Essays in Economics of Education

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Declaration

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

Chapter 1 is co-authored with Professor Adeline Delavande, Professor Emilia Del Bono, Dr Angus Holford and Dr Vedran Lesic.
Chapter 2 and 3 are exclusively mine.

Chapter 1 is written in line with the University of Essex Principal Regulations for Research Degrees.

Chapter 2 uses data from UCAS applications data which is available on Office for National Statistics' Secure Research Service. This work was produced using statistical data from ONS. The use of the ONS statistical data in this work does not imply the endorsement of the ONS in relation to the interpretation or analysis of the statistical data. This work uses research datasets which may not exactly reproduce National Statistics aggregates.

Chapter 2 also uses data from Higher Education Statistics Agency's Student Records and Destinations of Leavers from Higher Education Survey. Additionally Chapter 3 uses data from Higher Education Statistics Agency's Student Records, Staff Records, and Destinations of Leavers from Higher Education Survey. Copyright Higher Education Statistics Agency (HESA) Limited. Neither HESA Limited nor HESA Services Limited can accept responsibility for any inferences or conclusions derived by third parties from data or other information supplied by HESA Limited or HESA Services Limited.

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Summary

This thesis consists of three papers that study gender, socio-economic and racial inequalities in Higher Education.

Chapter 1 evaluates an RCT targeted at students' beliefs and study tips. The intervention provided students with information about the malleability of the brain and how study methods can help improve the brain. We find that our intervention increased students' beliefs about the productivity of effort in success as well as their academic outcomes while having no effect on students' effort but the way they study. We document that our intervention was more successful for male students than for female students.

Chapter 2 studies the effect of contextualized admissions, an SES-based affirmative action policy, on students' academic and labor market outcomes. Using staggered differences-in-differences method, I find that when universities implement this policy, they are more likely to receive applications from state school students and students with lower test scores. This increases enrolled students' likelihood of coming from state schools and from the most deprived areas and reduces the tariff scores of those coming from disadvantaged backgrounds. The policy results in students taking longer to graduate and graduate with worse academic outcomes with little effect on labor market outcomes.

Chapter 3 studies how being exposed to minority academics affect White and racial minor-

ity students' academic and labor market outcomes. In order to study the effect of minority academics, I define students' university-subject choice set and then run OLS regression. I find that White and South Asian students who are exposed to more minority academics graduate with better academic outcomes. When it comes to labor market outcomes, the results are mixed: White students are more likely to be in employment while minority students are less likely to be in employment but more likely to be in further study and mainly in PhD.

Introduction

It is a well know fact that gender, socio-economic and racial inequalities start to appear before individuals go into labor market. Female students outperform male students in every level of education from primary school to university. Jacob (2002) shows that male students are more likely to dropout than female students while Fortin *et al.* (2015) shows that high school GPAs of female students are significantly higher than that of male students. The differences also exist at university level. Across OECD countries, female students constitute a larger proportion of university students and for those in Higher Education, they have higher completion rates than male students (OECD, 2015).

Similar differences also exist by socio-economic status. In the UK, the gap in university participation between the top and bottom socio-economic quintile groups is 37.3 percentage point (Crawford, 2012). In addition, once at the university, the socio-economic gaps persist. Crawford (2014) shows that students from higher socio-economic groups are 3.4 percentage points less likely to dropout, 5.3 percentage points more likely to to complete and 3.7 percentage point more likely to achieve a good degree outcome, defined as achieving a first or an upper second class honors degree. The differences also persist into labor market outcomes. Higher Education Statistics Agency's statistics show that for graduates that finished their undergraduate studies in 2018/19 academic year, the gap in full-time employment between the top and bottom deprivation quintiles is 19 percent (HESA, 2021).

Unsurprisingly, there are also ethnic gaps in academic and labor market outcomes. Higher Education Statistics Agency's statistics show that of those who graduated in 2019/20, 82% of White university students graduated with a first or an upper second class honors degree while only 64% of Black students did so. Similarly, compared with 54% of the Black graduates, 62% of White graduates were in full-time employment 6 months after graduation.

