; Furtado & Theodoropoulos, 2010).

[2] Previous studies show how physically close networks are key channels for finding a job for ethnic minorities. However, they are not always the most effective way of finding just any job, or one of high quality, and their effectiveness varies greatly among different ethnic groups (Battu, Seaman, & Zenou, 2011; K. Clark & Drinkwater, 2002; Frijters, Shields, & Price, 2005; Patacchini & Zenou, 2012). Moreover, it has been shown that living in co-ethnic areas is associated with a higher persistence of the culture and social norms of the original ethnic group, with lower custom adoption and lower English fluency (Modood et al., 1997; Van Tubergen & Kalmijn, 2005).

context of the country studied. Our favoured approach is the latter because in the UK a lack of integration and disadvantages in the labour market are not only peculiarities of the migrant population but also, in different degrees, of the whole ethnic minority population.

Partner choice is an endogenous issue most likely influenced by characteristics that are unobservable by researchers. Observable and unobservable traits of the individual might affect both the choice of the partner and labour market outcomes. For example, an individual with certain features might be more likely to end up in an inter-ethnic partnership and at the same time, these qualities might help him or her to be more successful in the labour market. In this case estimates of the impact of having a majority partner will be overestimated or biased upwards. Most studies of inter-ethnic partnerships and labour market outcomes model self-selection into the type of partnership by using local marriage market ratios (by combining sex, ethnicity, and age distribution at a certain geographical level) as exclusion restrictions or as an instrumental variable. Some of them conclude that the individuals who sort in the different kinds of partnerships differ so much in their characteristics that it is not possible to infer any (dis)advantages from being in one type of partnership rather than another, e.g. Kantarevic (2004) in the U.S. Other studies, instead, find that the two groups are comparable in their characteristics and estimate the premium of being in an inter-ethnic partnership.[3] Different findings could be driven by the different institutional settings in which the topic has been studied. Countries differ in their migration history; some papers study first generation migrants while other consider all ethnic minorities. Furthermore, some consider only marriages, while others include cohabiting partnerships too.

We contribute to this literature by providing evidence on the comparability of ethnic minorities in inter- and co-ethnic partnerships from the UK. We can do

[3]More specifically, Meng and Gregory (2005) in Australia and Meng and Meurs (2009) in France find a positive effect of inter-ethnic partnerships on earnings. Meng and Meurs (2009) shows that this is the case especially for those with a strong base in French. Furtado and Theodoropoulos (2010) in the U.S. find a positive effect of inter-ethnic partnerships on immigrant employment rates. This is explained by the social networks obtained through marriage with a native.

this because we have a very rich dataset with a large sample of ethnic minorities. We use data from the first wave of Understanding Society, a UK Longitudinal Household Survey (UKHLS) that started in 2009. This data includes several pieces of information on both the person from the ethnic minority and the partner. It is important to have access to the characteristics of both partners to take into account the role that assortative matching plays in partnership formation.[4]

There are only two other studies which use the comparison between co- and inter-ethnic partnerships to infer the role of social integration in several outcomes of ethnic minorities in the UK.[5] Muttarak (2011) looks at the difference in the probability of moving to a higher occupation between ethnic minorities in different types of partnership statuses (inter-ethnic, co-ethnic and single) in England and Wales. Muttarak uses the ONS Longitudinal Study which links successive UK Censuses between 1971 and 2001. She finds a positive premium of being in an inter-ethnic partnership on average, and for some ethnic groups more than others. Muttarak's results are drawn from a bivariate probit, where the selection into an inter-ethnic partnership and the probability of upward occupational mobility are simultaneously estimated. The strategy that she uses to infer whether there has been an upward mobility occupation is by considering two points in time: 1971, where all individuals were single and 2001 where some of them were still single and

[4] It could indeed be the case that individuals that sort into inter-ethnic partnerships value certain characteristics in their partner which are not valued, or not to the same extent, by individuals in co-ethnic partnerships. Consequently, the joint utility of inter-ethnic partnerships could differ from that of co-ethnic partnerships. For instance, several studies in the United States (Chiswick & Houseworth, 2011; Furtado, 2012; Furtado & Theodoropoulos, 2011) find that individuals are more likely to marry inside their ethnicity, and they choose to marry with someone of another ethnicity when there is scarce availability of possible partners with suitable characteristics in their own ethnic group. In particular, disparity in one's own education and the average education of one's own ethnic group is considered as a push factor to marry someone of another ethnicity but with a similar education.

[5] There are several other studies in the UK that looked at the correlation between the characteristics of individuals and their likelihood of ending up in an inter-ethnic partnership. The main finding is that different ethnicities have a different likelihood of ending up in this kind of partnership even after controlling for many different characteristics (Muttarak & Heath, 2010; Platt, 2010; Voas, 2009). White British and South Asian ethnic groups are generally those with the lowest rates of inter-ethnic partnerships, while Caribbean, mixed, and white ethnic groups other than British are those with the highest rate. Differences in gender within the same ethnic group have also been found to be important (e.g. Chinese women have a higher rate of intermarriage than Chinese men).

others partnered with a co-ethnic or white British person. She then compares the occupational positions of these individuals between these two years. It is, however, not clear whether the partnership began before or after the occupation observed in 2001 because the dataset does not contain any information about the formation of the partnership. Furthermore, the only information considered about the partner is his or her education. Thus, in the partnership selection equation, Muttarak considers aggregate measures of the local (at county level) marriage market, such as sex ratio and ethnic group size, as proxies of assortative matching.

The second relevant paper for our study is Platt (2012). Platt studies outcomes of children where parents are in co- and inter-ethnic partnerships. This paper does not claim any causal estimates since it is only comparing the outcomes of children in the two types of relationships. However, it partly attempts to reduce the selection bias concern by applying a propensity score matching approach when using the General Household Labour Survey.

Unlike the two previous papers, we have a large amount of information on both the ethnic minority person and his or her partner. We will hence use those to establish whether inter-ethnic and co-ethnic partnerships are comparable. We will not restrict our choice of variables to those characteristics which are similar across the two groups, as Platt (2012) did. This is because our main aim is to establish whether, based on observable characteristics, we are comparing "apples with apples" instead of "apples with pears".

From the raw data it occurs that ethnic minorities in the two types of partnerships greatly differ in their labour market outcomes across several dimensions (we look at activity status, occupation, and salary). For example, women in inter-ethnic partnerships are less likely to be inactive than women in co-ethnic partnerships. Furthermore, a higher percentage of both men and women in inter-ethnic partnerships work in high occupational positions and earn more than their counterparts.

To investigate the impact of the partner's ethnicity on labour market outcomes of ethnic minorities we use Propensity Score Matching (PSM). One advantage of PSM is that it provides diagnostic tests to check the similarity of the groups of interest in their observable characteristics. We find that ethnic minority men and women in co- and inter-ethnic partnerships are almost never comparable. This is true when conditioning on the characteristics of ethnic minority individuals only, and when also conditioning on those of their partners. For women only we find some cases in which we observe good quality matches. However, we do not see that women in inter-ethnic partnerships have outcomes that are statistically significantly different from those women in co-ethnic partnerships (and when they do, the sign is in the opposite direction compared to the raw data). We also repeat our analysis for more homogeneous subgroups, but even among them we conclude that the two groups are too different to be comparable.

The structure of the chapter is as follows. Section 3.2 outlines the empirical strategy and the implementation of PSM. Section 3.3 describes the data and Section 3.4 shows and comments on the main findings. Finally, Section 3.5 concludes.

3.2 Empirical strategy

We consider only individuals in a partnership. Each ethnic minority individual is observed being either in a co- or inter-ethnic partnership. We can think about the kind of partnership as a treatment t. Let's denote the outcomes of those in a co-ethnic partnership, i.e. when $t = 0$, y_0 and those in an inter-ethnic partnership, i.e. when $t = 1$, y_1. For each individual we hence observed one of the two *outcome equations*, which we assume to be linear functions of X, which represents the observable components and e, the unobserved part:

$$y_0 = \beta_0 X + e_0, \tag{3.1}$$

$$y_1 = \beta_1 X + e_1. \tag{3.2}$$

Hence, the outcome is either equal to y_0 or y_1, depending on whether the individual is observed being in an inter-ethnic partnership:

$$y = (1 - t)y_0 + ty_1, \tag{3.3}$$

where $t = 1$ if $\gamma W + u > 0$ and $t = 0$ otherwise. W is a vector of observable characteristics and u is the unobservable error term and constitute the *selection equation*. We assume that $cov(e, u) = 0$.

Given the richness of our data on the pre-partnership characteristics of both the ethnic minority person and partner, we argue that we have enough information to set up a credible model of the selection process regarding whether an ethnic minority has a co-ethnic partner or not. We use PSM as our favoured method. With this method we can obtain the average treatment effect for the treated population (ATT from now on), i.e. the effect of having a white majority partner for those who actually are in an inter-ethnic partnership. Furthermore, PSM allows us to assess whether ethnic minority persons in co- and inter-ethnic partnerships are actually comparable in their socio-economic and demographic characteristics which do not depend on the partnership itself. We will discuss the PSM strategy that we implement in more detail in the subsequent section.

In order for PSM to provide estimates of the causal impact of the partnership on labour market outcomes of ethnic minorities we have to rely on several assumptions. These are the weak overlap condition and the unconfoundeness for controls or conditional independence assumption (CIA). The former states that in the comparison group we always observe individuals to match with persons in the treated group.[6] In other words, ethnic minority people in co-ethnic partnerships should be similar in their observable characteristics to ethnic minority people in inter-ethnic partnerships. Unlike the CIA, this assumption is testable. The CIA states that for those in the comparison group, once we condition on the observable variables, we do not observe any relevant differences with the treated

[6] Since we are not interested in the average treatment effect we do not need to have individuals in the treated group to match with the persons observed in the control group.

group. In our context, CIA implies that conditional on all pre-partnership covariates, potential labour market outcomes are independent of treatment assignment (whether being in an inter-ethnic partnership). We believe that we have a rich set of pre-treatment (pre-marriage or pre-cohabiting) control variables which we present and discuss in Section 3.3.

However, the unconfoundeness assumption is still a strong one, especially in our case where we are trying to model selection into interpersonal relationships. Hence, we try to hypothesise in which directions our results might be biased given the existence of a possible unobserved confounder. The estimated impact of partner's ethnicity on labour market outcomes of ethnic minorities may be possibly biased if those unobservable characteristics that make an individual more likely to get into an inter-ethnic partnership have a positive impact on their labour market outcomes. There is a possibility that an ethnic minority person is very willing to integrate into the British society, and hence works very hard to fare well in the labour market, and at the same time this attitude makes him or her more prone to having a white majority partner since he or she is less emotionally attached to his or her cultural background. However, this seems a very strong assumption and in a certain sense it implies that ethnic minority individuals in co-ethnic partnerships are less willing to be successful in the labour market and that having a white majority (or white British) partner means being less attached to his or her own culture of origin. Furthermore, Meng and Gregory (2005), Meng and Meurs (2009), and Muttarak (2011) found that some characteristics that make a person more likely to be in an inter-ethnic partnership are at the same time negatively correlated with achieving a better occupational position, so that selection into inter-ethnic unions contribute negatively to their occupational status. Muttarak (2011) explains this result for England and Wales by hypothesising that, while ethnic minority individuals who are inter-married enhance their social capital thanks to their partners' ethnicity, they are less ambitious or materialistic than their co-ethnic partnered counterparts. If this is true, then our estimates would be downward biased.