While these differences exist, it is important to understand how we can mitigate them. In this thesis, I explore three possible ways to mitigate these differences. In the first chapter, we focus on gender differences in academic achievement and using novel longitudinal survey data, we study how we can mitigate these differences with a randomized controlled trial. We designed our treatment to provide students with information about the malleability of brain. Students in the treatment group watched a 10-minute video where three psychology professors talked about the malleable features of the brain and emphasized that brain is like a muscle and it can grow. Additionally, they gave tips on effective study techniques that would make the brain grow while emphasizing that these tips are coming from psychology research. Those in the control group, on the other hand, watched a video featuring the same psychology professors but talking about the neurological basis of the brain with no mention of malleability of the brain.

We study the effect of our intervention on students' beliefs, short- and long-term outcomes, effort and study techniques. The results show that our intervention shaped students' beliefs: They are more likely to believe that success come from effort rather than innate ability. While we do not find any effect on students' effort decisions, we find that students changed their study methods and habits. Treated students are more likely to test themselves while they study and are also more likely to prioritize what they are doing worst. Both of these results are consistent with the messages of our intervention. These changes result in students having better academic outcomes. Our intervention increased students' first-year GPA by 0.14 of standard deviation while we also find that the effects persist into graduation GPA. Additionally, we document some interesting results on heterogeneous effects by gender. We find that our intervention was more successful for male students than female students both in terms of study methods and habits and in terms of academic achievement with implications for gender gap in academic achievement.

In the second chapter, I study the effect of contextualized admissions on the applications that universities receive, composition of the student population and students' academic and labor market outcomes. Contextualized admissions is an affirmative action policy based on socio-economic factors. It aims to improve the access of disadvantaged students into universities and has been implemented by British universities starting from 2006. I use administrative data on university applications from UCAS and on student records from HESA, survey data from HESA's Destination of Leavers from Higher Education Survey (DLHE). Additionally, I collect my own data (contextualized admission data from this point on) on the implementation of contextualized admissions, using universities' access and participation plans that are freely available on the Office for Students' website. I link applications data to contextualized admission data to study how implementation of this policy change the applications that the universities receive. Then, I link HESA student records to DLHE and to contextualized admissions data to study the effect of this policy on the student population as well as students' academic and labor market outcomes. I implement a staggered differences-in-differences design to study the causal effect of this policy on students' outcomes. I use data from 2001-2014 entry cohorts and I focus on British students studying at English universities.

I find that when the universities implement this admission policy, they are more likely to receive applications from state school students and from students with lower pre-university test scores. When it comes to enrolled students, I find that this policy increases the proportion of enrolled students coming from state schools and from the most deprived areas of the country (defined as POLAR Quintiles 1 and 2). Additionally, this policy allows students coming from disadvantaged students to be enrolled into universities with lower test scores. These three results show that the policy is working as intended. When it comes to academic outcomes, I find that this policy reduces students' probability of achieving a first class honors degree and a good degree outcome[1]. While I do not find any effect on students' dropout behavior, I find that students are less likely to graduate on time. This shows that this policy results in students graduating later *and* with worse outcomes. I find little to no effect on labor market outcomes: The policy does not affect students' employment outcomes but students are less likely to be in further study upon graduating from their undergraduate degree program which might have long-term impact on their labor market outcomes.

When it comes to heterogeneous effects of this policy, I find that the policy affects both disadvantaged and non-disadvantaged students but the effects are stronger for non-disadvantaged students in academic outcomes. When we look at the private school students, a group that is definitely not targeted by this admission policy, I find that the policy increases their likelihood of dropping out of university in addition to the reductions in their likelihood of graduating on time, graduating with a first and a good degree outcome. The effects are, in fact, stronger for private school students than those coming from state schools and these differences are statistically significant when it comes to academic outcomes while

[1]Good degree is defined as achieving a first class or an upper second class honors degree.

there is no statistical difference for the labor market outcomes. This shows that the policy affects the non-target students more than it does for those that are targeted by this policy. On the other hand, students coming from POLAR Quintile 1 & 2 areas, areas where Higher Education Attainment is low, are affected at the similar magnitudes from this policy than others. Considering coming from an area where Higher Education attainment is low is one of the most used factors to decide whether a student can benefit from this admission policy, this shows that *possibly* targeted students are also negatively affected from this policy.