3.2.1 Implementation of PSM

PSM allows us to control for the selection into the kind of partnership exclusively based on the observable characteristics, in this way removing all bias generated by differences in observable factors among the two groups (Imbens, 2004). This is because by conditioning on the propensity score (PS), i.e. the estimated predicted probability of being in an inter-ethnic partnership versus a co-ethnic one, we compare similar observations in the treated and control group with respect to their likelihood of being in an inter-ethnic partnership. We hence match observations of individuals who are very similar in their observable characteristics except for the fact that those in the treated group have a white majority partner and those in the control group have a co-ethnic partner. We will now describe the framework in which we implement the PSM estimator in a more detailed way.

We assume that individuals end up in an inter-ethnic partnership when the utility of a match between the individual and his or her partner passes a certain threshold (which we normalise to zero). In order to estimate the probability of being in the treatment group given the observed covariates we implement a propensity score, $p(X)$, which estimates the conditional probability of being in an inter-ethnic partnership: $P(t = 1|X)$. This is estimated with a logistic regression on inter- versus co-ethnic partnership. Since an individual's choice of partner is determined by the characteristics of both the individual and of the partner it is important to condition on the characteristics of both individuals. Hence, in the empirical analysis we specify a selection model where we condition only on the characteristics of the ethnic minority person characteristics (Specification 1 or S1). In a second specification, our preferred one, we also include the partner's characteristics (Specification 2 or S2). For both, we include in the model only those features that simultaneously influence the likelihood of being in an inter-ethnic partnership and the labour market outcome variables that *are not* affected by the partnership itself (Caliendo & Kopeinig, 2008). Here, we use several variables related to demography, information on the socio-economic situation and on the ethnicity of the native family of both partners, and characteristics related to ethnic minority status of the ethnic minority person (e.g. language, generation of migration).

To implement the matching between ethnic minorities in a co-ethnic and in an inter-ethnic partnership, we use the Kernel algorithm which measures the distance between all individuals in the control group and the observation in the treated group with Kernel weights (the higher the distance, the higher the weight).[7] The weighted average of the outcome of the control group is then used as the counterfactual outcome. As Caliendo and Kopeinig (2008) argue, this method has lower variance because it uses all the information in the control group. However, because all observations are used, some of these could be very distant and could contribute to create bad matches. This is why it is important to impose the condition of the common support (e.g. we only consider the region where the propensity score densities of inter- and co-ethnic groups overlap) and to set bandwidth parameters (i.e. the maximum distance allowed between the treated and control observations). In our analysis we will choose a relatively low and high bandwidth value (0.01 and 0.10, respectively). The higher the bandwidth value, the smoother the density function.

To assess the matching quality we use the standardised mean bias, the pseudo-R squared, and the p-value of the chi-square test. The first of these was introduced by Rosenbaum and Rubin (1985) to evaluate the distance in marginal distributions of the covariates. Before the matching this value is normally high, but after the matching it is usually viewed as sufficient for it to be below 5% for the match to be considered of good quality - even if for matching in sub-groups of individuals it is also accepted to be up to 7% (Caliendo, 2006). The pseudo-R squared is

[7] To perform the PSM we use the programme written by Leuven, Sianesi, et al. (2015) in STATA. The standard errors are computed with bootstrap techniques (200 replications) to account for the fact that the matching process is performed on the estimated propensity score.

derived by the re-estimation of the propensity score on the matched sample, so that it indicates how well the regressors explain the probability of ending up in an inter-ethnic partnership. The chi-square test indicates that we have a good quality match if before performing it the covariates were jointly significant in explaining the likelihood of being in the treated group and after the matching they are not. When the overall balance is unacceptable, as indicated by the measures just discussed above, we conclude that ethnic minority people in co- and inter-ethnic partnerships are too different to be compared. Being able to see whether the groups we are considering for the comparison are actually comparable is one of the main advantages of the PSM technique compared to traditional empirical methods like linear regression.

After estimating the propensity score and matching the observations, to assess the outcomes of interest we ascertain the ATT as: $E(y1 - y0|t = 1)$. In this way we can see whether having a white majority partner makes a difference in the labour market outcomes for those in an inter-ethnic partnership.

3.3 Data and descriptive statistics

3.3.1 Data and sample

We use data from the first wave of Understanding Society (UKHLS), 2009/2010, because of its vast array of questions across different aspects of a person's life, including their socio-demographic characteristics, labour market activities, partnership and fertility patterns. This panel dataset also has an ethnic minority boost sample of approximately 4,000 households. The large sample size and the ethnic minority boost sample enables us to analyse inter-ethnic partnerships. In this way, we bring up to date the inter-ethnic literature in the UK by using the most recent data. We restrict our analysis to opposite sex couples that are legally married or in cohabiting partnerships. We consider members of ethnic minority groups as being in a co-ethnic partnership when their partner belongs to the same ethnic group as their own ethnic group, and we consider them to be in an inter-ethnic partnership when their partner is of the white majority group. We categorise those who report their ethnic group to be white-British/English/Scottish/Welsh/Northern Irish as white majority. Table 3.1 shows the various restrictions and selections we made in our sample. From an initial sample of about 51,000 individuals our intermediate sample is composed of about 23,000 individuals because we keep only those individuals who are of working age, which report being in a well defined ethnic group (white British, Irish, white other[8], Caribbean, Indian, Bangladeshi, Pakistani, Chinese or African), and that are observed living together with a partner, whether married or cohabiting.

Our major selection happens when we keep only ethnic minorities who are either in a partnership with a white majority person or with someone of their own ethnicity[9] and that are either active in the labour market or are looking after their family.[10] These restrictions leave us with 3,096 individuals, from which we further exclude those partnerships that started before the ethnic minority person arrived in the UK (if the person is observed being a first generation migrant). The aim of this selection is mainly to try to mimic the situation of an experiment by comparing individuals that are as similar as possible to each other. For example, we want to be sure that the individuals faced the same opportunities and the same socio-cultural and institutional environment with respect to the probability of getting into an inter-ethnic partnership (Heckman, Ichimura, & Todd, 1997; Michalopoulos, Bloom, & Hill, 2004). Hence, we restrict our sample to those migrants that created their partnership after their arrival in the UK. In this way, the

[8]More than three quarters of individuals in this group are Europeans.

[9]We are excluding ethnic minorities in a partnership with a partner of a different ethnic minority group because we are specifically interested in understanding how having a partner from the majority group influences labour market outcomes of ethnic minorities through several channels (e.g. language, social connections). Such unions between two individuals of different minority ethnic groups are a very small proportion (9%) of all inter-ethnic unions.

[10]Since we are interested in labour market outcomes (employment and occupational choice), we restrict our sample to those ethnic minorities who replied to the question "Which of these best describes your current employment situation?" with the responses: self employed, in paid employment (full or part-time), unemployed and looking after family or home. That is, we exclude those who are on maternity leave, retired, students, in training and the long term sick or disabled.

marriage market that our sample faced is culturally similar because it is restricted to the same country. This crucial selection is possible because our survey is very rich in data concerning time. For example, the date of the start of the partnership is missed in most other important surveys, like the Labour Force Survey. Our final sample is composed of 2,118 individuals.[11]

3.3.2 Description of the covariates and the labour market outcomes

Tables 3.2 and 3.3 compare the mean and standard deviation of the covariates that we use in our analysis between inter- and co-ethnic partnerships for men and women, separately. These are divided into characteristics of the ethnic minority person and his or her partner, which are either fixed over time (such as ethnicity and whether English is the first language) or that cannot be changed by the fact of being in the partnership itself (such as age). These are shown in panel (a) and (b) and are used to model the PS equation. Across all these characteristics, notice that we have: whether the individual's first language is English, the parents' occupation when the individual was aged fourteen years old, and the individual's migration status. For ethnic minority individuals, we exploit several pieces of information about the migration history to construct the following categories: not born in the UK and arrived before she or he was fourteen years old; arrived in the UK at an age greater than fourteen years old and within five years of the UKHLS interview; arrived in the UK at an age greater than fourteen years old and more than five years before the UKHLS interview year; whether the ethnic minority is a 2nd generation migrant (i.e. born in the UK from at least one parent who is not born in the UK); and whether the ethnic minority is a 3rd generation migrant (i.e. born in the UK but at least one of the grandparents was not born

[11]Because all individuals with missing information on the generation of migration and on the number of children they have are in co-ethnic partnerships we deleted them from the sample (for perfect collinearity with our main variable of interest, inter-ethnic partnership) but this does not affect the size of our sample much as shown in Table 3.1.

the UK). Given the limited variation in migrant generation for partners in inter-ethnic partnerships, for partners we create an indicator for whether the person is a first generation migrant or not, i.e. whether she or he was born in the UK.

In panel (c) we then include other characteristics that concern the household, such as whether they live in London or in an area with a low density of ethnic minority residents (LDA)[12], whether there are children aged 0/4 and 5/15 years old, the activity status of the partner, and whether the ethnic minority person is responsible for someone disabled or long-term sick in the household. These characteristics could themselves be influenced by the type of partnership. Thus, we will not use them for building the PS, but instead to investigate whether the two partnerships differ in these characteristics, and whether this could partly explain their differences in the labour market outcomes.

Tables 3.2 and 3.3 show that for both women and men the ethnic minority groups which are more likely to have a white majority partner are Irish and other white, while Indian, Pakistani and Bangladeshi are much more likely to be in co-ethnic partnerships. Furthermore, those ethnic minorities in inter-ethnic partnerships are more likely to be English mother-tongue (76% for men and 63% for women) and to be non-religious (46% and 39% for men and women, respectively). Ethnic minorities in inter-ethnic partnerships (and their partners) are largely from second or third/fourth generations. Ethnic minorities in inter-ethnic partnerships are also more likely to have acquired a higher qualification and to have a mother who worked in higher occupation. As we would expect, the most striking differences between co- and inter-ethnic partnerships lie in the partner's characteristics. Almost all partners in inter-ethnic partnerships are born in the UK and are English native speakers.

Finally, inter-ethnic partnerships have fewer children, are less likely to be married, and are more likely to live outside London and in an LDA. White majority partners, and especially women, are more likely to be employed than co-ethnic

[12]The LDA is defined by whether the household lives in a postal sector with an estimated share of non-white British residents less than 5%.

partners. We conclude that there are several differences between inter- and co-ethnic partnerships, which are in large part very similar between men and women. However, we will conduct the analysis separately by gender because of the important differences in the labour market between men and women.

The labour market outcomes are divided by activity status and, for employees, socio-occupation.[13] The latter is a categorical variable with five ordered occupational categories for employed persons: 1) large employers, higher management and higher professional; 2) lower management, lower professional and intermediate; 3) small employers, own account; 4) lower supervisory and technical; and, 5) semi-routine and routine.[14] The last outcome that we analyse is the gross pay per month from the current job for full-time employees only.