The last chapter studies how academic role models affect minority students' academic and labor market outcomes. In this chapter, I use HESA's student and staff records as well as HESA's DLHE survey. Using staff records, I calculate the proportion of minority academics and academics from each racial group in departments at all UK universities and use this as a measure of exposure to minority academics. I estimate the effect of the exposure to minority academics on students' academic and labor market outcomes by implementing a simple empirical strategy where I control for university, subject and cohort fixed effects as well as department level characteristics and university group $\times$ subject group fixed effects. The main assumption in this strategy is that students' exposure to minority academics is random in a given university group - subject group set. This is not a strong assumption as in the UK, the university admissions system is mainly based on pre-university test scores and that some courses require specific pre-university test scores from specific subjects.

I find that exposure to minority academics positively affects White students' academic outcomes while not affecting minority students' academic outcomes. When it comes to labor market outcomes, I find that students who are more exposed to minority academics are more likely to be in employment while this effect is the opposite for the minority students. On the other hand, exposure increases minority students' likelihood of being in further study while it negative affects White students' likelihood of being in further study. I discuss that this might be because high ability minority students go on to study for a further degree when they are exposed to more minority academics. If these students are also the ones who would have gotten employment quickly in the labor market, then it is expected that there are negative effects on the employment outcomes as exposure to minority instructors might adjust students' pathways. When I look at the effects of academics from racial groups (Black, South Asian, Other) on students from different racial groups (Black, South Asian, Other), I find positive effects of minority academics on South Asian students' academic outcomes while the results are consistent with the main results for other minority groups and White students.

Chapter 1

Skills Accumulation and Expectations about the Education Production Function: Evidence from a Randomized Information Intervention

1.1 Introduction

Worldwide, girls outperform boys in terms of educational attainment in school and spend more time and effort on schoolwork. They are also more likely to enroll and complete tertiary education, and they graduate from university with a higher grade point average (GPA) (OECD, 2015; Conger & Long, 2010). Various hypotheses have been put forward to explain this gender gap, sometimes labeled as the "boy crisis", such as differential returns to education and gender identity concerns, but a recurrent theme includes lower levels of non-cognitive skills among boys (Jacob, 2002; Goldin *et al.*, 2006; Becker *et al.*, 2010; Lundberg, 2020).[1]

Non-cognitive skills can include personal attributes such as conscientiousness and self-control; economic preferences such as patience and altruism; and beliefs such as growth mindset and self-efficacy. These attributes are important and are strong predictors of educational achievement, labor market outcomes, health and criminality (Heckman *et al.*, 2006; Almlund *et al.*, 2011; Moffitt *et al.*, 2011; Caliendo *et al.*, 2020; Cobb-Clark *et al.*, 2014). Although sometimes labeled as traits, they are mostly referred to as skills as there is growing evidence that they can be fostered, especially in the early years. A large body of work in recent years shows that general interventions in pre- and primary school have a positive effect on a range of non-cognitive skills (e.g., Kautz *et al.*, 2014, and references therein), while specific changes in the curriculum have been shown to impact on specific skills such as grit or patience (Alan & Ertac, 2018; Alan *et al.*, 2019). The evidence on late adolescence is much less abundant, although some workplace-based interventions such apprenticeships have shown positive effects on labor market outcomes plausibly because of their impact on non-cognitive skills (Lerman, 2013). There is however very little research to date on the success of interventions in shaping non-cognitive skills in early adulthood and about their potential to mitigate the gender gap in tertiary education enrollment and achievement.

In this paper, we evaluate the effect of a randomized information intervention targeted at first-year university students to enhance their beliefs that effort is productive, with a focus on heterogeneity by gender. Among all possible non-cognitive skills, we target beliefs as they may be easier to modify with a simple information intervention in early adulthood compared to other non-cognitive skills such as preferences. Our study has four distinctive features. First,

[1]It is not entirely clear why gender gap in non-cognitive skills emerges and persists, but some theories include different developmental trajectories as well boys' skill development being more vulnerable to disadvantages (Goldin *et al.*, 2006; Bertrand & Pan, 2013; Aucejo & James, 2019)

we observe the full chain of impacts arising from the intervention, starting from individual beliefs about the returns to effort, detailed data on academic inputs including quantity and quality– and overall academic achievement. Second, we analyze short and medium-term effects, as we measure academic achievement at the end of the first year of study (6 months after the intervention) and at graduation (about 2.5 years after the intervention). Our third contribution is related to the measurement of skills. Here, we augment existing ways of measuring beliefs about the productivity of effort using subjective expectations. Specifically, we measure individual expectations about the effect of academic inputs (effort) on ability and about the effect of academic inputs and ability on grades. Finally, we conduct the same intervention on a different group of students attending another institution and show that the main treatment effects are very similar to those we estimate in the main study, demonstrating external validity and the potential for scaling up this type of intervention.