The distribution of these outcomes is shown in Figure 3.1. Ethnic minority men in inter-ethnic partnerships do not differ much in their activity status from their counterparts in co-ethnic partnerships, although the latter are slightly more likely to be unemployed and less likely to be inactive in the labour market. More interesting differences are found for women. Those in inter-ethnic partnerships are statistically significantly less likely to be inactive and more likely to be working. For both men and women, we find significant differences in their occupational status when they are in work. Ethnic minorities in inter-ethnic partnerships are more likely to be in managerial occupations (58% of ethnic minorities in inter-ethnic partnerships are observed in this occupation vs. 41% in co-ethnic partnerships for men, while for women the percentages are 58% vs. 42%) and are less likely to be in semi-routine jobs (16% vs. 25% for men and 17% vs. 28% for women). Finally, the distribution of the (log) salary of individuals in inter-ethnic partnerships is shifted towards the right compared to that of those in co-ethnic partnerships, indicating that ethnic minority individuals in inter-ethnic partnerships are paid

[13]This is constructed based on the socio-economic classification (NS-SEC). This is a widely used measure developed from the sociological classification called the Goldthorpe Schema (Erikson & Goldthorpe, 2002; Goldthorpe & Jackson, 2007).

[14]For brevity reasons in the rest of the paper we will refer to these categories as: Managerial, Intermediate, Small employer, Lower supervisory, and Semi-routine.

more.

3.4 Results

3.4.1 Modelling the selection equation

Table 3.4 shows the average marginal effects (AMEs) from logit regressions on the probability of being in an inter-ethnic partnership. The first three columns report the results for ethnic minority men, and the last three for ethnic minority women. For each of the two sub-samples we implement a specification where we include only the characteristics of the ethnic minority individual and, a specification where we also also include the characteristics of the partner. We also implement a final specification (S3) where we include several household characteristics that could be influenced by the partnership itself. We do this to investigate whether they are associated with the type of partnership, once we condition on the characteristics that are most likely to be the main determinants of getting into an inter-ethnic partnership.

For both men and women, the characteristic that mainly predicts the probability of being in an inter-ethnic partnership, both in terms of statistical significance and magnitude of the marginal effect, is the ethnicity itself. Except for other white, all ethnic minority groups are less likely to have a white majority partner than Irish people. Being religious is also negatively associated with being in an inter-ethnic partnership. For women another important characteristic is migrant generation. For men, education is an important determinant: having a qualification lower than a degree is negatively correlated with being in an inter-ethnic partnership (S1), although education loses its statistical significance once the characteristics of the partner are included as covariates (S2). Being a non-native English speaker is negatively associated with the outcome for both men and women.

Conditioning on the characteristics of the partner improves the specification (pseudo-R^2) but does not greatly affect the AMEs on the characteristics of the ethnic minority person. The most relevant characteristics of the partner that predict being in an inter-ethnic partnership are being born in the UK, being an English native speaker, and not being religious. These are, unsurprisingly, almost perfect predictors. The activity status and occupation of the parents when the respondent was fourteen years old does not seem to be an important determinant of being in an inter-ethnic partnership for both ethnic minority individuals and their partners.

Finally, S3, includes several characteristics of the household. Except for the AME of living in a LDA dummy, all other AMEs are not statistically significant. The AME of LDA instead suggests that inter-ethnic partnerships are more likely to live in areas with a low density of ethnic minority residents.

Conditioning on the largest amount of information possible allows us to make a better comparison between treated and control individuals, but it also increases the likelihood of having some individuals outside of the common support. The literature advises on including as many variables as possible to build the propensity score (Emsley, Lunt, Pickles, Dunn, et al., 2008) and, as we have already stated, these should not by affected by the partnership itself (Caliendo & Kopeinig, 2008), i.e. the household variables included in S3. In the following analysis we will hence both use the first and second specification, S1 and S2, separately to model the selection equation. In S2 we have very strong predictors, such as whether the partner is English mother-tongue. Given the presence of very strong predictors in S2, we would expect that introducing them in the equation to derive the PS will reduce the similarity of its distribution between the two groups. However, we argue that characteristics such as whether the partner is born in the UK and whether he or she is an English native speaker are crucial to identify couples who are actually comparable. This is true especially when the main purpose of comparing the two types of partnerships is to infer the role of social integration on labour market outcomes. The fact that the partner, independently of whether she or he is white British or of any other ethnic group, was brought up in the country and is an English native speaker, might help the ethnic minority individual to a great extent, especially if he or she is a second generation migrant.[15] We hence consider that it is important to include these characteristics in the PS analysis. In the PSM analysis we use both specifications, S1 and S2, separately to see how the quality of the match and the ATT estimates respond to the inclusion of the partner's characteristics in the PS.

3.4.2 Are inter- and co-ethnic partnerships comparable?

Figures 3.2 and 3.3 show the density of the propensity score (i.e. the probability of ending up in a partnership with a white majority person) for ethnic minorities in an inter-ethnic and in a co-ethnic partnership, and separately so for men and women. For each outcome we have two graphs, one refers to the propensity score when we condition on the characteristics of the ethnic minority person only (S1), and the other refers to the specification where we additionally condition on the characteristics of the partner (S2). From all these graphs, two things emerge (which are valid for both men and women). The first one is that, although ethnic minority individuals in inter-ethnic partnerships have a propensity score distributed evenly across the whole distribution, especially when using S1, ethnic minorities in a co-ethnic partnerships have their probability mass concentrated near a propensity score equal to zero. This indicates that most of ethnic minorities in co-ethnic partnerships have a probability very close to zero of being in a relationship with a white majority person. Hence, ethnic minorities in the two types of partnerships are very different in their observable characteristics. The second thing to notice is that when we include the characteristics of the partner alongside those of the ethnic minority person, the two groups of ethnic minorities become even less comparable: the density of the co-ethnic group is even more

[15] Think, for example, about proof-reading CVs and cover letters for job interviews, as well as understanding several institutional aspects of the job market which might not be obvious for someone who is not familiar with such a system.

skewed to the left of the graph, and that of the inter-ethnic partnerships is mainly concentrated towards the right of the graph.

Table 3.5 and Table 3.6 show the estimates from the PSM estimator. The outcomes are divided into three panels. Panel A shows the activity status outcomes, Panel B the occupational outcomes, and Panel C the salary outcome. For each of them we show the ATT obtained by imposing a caliper of 0.01 and of 0.10, and by using a propensity score with only the characteristics of the ethnic minority individual (S1) and with those of the ethnic minority person and his or her partner (S2). The last four columns report the three measures of quality of the matching discussed in Section 3.2.1 (the pseudo R squared, the p-value of the test of jointly significance, and the mean bias). These are reported before (the value within brackets) and after the matching is implemented to show how the covariates have been balanced after the matching has been realized. Finally, the last column shows the number of observations in co-ethnic and, after the semi-column, in inter-ethnic partnerships that has been used for each match depending on the caliper (either 0.010 or 0.10) and the PS (derived either from S1 or S2) used. In square brackets we report the number of observations in the inter-ethnic group that lie outside the common support.

As we would expect from the distributions of the propensity score, there are very few cases where a good balance of the characteristics of the matched individuals is achieved. For example, a MB equal or under 7 (this is the maximum of MB that is considered as acceptable in Caliendo (2006)) is never achieved for men and only in 5 cases out of 12 (4 different specifications across 3 different types of outcomes) for women. Looking at the bias by each variable (not shown in the tables), the characteristics that do not see a bias reduction after matching are: migrant generation, father and mother occupation (when we use S1), and also religiosity, ethnicity, and qualification of the ethnic minority person and his or her partner when we use S2.

Applying a caliper of 0.01 slightly increases the quality of the matches by excluding a few treated observations, as we would expect. Also from this we can see that including the partner's characteristics implies that a higher number of treated individuals fall outside the common support compared to when only ethnic minority characteristics are included as determinants of being in an inter-ethnic partnership. We can see this from the last column in the table, where we have the number of individuals in the common support who are in a co-ethnic partnership followed by, after the semicolon, those in an inter-ethnic partnership. Finally, in the square brackets we have the treated individuals who are out of the common support. Furthermore, when we use S2 for the propensity score and we use the largest caliper, i.e. we allow matches between observations which are very far away in terms of their likelihood of having a white British partner, we strongly reject the chi-square test and get relatively high values in the pseudo-R squared. All these suggest that the comparability of inter- and co-ethnic partnerships is particularly challenged when we also consider the partner's characteristics. Moreover, in several models the partner's characteristics are perfect predictors of being in an inter-ethnic partnership. For example, in Table 3.6 all white British partners are English native speakers for the occupational and salary outcomes. As a result, we exclude the partner's language from the list of the covariates used to get the PS (this specification is denoted as S2* in the tables). This is not surprising since in the previous section we saw that some of the partner's characteristics are almost perfect predictors of getting into an inter-ethnic partnership. These considerations reinforce the suggestion that the two groups are too different in their characteristics to be considered comparable and this is especially due to the difference in the characteristics of the partners in the two types of partnerships.

Finally, when we consider the cases where there is a good quality match (when MB $\leq$ 7), and, hence, we consider only women (Table 3.6), we find few statistically significant ATT. These indicate that women in inter-ethnic partnerships compared to their counterparts are less likely to be in a paid job (by 11 percentage points) and more likely to be unemployed when the PS is derived by both

S1 and S2 (by 4 percentage points) - Panel A - , which is opposite to the raw data. Furthermore, Panel B shows that among employees, women in inter-ethnic partnerships are more likely to work in intermediate jobs (by 8 percentage points) than in all other possible occupations. The results in Panel A of Table 3.6 are interesting because they are consistent with the previous literature suggesting that individuals who self-select into inter-ethnic partnerships share some characteristics which make them less likely to be successful in the labour market compared to co-ethnic individuals (see the discussion in the last paragraph of Section 3.2).

The main point to take away from the PSM analysis is that the differences in ethnic minorities' and their partners' characteristics are what explains the differences in labour market outcomes of ethnic minorities, rather than the kind of partnership itself.

3.4.3 Sub-sample analysis

It might be that the scarce comparability of the two groups is given by the fact that we allow them to be too heterogeneous. We hence restrict the samples of men and women to certain subgroups. This allows us to compare more comparable individuals. Furthermore, this strategy also allows us to test several hypotheses, (conditioning on achieving good quality matches) on the possible channels driving the differences in labour market outcomes of ethnic minorities in co- and inter-ethnic partnerships.

Being with a white majority partner could affect the language proficiency of ethnic minorities. This implies that the lower the initial, pre-partnership English proficiency level, the greater the benefit of having a partner whose first language is English. However, those with pre-partnership English proficiency could profit more from a partnership with a majority person. Hence, we test this hypothesis by looking at the sub-sample of ethnic minority individuals for which English is the first language. We cannot implement it for individuals who are not English mother-tongue because we would have too few observations to match.

Second, in line with the findings of different degrees of penalties among generations of migrants (K. Clark & Lindley, 2006; Dustmann et al., 2011; Heath & Cheung, 2007; Modood et al., 1997), we implement our model separately for ethnic minorities born in the UK and not born in the UK so that we can ascertain whether pre-partnership integration has a particular relevant role in this context.