Our focus is on individual beliefs about the productivity of effort within education. There is a strong parallel between the idea that effort, and not just ability, is an important determinant of academic success and the concept of "growth mindset", a construct that originated in the psychological literature (Dweck, 2008). An individual endowed with a growth mindset sees ability as something that can be modified with effort and is likely therefore to attribute a larger importance to effort. An individual's growth mindset, as well as other beliefs and attitudinal traits, are traditionally measured by a scale based on self-evaluation (e.g. "How strongly do you agree with the statement that you can learn new things?"), but this raises important questions about measurement (Almlund *et al.*, 2011). Different people may attribute different meaning to concepts such as "learning" or "ability" and to statements such as "strongly agree" or "strongly disagree". As a result, vignettes, behaviors (such as school absence), and incentivized or hypothetical task-based measurements have been advocated as a more promising way to measure non-cognitive skills (Alan *et al.*, 2019; Heckman *et al.*, 2021).

In this paper, we measure subjective beliefs about the productivity of effort using a novel approach. We draw on the literature eliciting subjective expectations in surveys, which shows that respondents are able and willing to report expectations about well-defined events relevant to their lives, that answers are internally consistent and have considerable predictive power for past and future behaviors, that expectations vary with covariates in the same way as actual outcomes (e.g., survival expectations decreases with onset of diseases), and that they are able to capture substantial heterogeneity across individuals (Manski, 2004; Hurd, 2009; Delavande, 2014). Specifically, we elicit individual-specific expectations about (i) how attendance and study time affect one's ability, and (iii) how attendance, study time and ability affect academic achievement. In other words, we decompose the effect of effort on grades into a direct effect and one that operates indirectly through ability. These expectations are elicited using counterfactual scenarios where students report how their expected grades and ability (interpreted as one's ranking in an IQ test) vary with different combinations of inputs. These scenarios allow us to estimate individual-specific subjective beliefs about the production function of academic achievement.

There are various reasons that motivate our new approach. First, it gives us measures of non-cognitive skills expressed in terms of well-defined outcomes (grades) and inputs (attendance and hours of study), so that they can be easily integrated into an economic model of educational investment. Second, the measures are anchored to an objective outcome that limits reference bias and the interpretation issues discussed above. Third, through this approach we can decompose the effect of effort on grades into a direct effect and an indirect one, which captures the effect of effort on ability. This leads to a better understanding of the conceptual mechanisms through which ours and other interventions on beliefs may operate. For example, there have been various studies aimed at changing students' growth mindset and some, but not all, have proved successful at increasing academic outcomes (Sisk *et al.*, 2018). It is unclear whether some interventions succeed because they emphasize the importance of effort for academic achievement, or because they lead individuals to think of their ability as improving with effort.[2] In the latter case, it would be reasonable to assume that this type of intervention might have positive effects in other domains.

Our baseline data were collected during the first term at university of a cohort of undergraduate students in the UK. The data reveal striking gender differences in terms of academic inputs and non-cognitive skills consistent with the patterns discussed above. Girls study 2.7 hours more per week and attend 2ppt more of their scheduled lectures and classes than boys. They have different study habits, for example they are more likely to take notes but do less test practice, they also tend to space out the study topics according to what is due or scheduled rather than what interest them most. Girls are also equipped with different beliefs at baseline: they are more likely to expect that attendance and study can increase ability and academic achievement, and correspondingly exhibit a stronger growth mindset score. When looking at other non-cognitive skills, we observe that female students have higher levels of grit and a better propensity to plan ahead. The differences are statistically significant and quite large (for example, 0.26 of a standard deviation for the growth mindset score and 0.11 of a standard deviation for grit). Importantly, we document that all our beliefs measures,