Third, we assess the social network hypothesis, i.e. whether white British partners facilitate the access to networks mainly composed of other majority individuals. Although we do not have a proper measure of social network, we do have information about whether the individuals are living in a LDA, i.e. an area with a low density of ethnic minority residents. We will use this as a crude proxy of social connections. Living in a non-LDA indicates that the person is living in a zone with a high concentration of non-white British, possibly co-ethnic, minority groups. While a person in an inter-ethnic partnership always has access to majority population networks (through their white majority partner), this is not obvious for an ethnic minority person with a co-ethnic partner, especially if they live in a non-LDA. However, to have enough observations we can only estimate the effects of being in an inter-ethnic partnership for individuals living in non-LDAs.

Finally, we divide the ethnic groups by their probability of being in an inter-ethnic union, so that we have a subgroup of Irish and other white origins (high probability of being in an inter-ethnic partnership), and one of the remaining ethnic groups (low probability of being with a white majority partner).[16]

For all these subgroups we implement a Kernel type PSM with a caliper equal to 0.01, the most restrictive one, and for each outcome we implement specifications S1 and S2. The results are shown in Table 3.7 and Table 3.8.

It is clear that, even among more homogeneous groups of ethnic minority men and women, the comparability between individuals in co- and inter-ethnic partnerships is very scarce. When we look at the outcomes, we find a few statistically significant ATT for women on the activity status and occupation but the qual-

[16] Several field experiments showed how especially visible ethnic minorities suffer from discrimination in the labour market (Wrench & Modood, 2001).

ity of the match remains pretty low, as indicated by the mean bias. However, for those outcomes for which we observe a mean bias less or equal to 7 (women born outside the UK and women who are English native speakers), we do not find any statistically significant effect of being in a co- and inter-ethnic partnership on labour market outcomes. If we consider even worse quality matches (a mean bias up to 8) we find statistically significant results for women living in LDA that go in the same direction of the findings in the previous section, i.e. lower likelihood of being employed for women with a white British partner. Overall, given the lack of comparability between the two types of partnerships, we are unable to shed any light on the possible mechanisms explaining differences in ethnic minority labour market outcomes.

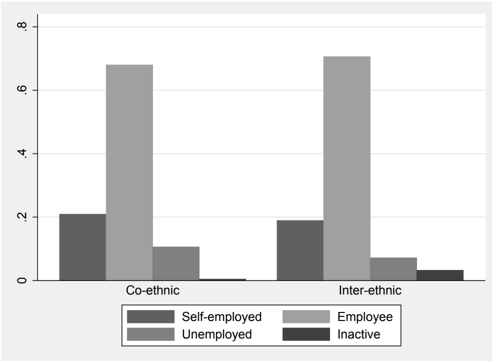
3.5 Conclusion

In this chapter we contribute to the literature on ethnic minority disadvantages in the UK labour market. We do so by establishing whether a recent way of inferring the ethnic minority penalties in the labour market could be adopted in the context of the UK. This method compares the labour market outcomes of individuals in a partnership with a co-ethnic person with those in a partnership with an individual belonging to the majority group. The dataset that we use, Understanding Society, is very rich in the characteristics of both individuals in partnerships. Thus, we build our analysis on the observable characteristics of the individuals observed in the partnership. By using the diagnostic tests on the match quality provided by propensity score matching we show that ethnic minority individuals in the two types of partnerships are rarely comparable in their observable characteristics.

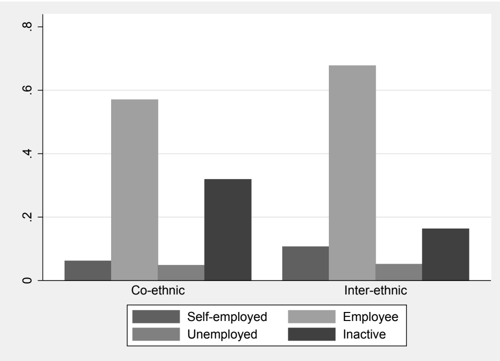
The raw data show differences between ethnic minority individuals in co- and inter-ethnic partnerships in several dimensions of the labour market: activity status, socio-economic occupation, and salary. However, our results suggest that these differences are not driven by the partnership itself, but by the differences in the characteristics between ethnic minorities in the different type of partnerships and the characteristics of their partners.

Figure 3.1: Labour market outcomes: inter- and co-ethnic partnerships

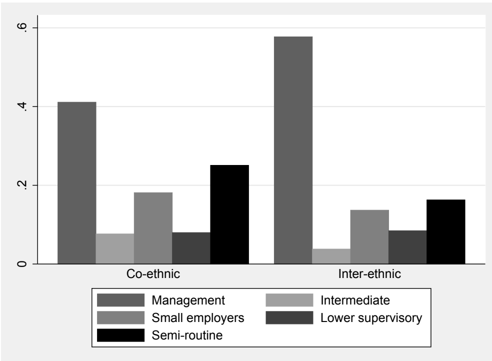
(a) Activity status - men



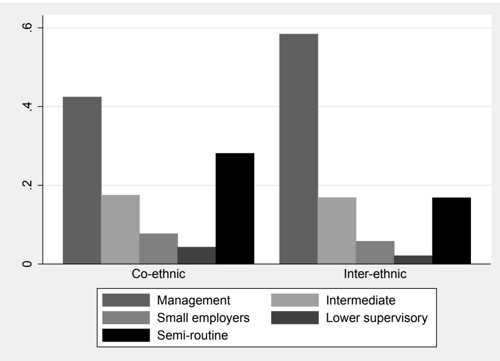
(b) Activity status - women



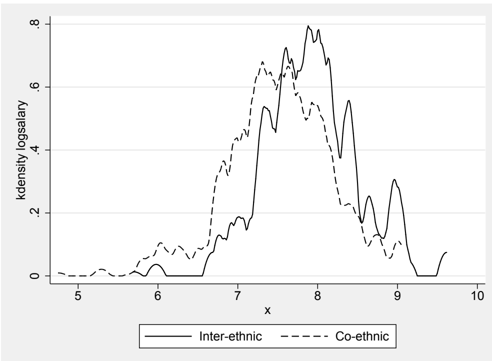
(c) Occupation - men



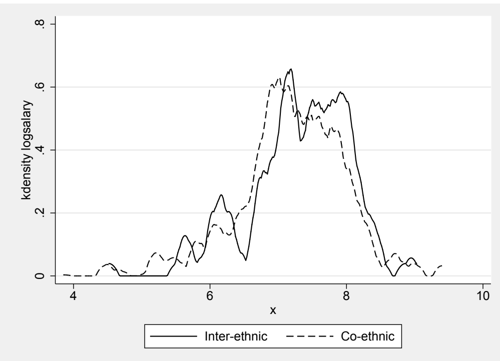
(d) Occupation - women



(e) Salary - men



(f) Salary - women



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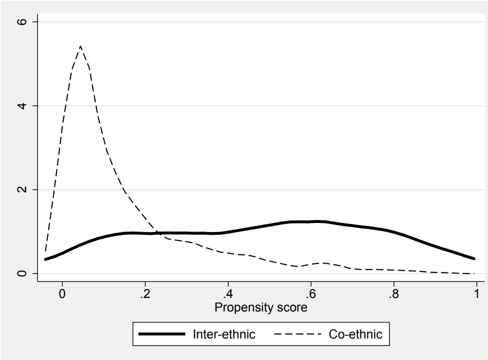
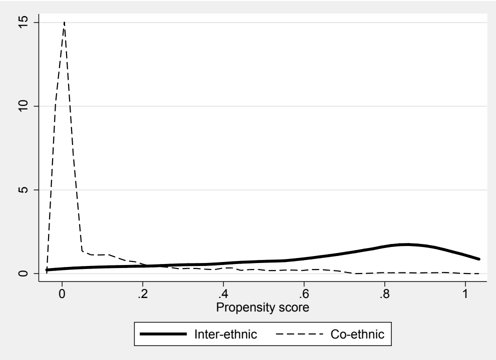
Notes. Descriptive statistics of labour market outcomes by gender and type of relationship on the final sample described in Section 3.3.1. The outcomes are described in Section 3.3.2

Figure 3.2: PS kernel densities: men

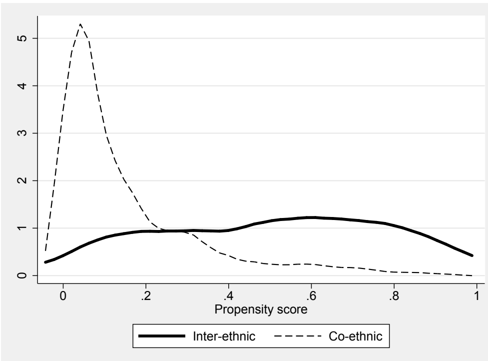
(a) Activity status S1



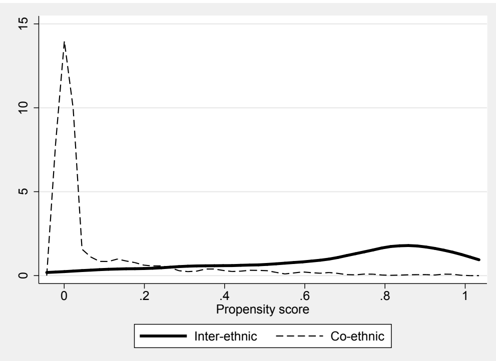
(b) Activity status S2



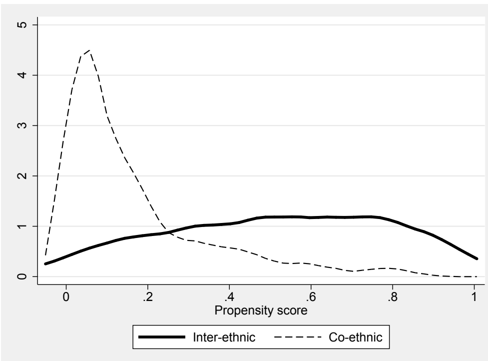
(c) Occupation S1



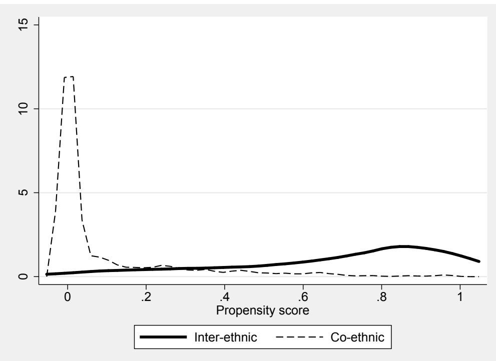
(d) Occupation S2



(e) Salary S1



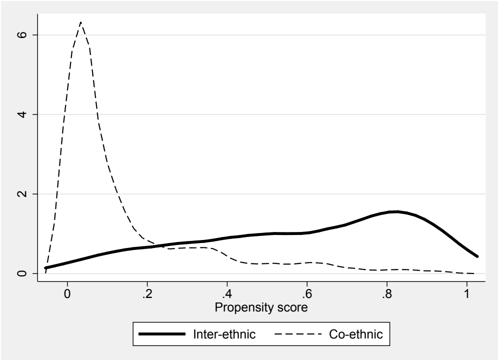
(f) Salary S2



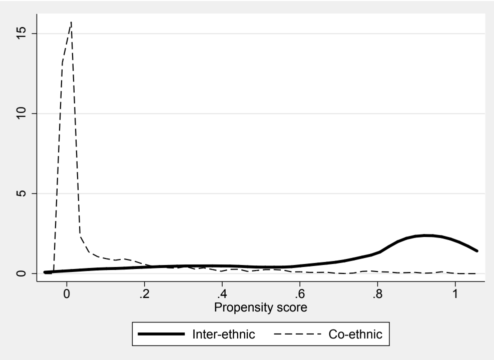
Notes. Kernel densities of the propensity score by type of partnership derived from a logit regression where we use either specification S1 or specification S2, as described in Section 3.4.1.

Figure 3.3: PS kernel densities: women

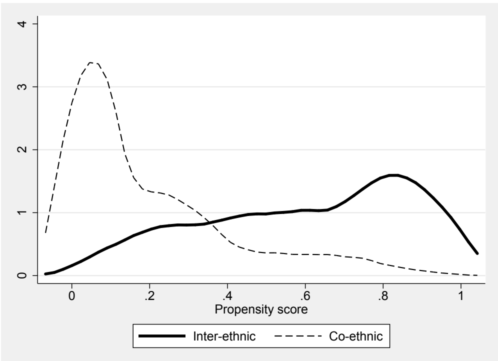
(a) Activity status S1



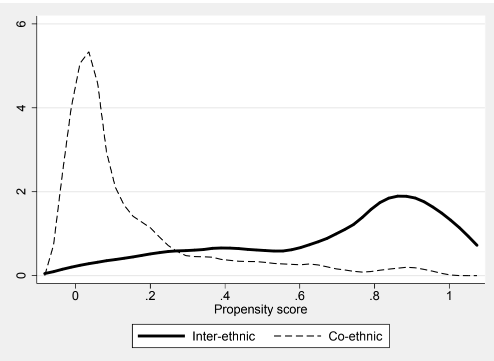
(b) Activity status S2



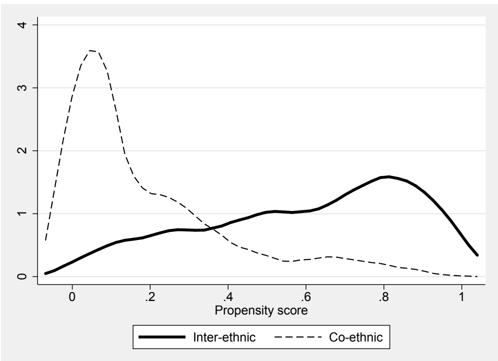
(c) Occupation S1



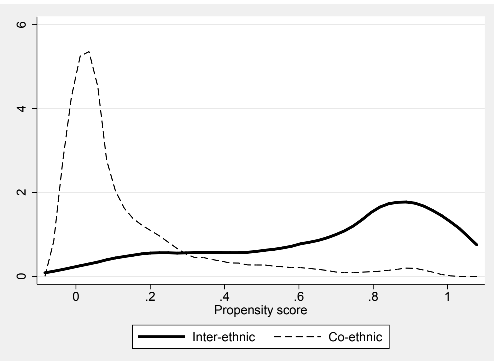
(d) Occupation S2



(e) Salary S1



(f) Salary S2



Notes. Kernel densities of the propensity score by type of partnership derived from a logit regression where we use either specification S1 or specification S2, as described Section in 3.4.1.

Table 3.1: Sample selection and restrictions

	N
Original sample	50,994
Keep full respondent	47,732
Keep population between 18/64 years old	37,497
Keep married or living as couple	24,295
Keep only ethnicity well defined (drop unknown/gipsy traveller/mixed/other Asian or Black background)	23,192
Keep only if we find a match of the person with someone of opposite sex defined as: husband/wife or partner/cohabitee	22,955
Intermediate sample	22,955
Drop white British in co-ethnic partnerships	4,988
Drop ethnic minority outside of the labour market (retired, students, disabled, in training), homosexual couples and couples not living in the same hh	3,096
Keep if partnership started after ethnic minorities arrived in the UK (for first generation migrant)	2,161
Drop if number of childrens is unknown	2,158
Drop if generation of migration is unknown	2,118
Final sample	2,118

Notes. List of all sample selections and restrictions made from the initial number of observations in the dataset to the the the final sample as described in 3.3.1.

Table 3.2: Summary statistics: men

Variable	Co-ethnic Mean	Co-ethnic Std. Dev.	Inter-ethnic Mean	Inter-ethnic Std. Dev.
a) Ethnic minority's characteristics				
Age	38.804	9.394	42.394	10.602
Irish	0.085	0.279	0.296	0.457
White other	0.234	0.424	0.405	0.491
Indian	0.301	0.459	0.079	0.270
Pakistani	0.156	0.363	0.033	0.179
Bangladeshi	0.040	0.195	0.053	0.225
Chinese	0.029	0.168	0.016	0.125
Caribbean	0.049	0.215	0.078	0.269
African	0.106	0.308	0.038	0.192
Religious	0.829	0.376	0.544	0.498
1st generation $\leq$14y.o.	0.128	0.334	0.130	0.336
1st generation >14y.o. & YSA$\leq$5	0.177	0.382	0.065	0.246
1st generation >14y.o. & YSA>5	0.424	0.494	0.305	0.461
2nd generation	0.210	0.407	0.341	0.474
3rd+ generation	0.060	0.238	0.159	0.366
Degree	0.382	0.486	0.518	0.500
Other higher	0.122	0.328	0.112	0.316
A level	0.142	0.349	0.154	0.361
GCSE	0.127	0.333	0.112	0.316
Other qual or no qualification	0.226	0.419	0.103	0.304
English first language	0.423	0.494	0.762	0.426
English not first language	0.577	0.494	0.238	0.426
Father occ.: managerial/professional	0.248	0.432	0.220	0.415
Father occ.: intermediate/small employer	0.268	0.443	0.195	0.396
Father occ.: lower/semi-routine/unemployed	0.317	0.465	0.382	0.486
Father occ.: not working	0.081	0.273	0.078	0.268
Father occ.: other/unknown	0.086	0.280	0.124	0.329
Mother occ.: managerial/professional	0.135	0.342	0.209	0.407
Mother occ.: intermediate/small employer	0.082	0.274	0.144	0.351
Mother occ.: lower/semi-routine/unemployed	0.168	0.374	0.213	0.409
Mother occ.: not working	0.597	0.491	0.413	0.492
Mother occ.: other/unknown	0.018	0.134	0.020	0.141
b) Partner's characteristics				
Age	35.412	9.396	40.661	10.531
Religious	0.859	0.348	0.534	0.499
Born in the UK	0.675	0.468	0.973	0.162
Degree	0.369	0.483	0.388	0.487
Other higher	0.152	0.359	0.157	0.364
A level	0.133	0.340	0.165	0.371
GCSE	0.122	0.327	0.221	0.415
Other qual or no qualification	0.073	0.260	0.018	0.131
English first language	0.378	0.485	0.990	0.099
Father occ.: managerial/professional	0.268	0.443	0.365	0.481
Father occ.n: intermediate/small employer	0.206	0.404	0.181	0.385
Father occ.: lower/semi-routine/unemployed	0.317	0.465	0.310	0.463
Father occ.: not working	0.104	0.305	0.067	0.250
Father occ.: other/unknown	0.105	0.307	0.076	0.266
Mother occ.: managerial/professional	0.152	0.359	0.239	0.427
Mother occ.: intermediate/small employer	0.070	0.255	0.154	0.360
Mother occ.: lower/semi-routine/unemployed	0.206	0.404	0.251	0.434
Mother occ.: not working	0.556	0.497	0.340	0.474
Mother occ.: other/unknown	0.016	0.127	0.016	0.125
c) Household's characteristics				
Cohabiting	0.148	0.355	0.226	0.419
Living in London	0.347	0.476	0.170	0.375
Living in LDA	0.154	0.361	0.503	0.500
Total N of childrens	1.197	1.209	1.009	1.137

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Table 3.2 – *Continued from previous page*

Variable	Co-ethnic Mean	Co-ethnic Std. Dev.	Inter-ethnic Mean	Inter-ethnic Std. Dev.
Presence of children(s) 0-4 y.o.	0.415	0.493	0.275	0.446
Presence of children(s) 5-15 y.o.	0.380	0.485	0.392	0.488
Cares for disabled/long-term sick in hh	0.046	0.210	0.038	0.192
Partner: Employed	0.585	0.493	0.713	0.452
Partner: Unemployed	0.047	0.212	0.029	0.169
Partner: Other	0.368	0.482	0.258	0.437
N	870		161	

Notes. The sample is composed of ethnic minorities in a partnership with a co-ethnic person (co-ethnic) or with a white British person (inter-ethnic). "YSA" stands for Years Since Arrival and denotes the years since first generation migrants arrived in the UK. "LDA" stands for Low Density Area and indicates a neighbourhood in which the density of ethnic minority residents is low. A detailed description of the sample is available in Section 3.3.1 and of the variables in Section 3.3.2.

Table 3.3: Summary statistics: women

	Co-ethnic		Inter-ethnic	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
a) Ethnic minority's characteristics				
Age	36.414	9.808	39.004	9.316
Irish	0.089	0.284	0.237	0.425
White other	0.224	0.417	0.618	0.486
Indian	0.311	0.463	0.033	0.179
Pakistani	0.162	0.368	0.014	0.116
Bangladeshi	0.046	0.209	0.014	0.117
Chinese	0.029	0.168	0.020	0.138
Caribbean	0.051	0.219	0.049	0.216
African	0.089	0.285	0.015	0.123
Religious	0.875	0.330	0.612	0.487
1st generation $\leq$14y.o.	0.136	0.343	0.110	0.313
1st generation >14y.o. & YSA$\leq$5	0.170	0.376	0.120	0.325
1st generation >14y.o. & YSA>5	0.408	0.491	0.478	0.500
2nd generation	0.236	0.425	0.240	0.427
3rd+ generation	0.050	0.217	0.052	0.221
Degree	0.337	0.473	0.535	0.499
Other higher	0.154	0.361	0.149	0.356
A level	0.135	0.342	0.090	0.286
GCSE	0.144	0.352	0.084	0.278
Other qual or no qualification	0.230	0.421	0.142	0.349
English first language	0.392	0.488	0.631	0.482
English not first language	0.608	0.488	0.369	0.482
Father occ.: managerial/professional	0.228	0.420	0.324	0.468
Father occ.: intermediate/small employer	0.202	0.401	0.199	0.399
Father occ.: lower/semi-routine/unemployed	0.340	0.474	0.327	0.469
Father occ.: not working	0.120	0.325	0.046	0.209
Father occ.: other/unknown	0.109	0.312	0.104	0.305
Mother occ.: managerial/professional	0.138	0.345	0.247	0.431
Mother occ.: intermediate/small employer	0.059	0.236	0.136	0.343
Mother occ.: lower/semi-routine/unemployed	0.207	0.406	0.260	0.439
Mother occ.: not working	0.579	0.494	0.345	0.475
Mother occ.: other/unknown	0.016	0.127	0.012	0.107
b) Partner's characteristics				
Age	39.499	9.883	41.771	9.816
Religious	0.846	0.361	0.369	0.483
Born in the UK	0.708	0.455	0.970	0.172
Degree	0.358	0.479	0.447	0.497
Other higher	0.107	0.309	0.141	0.348
A level	0.151	0.358	0.124	0.330
GCSE	0.134	0.340	0.189	0.391
Other qual or no qualification	0.114	0.318	0.076	0.265
English first language	0.389	0.488	0.991	0.093
Father occ.: managerial/professional	0.248	0.432	0.378	0.485
Father occ.: intermediate/small employer	0.304	0.460	0.191	0.393
Father occ.: lower/semi-routine/unemployed	0.277	0.448	0.316	0.465
Father occ.: not working	0.084	0.277	0.056	0.230
Father occ.: other/unknown	0.087	0.282	0.059	0.235
Mother occ.: managerial/professional	0.127	0.333	0.182	0.386
Mother occ.: intermediate/small employer	0.087	0.283	0.149	0.356
Mother occ.: lower/semi-routine/unemployed	0.158	0.365	0.272	0.445
Mother occ.: not working	0.607	0.488	0.371	0.483
Mother occ.: other/unknown	0.022	0.145	0.026	0.160
c) Household's characteristics				
Cohabiting	0.144	0.352	0.297	0.457
Living in London	0.356	0.479	0.173	0.378
Living in LDA	0.147	0.354	0.476	0.499
Total N of childrens	1.220	1.254	0.843	0.967

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Table 3.3 – *Continued from previous page*

	Co-ethnic		Inter-ethnic	
Variable	Mean	Std. Dev.	Mean	Std. Dev.
Presence of children(s) 0-4 y.o.	0.381	0.486	0.240	0.427
Presence of children(s) 5-15 y.o.	0.407	0.491	0.356	0.479
Cares for disabled/long-term sick in hh	0.064	0.244	0.043	0.203
Partner: Employed	0.852	0.355	0.869	0.337
Partner: Unemployed	0.086	0.280	0.068	0.251
Partner: Other	0.062	0.241	0.063	0.244
N	858		229	

Notes. The sample is composed of ethnic minorities in a partnership with a co-ethnic person (co-ethnic) or with a white British person (inter-ethnic). "YSA" stands for Years Since Arrival and denotes the years since first generation migrants arrived in the UK. "LDA" stands for Low Density Area and indicates a neighbourhood in which the density of ethnic minority residents is low. A detailed description of the sample is available in Section 3.3.1 and of the variables in Section 3.3.2.

Table 3.4: The determinants of being in an inter-ethnic partnership

	Men			Women		
	S1	S2	S3	S1	S2	S3
a) Ethnic minority person's characteristics						
(Ethnicity: Irish)						
White other	-0.065	0.018	-0.007	0.061	0.115**	0.100*
	(0.082)	(0.040)	(0.040)	(0.085)	(0.043)	(0.046)
Indian	-0.358**	-0.178**	-0.168**	-0.491**	-0.331**	-0.309**
	(0.072)	(0.043)	(0.038)	(0.071)	(0.039)	(0.046)
Pakistani	-0.332**	-0.119*	-0.117*	-0.495**	-0.258**	-0.228**
	(0.079)	(0.056)	(0.053)	(0.076)	(0.059)	(0.063)
Bangladeshi	-0.069	0.094*	0.065	-0.357**	-0.126+	-0.132+
	(0.109)	(0.044)	(0.045)	(0.112)	(0.068)	(0.070)
Chinese	-0.354**	-0.181**	-0.188**	-0.324**	-0.128	-0.121
	(0.102)	(0.069)	(0.052)	(0.111)	(0.086)	(0.076)
Caribbean	-0.222**	-0.131**	-0.115**	-0.372**	-0.227**	-0.203**
	(0.081)	(0.046)	(0.044)	(0.073)	(0.046)	(0.052)
African	-0.288**	-0.146*	-0.144*	-0.476**	-0.236**	-0.212**
	(0.084)	(0.057)	(0.057)	(0.075)	(0.059)	(0.061)
Religious	-0.178**	-0.073*	-0.074*	-0.140**	-0.021	-0.014
	(0.043)	(0.029)	(0.033)	(0.041)	(0.028)	(0.027)
Age	-0.019	-0.034**	-0.030*	0.035**	0.013	0.018+
	(0.012)	(0.011)	(0.012)	(0.012)	(0.010)	(0.010)
Age2	0.000*	0.000**	0.000**	-0.000**	-0.000	-0.000+
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
(Migrant generation: 1st generation≤14y.o.)						
1st gen.>14y.o. & YSA≤5	-0.108	0.074	0.084+	-0.134*	-0.051	-0.057
	(0.068)	(0.048)	(0.049)	(0.068)	(0.052)	(0.052)
1st gen.>14y.o. & YSA>5	-0.034	-0.004	-0.003	-0.082+	-0.136**	-0.130**
	(0.053)	(0.037)	(0.034)	(0.048)	(0.030)	(0.030)
2nd generation	0.052	0.030	0.050	-0.030	-0.074**	-0.064*
	(0.054)	(0.031)	(0.032)	(0.048)	(0.027)	(0.027)
3rd/4th generation	-0.066	-0.043	-0.018	-0.227**	-0.207**	-0.188**
	(0.068)	(0.037)	(0.036)	(0.064)	(0.038)	(0.041)
(Qualification: degree)						
Other higher	-0.117*	-0.053	-0.047	-0.055	-0.016	-0.021
	(0.048)	(0.038)	(0.039)	(0.048)	(0.029)	(0.030)
A level	-0.120*	-0.045	-0.044	-0.091+	-0.066*	-0.062*
	(0.050)	(0.034)	(0.030)	(0.052)	(0.030)	(0.031)
GCSE	-0.139**	-0.035	-0.043	-0.055	-0.035	-0.024
	(0.047)	(0.034)	(0.032)	(0.055)	(0.036)	(0.035)
Other	-0.211**	-0.080*	-0.064+	-0.069	-0.046	-0.063*
	(0.039)	(0.037)	(0.036)	(0.044)	(0.029)	(0.032)
English no first language	-0.118**	0.043	0.053+	-0.159**	0.028	0.027
	(0.044)	(0.036)	(0.032)	(0.043)	(0.029)	(0.028)
(Father's occupation: Managerial/professional)						
Int./small empl.	0.012	-0.011	0.007	-0.058	-0.026	-0.031
	(0.044)	(0.035)	(0.028)	(0.048)	(0.034)	(0.032)
Lower/semi-routine/unemp.	0.096*	0.064+	0.063*	-0.060	-0.014	-0.011
	(0.046)	(0.034)	(0.027)	(0.043)	(0.026)	(0.026)
Not working	0.117+	0.091+	0.084+	-0.133*	-0.025	-0.017
	(0.069)	(0.050)	(0.046)	(0.060)	(0.043)	(0.040)
Other/Unknown	0.084	0.025	0.025	-0.016	-0.008	-0.015
	(0.053)	(0.040)	(0.035)	(0.052)	(0.036)	(0.036)
(Mother's occupation: Managerial/professional)						
Int./small empl.	0.026	0.021	0.011	0.058	0.062	0.059
	(0.065)	(0.050)	(0.043)	(0.059)	(0.040)	(0.037)
Lower/semi-routine/unemp.	-0.067	-0.016	-0.020	-0.003	0.024	0.018

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Table 3.4 – *Continued from previous page*

	Men			Women		
	S1	S2	S3	S1	S2	S3
	(0.054)	(0.039)	(0.034)	(0.051)	(0.030)	(0.027)
Not working	-0.065	-0.032	-0.016	-0.026	0.035	0.039
	(0.052)	(0.037)	(0.030)	(0.048)	(0.032)	(0.029)
Other/Unknown	0.027	0.054	0.052	0.002	0.141**	0.139*
	(0.103)	(0.069)	(0.062)	(0.155)	(0.053)	(0.057)
b) Partner's characteristics						
Religious		-0.137**	-0.110**		-0.101**	-0.083**
		(0.030)	(0.034)		(0.027)	(0.025)
Age		0.026*	0.027*		-0.006	-0.007
		(0.011)	(0.011)		(0.010)	(0.010)
Age squared		-0.000*	-0.000*		0.000	0.000
		(0.000)	(0.000)		(0.000)	(0.000)
Born in the UK		0.193**	0.174**		0.194**	0.167**
		(0.044)	(0.039)		(0.051)	(0.047)
(Qualification: degree)						
Other higher		0.032	-0.002		-0.026	-0.027
		(0.030)	(0.034)		(0.033)	(0.033)
A level		0.044	0.031		0.018	0.024
		(0.033)	(0.028)		(0.027)	(0.026)
GCSE		0.029	0.012		0.037	0.032
		(0.033)	(0.030)		(0.025)	(0.024)
Other		-0.089+	-0.098		0.017	0.031
		(0.052)	(0.062)		(0.046)	(0.047)
Unknown		-0.054	-0.061		-0.069	-0.062
		(0.039)	(0.040)		(0.060)	(0.052)
English not the first language		-0.356**	-0.349**		-0.466**	-0.461**
		(0.025)	(0.026)		(0.026)	(0.028)
(Father's occupation: Managerial/professional)						
Int./small empl.		-0.030	-0.032		-0.022	-0.023
		(0.035)	(0.034)		(0.027)	(0.026)
Lower/semi-routine/unemployed		-0.052*	-0.064*		-0.000	-0.009
		(0.026)	(0.025)		(0.024)	(0.024)
Not working		-0.049	-0.048		-0.010	-0.041
		(0.036)	(0.037)		(0.052)	(0.056)
Other/Unknown		-0.035	-0.021		-0.085*	-0.094**
		(0.040)	(0.039)		(0.033)	(0.030)
(Mother's occupation: Managerial/professional)						
Int./small empl.		0.009	0.013		0.024	0.021
		(0.050)	(0.043)		(0.050)	(0.047)
Lower/semi-routine/unemployed		-0.012	-0.001		0.054	0.051+
		(0.035)	(0.035)		(0.034)	(0.031)
Not working		-0.026	-0.021		-0.001	0.007
		(0.033)	(0.029)		(0.033)	(0.028)
Other/Unknown		0.027	0.009		0.114*	0.119*
		(0.078)	(0.072)		(0.057)	(0.059)
c) Household's characteristics						
Married			-0.027			-0.011
			(0.033)			(0.028)
Living in London			-0.038			-0.038
			(0.025)			(0.028)
Presence of childrens 0-4 y.o.			-0.029			-0.001
			(0.029)			(0.035)
Presence of childrens 5-15 y.o.			-0.002			0.020
			(0.033)			(0.032)
N of childrens			0.007			-0.017
			(0.018)			(0.019)
(Partner's activity: employed)						
Unemployed			0.078			0.038

Continued on next page

Table 3.4 – *Continued from previous page*

	Men			Women		
	S1	S2	S3	S1	S2	S3
			(0.053)			(0.036)
Other			0.034			-0.018
			(0.027)			(0.037)
Living in LDA			0.132**			0.081**
			(0.030)			(0.028)
Responsible for disable person			-0.019			-0.021
			(0.048)			(0.037)
Observations		1,031			1,087	
Pseudo-R2	0.319	0.582	0.623	0.385	0.668	0.688

Notes. This table displays average marginal effects from logit regressions on the probability of being in an inter-ethnic partnership. For each gender, two specifications are used: S1 includes only ethnic minority persons' characteristics, S2 also includes partners' characteristics, and S3 includes household's characteristics. Robust standard errors in parentheses. ** p<0.1, * p<0.05, + p<0.01.

Table 3.5: PSM estimates: men

A	**Self-emp.**	**Employee**	**Unemp.**	**Inactive**		**Caliper**	**Ps-R2**	**p>chi2**	**MB**	**CS[out]**
ATT S1	0.007	0.005	-0.047	*0.035*		0.010	(0.299)0.054	(0.000)0.786	(27.4)8.8	870;141[20]
	0.050	0.065	0.040	0.021						
ATT S1	-0.024	0.012	-0.021	0.033		0.100	(0.299)0.053	(0.000)0.643	(27.4)8.4	870;141
	0.047	0.058	0.028	0.017						
ATT S2	0.062	-0.101	0.024	0.015		0.010	(0.503)0.120	(0.000)0.588	(31.4)11.6	870;127[34]
	0.058	0.064	0.038	0.017						
ATT S2	0.027	-0.064	-0.001	0.038		0.100	(0.503)0.133	(0.000)0.073	(31.4)10.8	870;161
	0.068	0.067	0.034	0.016						
Obs.	1031	1031	1031	1031						
B	**Manag.**	**Interm.**	**Small emp.**	**Lower sup.**	**Semi-routine**	**Caliper**	**Ps-R2**	**p>chi2**	**MB**	**CS[out]**
ATT S1	-0.044	-0.029	0.027	0.029	0.017	0.010	(0.311)0.059	(0.000)0.831	(27.5)9.1	723;122[16]
	0.067	0.035	0.043	0.032	0.046					
ATT S1	-0.011	-0.037	0.004	0.009	0.034	0.100	(0.311)0.049	(0.000)0.885	(27.5)8.7	723;138
	0.066	0.028	0.051	0.028	0.042					
ATT S2	-0.013	-0.051	0.095	-0.003	-0.028	0.010	(0.512)0.168	(0.000)0.428	(31.4)12.8	723;99[39]
	0.104	0.059	0.055	0.055	0.073					
ATT S2	-0.006	-0.078	0.027	-0.002	0.059	0.100	(0.512)0.161	(0.000)0.050	(31.4)13.4	723;138
	0.106	0.069	0.065	0.061	0.047					
Obs.	861	861	861	861	861					
C	**(log)Salary**					**Caliper**	**Ps-R2**	**p>chi2**	**MB**	**CS[out]**
ATT S1	**0.203**						(0.307)0.110	(0.000)0.282	(28.7)13.8	539;97[13]
	0.089									
ATT S1	**0.168**					0.100	(0.307)0.079	(0.000)0.566	(28.7)11.6	539;110
	0.072									
ATT S2	0.038					0.010	(0.531)0.165	(0.000)0.863	(32.6)12.3	539;74[36]
	0.133									
ATT S2	0.060					0.100	(0.531)0.214	(0.000)0.020	(32.6)15.0	539;110
	0.112									
Obs.	649									

Notes. This table displays the estimated average treatment effects for the treated from a Kernel type PSM estimator. Either S1 or S2 are implemented to derive the propensity score. The standard errors (bootstrapped with 200 reps) are reported below each ATT. *italic* $p<0.1$, **bold** $p<0.05$, ***italic and bold*** $p<0.01$. Two different calipers are applied. The columns Ps-R2, p>chi2, and MB show the quality of the matches (before) and after the matching is implemented. The last column reports the number of individuals in co-ethnic partnerships and in inter-ethnic partnerships who are in the common support [number of observations in inter-ethnic partnerships outside the common support].

Table 3.6: PSM estimates: women

A	**Self-emp.**	**Employee**	**Unemp.**	**Inactive**		**Caliper**	**Ps-R2**	**p>chi2**	**MB**	**CS[out]**
ATT S1	0.014	**-0.115**	**0.041**	0.060		0.010	(0.432)0.040	(0.000)0.640	(29.6)7.1	858;213[16]
	0.036	0.051	0.018	0.039						
ATT S1	0.019	-0.070	**0.039**	0.012		0.100	(0.432)0.029	(0.000)0.898	(29.6)5.5	858;229
	0.037	0.052	0.016	0.045						
ATT S2	0.064	***-0.152***	**0.048**	0.039		0.010	(0.628)0.121	(0.000)0.121	(33.2)10.7	858;168[61]
	0.045	0.058	0.021	0.044						
ATT S2	0.052	***-0.165***	***0.051***	0.062		0.100	(0.628)0.164	(0.000)0.000	(33.2)10.1	858;229
	0.046	0.052	0.016	0.032						
Obs.	1087	1087	1087	1087						
B	**Manag.**	**Interm.**	**Small emp.**	**Lower sup.**	**Semi-routine**	**Caliper**	**Ps-R2**	**p>chi2**	**MB**	**CS[out]**
ATT S1	-0.086	0.072	0.010	-0.016	0.021	0.010	(0.395)0.041	(0.000)0.906	(23.7)5.8	458;159[15]
	0.065	0.051	0.032	0.019	0.041					
ATT S1	-0.083	**0.079**	0.019	-0.011	-0.004	0.100	(0.395)0.046	(0.000)0.728	(23.7)7.1	458;174
	0.052	0.035	0.026	0.016	0.039					
ATT S2*	-0.001	-0.021	0.040	-0.032	0.015	0.010	(0.504)0.206	(0.000)0.033	(26.9)10.4	458;132[42]
	0.084	0.068	0.031	0.032	0.058					
ATT S2*	-0.026	-0.001	**0.044**	-0.039	0.022	0.100	(0.504)0.195	(0.000)0.005	(26.9)10.0	458;174
	0.089	0.070	0.019	0.031	0.058					
Obs.	632	632	632	632	632					
C	**(log)Salary**					**Caliper**	**Ps-R2**	**p>chi2**	**MB**	**CS[out]**
ATT S1	-0.050					0.010	(0.400)0.071	(0.000)0.469	(23.9)8.6	425;134[17]
	0.125									
ATT S1	-0.116					0.100	(0.400)0.050	(0.000)0.796	(23.9)7.1	425;151
	0.126									
ATT S2*	-0.069					0.010	(0.499)0.204	(0.000)0.167	(27.0)15.0	425;117[34]
	0.168									
ATT S2*	-0.179					0.100	(0.499)0.191	(0.000)0.019	(27.0)8.5	425;151
	0.157									
Obs.	576									

Notes. This table displays the estimated average treatment effects for the treated from a Kernel type PSM estimator. Either S1 or S2 are implemented to derive the propensity score. S2* denotes a specification where the variable denoting whether the partner is an English native speaker has been omitted because it would be a perfect predictor of being in an inter-ethnic partnership. The standard errors (bootstrapped with 200 reps) are reported below each ATT. *italic* p<0.1, **bold** p<0.05, ***italic and bold*** p<0.01. Two different calipers are applied. The columns Ps-R2, p>chi2, and MB show the quality of the matches (before) and after the matching is implemented. The last column reports the number of individuals in co-ethnic partnerships and in inter-ethnic partnerships who are in the common support [number of observations in inter-ethnic partnerships outside the common support].

Table 3.7: Subgroups: men

			Born in the UK				
A	**Self-emp.**	**Employee**	**Unemp.**	**Inactive**		**MB**	**CS[out]**
ATT S1	-0.032	0.023	-0.063	**0.072**		(28.2)10.9	227;68[19]
	0.084	0.097	0.057	0.032			
ATT S2*	-0.022	-0.001	-0.017	0.040		(28.6)13.5	227;50[37]
	0.097	0.123	0.065	0.032			
B	**Manag.**	**Interm.**	**Small emp.**	**Lower sup.**	**Semi-routine**	**MB**	**CS[out]**
ATT S1	-0.116	0.038	-0.002	0.019	0.062	(28.4)14.0	194;52[23]
	0.113	0.056	0.074	0.055	0.091		
ATT S2*	-0.080	0.020	0.049	0.020	-0.009	(28.9)15.5	194;42[33]
	0.159	0.081	0.104	0.033	0.132		
C	**(log)Salary**					**MB**	**CS[out]**
ATT S1	**0.318**					(28.7)14.4	152;43[20]
	0.160						
ATT S2*	-0.340					(30.2)21.4	152;31[32]
	0.372						
			Not born in the UK				
A	**Self-emp.**	**Employee**	**Unemp.**	**Inactive**		**MB**	**CS[out]**
ATT S1	0.041	-0.101	0.047	0.013		(24.8)10.2	632;47[27]
	0.087	0.093	0.052	0.026			
ATT S2	-0.058	0.067	-0.041	0.032		(29.9)15.1	572;30[44]
	0.115	0.139	0.090	0.075			
B	**Manag.**	**Interm.**	**Small emp.**	**Lower sup.**	**Semi-routine**	**MB**	**CS[out]**
ATT S1	0.026	-0.021	-0.014	0.040	-0.031	(25.6)13.0	519;43[20]
	0.128	0.049	0.094	0.057	0.078		
ATT S2	-0.029	-0.025	0.002	0.043	0.009	(32.0) 16.2	519;30[33]
	0.151	0.079	0.131	0.055	0.113		
C	**(log)Salary**					**MB**	**CS[out]**
ATT S1	0.001					(28.6)13.5	380;27[20]
	0.131						
ATT S2	0.193					(33.4)45.4	342;27[20]
	0.209						
			English first language				
A	**Self-emp.**	**Employee**	**Unemp.**	**Inactive**		**MB**	**CS[out]**
ATT S1	0.035	-0.049	-0.021	0.034		(13.7)8.6	368;106[18]
	0.066	0.071	0.044	0.024			
ATT S2*	0.037	-0.026	-0.019	0.008		(24.8)13.1	368;97[27]
	0.079	0.091	0.051	0.034			
B	**Manag.**	**Interm.**	**Small emp.**	**Lower sup.**	**Semi-routine**	**MB**	**CS[out]**
ATT S1	-0.058	-0.039	0.078	0.008	0.010	(12.7)9.5	313;91[18]
	0.077	0.050	0.059	0.040	0.063		
ATT S2*	0.061	-0.048	-0.037	0.032	-0.007	(25.4)12.9	313;75[34]
	0.097	0.054	0.092	0.063	0.068		
C	**(log)Salary**					**MB**	**CS[out]**
ATT S1	**0.284**					(23.3)16.1	243;58[26]
	0.123						
ATT S2*	0.009					(27.7)19.0	243;58[25]
	0.128						
			Living in an area with a low density of ethnic minorities				
A	**Self-emp.**	**Employee**	**Unemp.**	**Inactive**		**MB**	**CS[out]**
ATT S1	0.004	-0.018	-0.033	*0.047*		(26.7)10.3	820;93[11]
	0.062	0.078	0.055	0.025			
ATT S2	0.009	-0.072	0.019	0.043		(30.1)11.4	820;70[34]
	0.074	0.081	0.056	0.034			
B	**Manag.**	**Interm.**	**Small emp.**	**Lower sup.**	**Semi-routine**	**MB**	**CS[out]**
ATT S1	0.015	0.006	0.055	-0.057	-0.020	(27.6)8.9	676;73[14]
	0.083	0.042	0.053	0.049	0.061		
ATT S2	0.008	-0.004	0.023	0.031	-0.057	(30.9)17.1	676;63[24]
	0.095	0.070	0.083	0.053	0.074		
C	**(log)Salary**					**MB**	**CS[out]**
ATT S1	**0.327**					(29.5)13.9	502;48[19]
	0.124						
ATT S2	0.066					(32.7)17.0	502;41[26]
	0.115						
			White ethnicity				
A	**Self-emp.**	**Employee**	**Unemp.**	**Inactive**		**MB**	**CS[out]**
ATT S1	0.039	-0.103	0.033	0.031		(27.8)12.8	131;65[26]
	0.092	0.109	0.068	0.025			
ATT S2*	*0.185*	***-0.310***	0.088	0.037		(29.1)24.0	130;53[38]
	0.099	0.109	0.080	0.035			
B	**Manag.**	**Interm.**	**Small emp.**	**Lower sup.**	**Semi-routine**	**MB**	**CS[out]**
ATT S1	-0.173	-0.031	*0.136*	0.061	0.008	(28.9)10.1	115;52[27]
	0.124	0.054	0.072	0.085	0.085		
ATT S2*	-0.171	-0.063	*0.176*	0.025	0.034	(29.6)25.0	117;36[43]
	0.132	0.110	0.105	0.095	0.083		
C	**(log)Salary**					**MB**	**CS[out]**
ATT S1	0.234					(29.9)25.7	90;37[26]
	0.208						
ATT S2**	0.020					(31.5)23.2	90;20[43]
	0.244						
			Non-white ethnicity				
A	**Self-emp.**	**Employee**	**Unemp.**	**Inactive**		**MB**	**CS[out]**
ATT S1	-0.006	0.035	-0.055	0.027		(25.1)12.0	739;58[7]
	0.075	0.087	0.055	0.026			
ATT S2*	0.049	-0.081	-0.013	0.045		(30.3)13.7	670;44[21]
	0.085	0.107	0.063	0.040			
B	**Manag.**	**Interm.**	**Small emp.**	**Lower sup.**	**Semi-routine**	**MB**	**CS[out]**
ATT S1	0.120	-0.092	0.024	0.005	-0.056	(24.7)9.9	606;47[7]
	0.097	0.062	0.065	0.050	0.088		
ATT S2*	-0.007	-0.090	0.003	0.049	0.046	(30.6)18.5	556;34[20]
	0.148	0.081	0.105	0.062	0.098		

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Table 3.7 – *Continued from previous page*

C	**(log)Salary**	**MB**	**CS[out]**
ATT S1	0.153	(25.0)12.1	449;33[10]
	0.139		
ATT S2**	0.043	(31.0)22.7	415;26[17]
	0.140		

Notes. This table displays the estimated average treatment effects for the treated from a Kernel type PSM estimator by different sub-samples. Either S1 or S2 are implemented to derive the propensity score. S2* denotes a specification where the variable denoting whether the partner is an English native speaker has been omitted and S2** also omit partner's education because they would be a perfect predictor of being in an inter-ethnic partnership. The standard errors (bootstrapped with 200 reps) are reported below each ATT. *italic* p<0.1, **bold** p<0.05, ***italic and bold*** p<0.01. The last two columns show: the mean bias, MB, (before) and after the matching is implemented; and the the number of individuals in the co-ethnic partnerships and in inter-ethnic partnerships who are in the common support [number of individuals in inter-ethnic partnerships outside the common support].

Table 3.8: Subgroups: women

			Born in the UK				
A	**Self-emp.**	**Employee**	**Unemp.**	**Inactive**		**MB**	**CS[out]**
ATT S1	0.024	-0.079	0.052	0.003		(35.3)12.5	257;44[35]
	0.041	0.113	0.042	0.094			
ATT S2	-0.023	-0.059	0.067	0.016		(33.5)26.7	198;24[55]
	0.039	0.161	0.064	0.165			
B	**Manag.**	**Interm.**	**Small emp.**	**Lower sup.**	**Semi-routine**	**MB**	**CS[out]**
ATT S1	-0.042	0.151	0.019	-0.078	-0.051	(28.3)15.8	161;32[28]
	0.168	0.110	0.043	0.062	0.105		
ATT S2*	0.400	*0.229*	0.055	-0.022	-0.663	(26.8)18.3	113;34[26]
	0.401	0.138	0.049	0.074	0.418		
C	**(log)Salary**					**MB**	**CS[out]**
ATT S1	-0.066					(28.7)18.6	152;34[21]
	0.150						
ATT S2*	0.437					(28.0)72.6	138;36[19]
	0.506						
			Not born in the UK				
A	**Self-emp.**	**Employee**	**Unemp.**	**Inactive**		**MB**	**CS[out]**
ATT S1	0.057	-0.111	0.043	0.010		(31.3)6.4	492;128[22]
	0.043	0.083	0.031	0.062			
ATT S2	**0.088**	**-0.206**	**0.081**	0.036		(33.7)23.8	492;82[68]
	0.044	0.107	0.042	0.090			
B	**Manag.**	**Interm.**	**Small emp.**	**Lower sup.**	**Semi-routine**	**MB**	**CS[out]**
ATT S1	0.081	0.004	-0.020	0.012	-0.077	(26.2)8.1	271;81[33]
	0.091	0.083	0.060	0.034	0.081		
ATT S2*	0.106	-0.066	0.006	0.029	-0.075	(25.2)11.7	271;74[40]
	0.109	0.080	0.067	0.030	0.095		
C	**(log)Salary**					**MB**	**CS[out]**
ATT S1	-0.182					(26.9)10.4	248;69[27]
	0.227						
ATT S2*	-0.136					(26.4)13.6	248;59[37]
	0.242						
			English first language				
A	**Self-emp.**	**Employee**	**Unemp.**	**Inactive**		**MB**	**CS[out]**
ATT S1	-0.010	-0.037	**0.058**	-0.010		(22.9)8.9	326;129[24]
	0.050	0.081	0.025	0.064			
ATT S2	0.031	**-0.173**	*0.054*	0.088		(25.5)12.1	326;107[46]
	0.053	0.071	0.029	0.057			
B	**Manag.**	**Interm.**	**Small emp.**	**Lower sup.**	**Semi-routine**	**MB**	**CS[out]**
ATT S1	**-0.159**	***0.149***	**0.066**	*-0.067*	0.012	(21.5)9.2	229;83[35]
	0.072	0.056	0.033	0.040	0.055		
ATT S2*	-0.107	0.043	0.045	-0.015	0.034	(21.7)13.8	229;77[41]
	0.104	0.087	0.032	0.019	0.054		
C	**(log)Salary**					**MB**	**CS[out]**
ATT S1	-0.218					(21.6)6.9	218;84[20]
	0.198						
ATT S2*	0.008					(23.2)11.2	218;67[37]
	0.280						
			Living in an area with a low density of ethnic minorities				
A	**Self-emp.**	**Employee**	**Unemp.**	**Inactive**		**MB**	**CS[out]**
ATT S1	0.041	**-0.146**	*0.048*	0.057		(29.7)8.5	813;125[17]
	0.034	0.059	0.029	0.052			
ATT S2	*0.076*	***-0.200***	*0.054*	0.070		(32.5)8.1	813;102[40]
	0.044	0.062	0.030	0.057			
B	**Manag.**	**Interm.**	**Small emp.**	**Lower sup.**	**Semi-routine**	**MB**	**CS[out]**
ATT S1	-0.068	0.088	0.028	*-0.021*	-0.027	(22.9)8.3	424;82[24]
	0.081	0.070	0.042	0.013	0.055		
ATT S2	-0.037	-0.032	0.050	-0.018	0.037	(23.5)10.2	424;83[23]
	0.112	0.098	0.040	0.021	0.054		
C	**(log)Salary**					**MB**	**CS[out]**
ATT S1	-0.100					(23.2)8.0	398;77[17]
	0.143						
ATT S2*	-0.111					(24.5)12.2	384;66[28]
	0.173						
			White ethnicity				
A	**Self-emp.**	**Employee**	**Unemp.**	**Inactive**		**MB**	**CS[out]**
ATT S1	0.009	-0.041	0.035	-0.004		(20.2)9.1	122;150[16]
	0.052	0.085	0.028	0.066			
ATT S2	0.060	***-0.293***	0.081	*0.152*		(25.4)21.0	122;62[104]
	0.069	0.120	0.051	0.095			
B	**Manag.**	**Interm.**	**Small emp.**	**Lower sup.**	**Semi-routine**	**MB**	**CS[out]**
ATT S1	-0.054	0.031	0.029	-0.049	0.043	(20.0)11.3	89;98[31]
	0.081	0.064	0.046	0.047	0.077		
ATT S2*	-0.034	-0.002	0.042	-0.044	0.038	(23.2)14.7	89;80[47]
	0.148	0.118	0.044	0.069	0.090		
C	**(log)Salary**					**MB**	**CS[out]**
ATT S1	-0.114					(20.0)17.5	78;83[29]
	0.220						
ATT S2*	-0.067					(23.1)17.4	78;110[52]
	0.170						
			Non-white ethnicity				
A	**Self-emp.**	**Employee**	**Unemp.**	**Inactive**		**MB**	**CS[out]**
ATT S1	0.029	-0.050	0.029	-0.008		(34.5)10.3	736;51[11]
	0.049	0.087	0.037	0.075			
ATT S2	0.082	-0.182	0.058	0.043		(37.1)14.8	736;39[23]
	0.071	0.123	0.055	0.116			
B	**Manag.**	**Interm.**	**Small emp.**	**Lower sup.**	**Semi-routine**	**MB**	**CS[out]**
ATT S1	-0.109	0.139	0.019	-0.024	-0.026	(28.7)14.8	339;34[11]
	0.133	0.117	0.034	0.020	0.084		
ATT S2*	-0.111	0.185	0.025	-0.021	-0.077	(27.9)15.2	255;45[22]

Continued on next page

	0.163	0.137	0.061	0.037	0.135		
C	**(log)Salary**					**MB**	**CS[out]**
ATT S1	0.070					(29.0)11.9	318;27[11]
	0.221						
ATT S2*	-0.035					(27.2)23.0	202;17[21]
	0.275						

Notes. This table displays the estimated average treatment effects for the treated from a Kernel type PSM estimator by different sub-samples. Either S1 or S2 are implemented to derive the propensity score. S2* denotes a specification where the variable denoting whether the partner is an English native speaker has been omitted because it would be a perfect predictor of being in an inter-ethnic partnership. The standard errors (bootstrapped with 200 reps) are reported below each ATT. *italic* p<0.1, **bold** p<0.05, ***italic and bold*** p<0.01. The last two columns show: the mean bias, MB, (before) and after the matching is implemented; and the the number of individuals in the co-ethnic partnerships and in inter-ethnic partnerships who are in the common support [number of individuals in inter-ethnic partnerships outside the common support].

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