[2] In a meta-analysis of growth mindset interventions on academic achievement, Sisk *et al.* (2018) find that almost half of the studies fail to find an effect on growth mindset. Moreover, the effectiveness of the interventions on academic achievement is only borderline significant when there is no effect on growth mindset, and not significant in studies where there is an effect on growth mindset, suggesting that the interventions might not operate via a change of growth mindset.

whether collected through the growth mindset scale or through questions about expectations on the returns to effort, are correlated with academic inputs at baseline. This suggests that an intervention that targets these beliefs has the potential to increase academic inputs and to reduce the gaps between girls and boys in academic inputs and educational achievement.

Our intervention aims at increasing students' expectations of the returns to effort. It took place in a social science laboratory, under controlled conditions, and consists of an information video followed by incentivized tasks. The first part of the video provided evidence from recent neuro-scientific studies that the structure of the brain continues to develop and modify even in adulthood when individuals are exposed to different stimuli and learning experiences, emphasizing that the brain is like a muscle that grows with exercise. The second part of the video provided suggestions, connected to evidence from neuroscience, on how to study more effectively, such as through testing oneself with practice questions and spacing out study sessions. The motivation to provide these suggestions is that students may not know the most effective activities to "exercise their brain" in the same way that they appear uninformed about the inputs in the education production function (Fryer Jr, 2011; Clark *et al.*, 2020). Upon viewing the information video, the students were given three multiple-choice questions and a writing task about the video's content, both of which were incentivized.

Our first key finding is that the intervention was successful at changing students' beliefs about the productivity of effort measured two months after its implementation. Based on the standard self-reported growth mindset score commonly used in the psychological literature, we find a positive and large treatment effect of about 0.25 of a standard deviation. Our expectations measures reveal, however, a more nuanced effect of the intervention. For example, at baseline, students expect on average that increasing attendance and ability by 10%

increases grades by 3% and 7% respectively. They also expect that a 10% increase in attendance increases one's ability by 1%. We also find that our treatment changes the perception of the productivity of effort on grades, with an increase of 0.15 of a standard deviation for the productivity of attendance. Importantly, however, we find no treatment effect on the belief that effort increases ability, with very small and imprecise coefficients. This is despite the fact that the expectation about the effect of effort on ability is conceptually closely related to the notion of growth mindset and was the mechanism emphasized in the intervention video. This suggests that the intervention was successful mainly because it emphasized the importance of effort for academic success, and not because it changed individual perceptions about the malleability of ability. In terms of gender, we find a positive treatment effect of similar magnitude for boys and girls, such that boys in the treatment group end up with beliefs that are comparable to girls in the control group.

Our second key finding is a positive treatment on overall GPA by 0.14 of a standard deviation, and an 8ppt increase in the probability of obtaining a first class grade (GPA$\geq$ 70%) from a mean of 44% in the first year at university. This is a relatively large effect size, sitting between the 50th and 60th percentile of effect size in education interventions (Kraft, 2020). Notably, the treatment effects are more than twice as large for boys compared to girls, with boys registering an increase of 0.20 of a standard deviation for overall GPA and 13ppt for obtaining a first class grade. Overall, our intervention was successful at reducing the gender gap in first-year achievement, with a gap of 0.12 of a standard deviation in the treatment group compared to 0.38 in the control group.

A unique feature of our data is that we have detailed information on various dimensions of academic inputs. This leads us to our third key findings. At the aggregate level, we find no treatment effect on the quantity of effort (hours of study and hours of attendance) but a positive effect on the quality of effort, with treated students being more likely to test themselves when studying (which was one of the study suggestions of the intervention) and to space the topics more effectively, focusing on those they are doing worse at or that they have not studied for a long time. However, there is marked heterogeneity in treatment effects by gender, with a positive and larger effect on the quantity (e.g., an increase of 1.7 hours of study for week and 0.28 of a standard deviation in overall quantity) and quality of effort for boys than for girls. These differential treatment effects on academic inputs essentially eliminate the gender gap in quantity and quality of effort among the treated group and are consistent with the differential effect on first year academic achievement by gender.

In terms of medium-term results, we find a sustained effect of the intervention on academic attainment at graduation, which is approximately 0.13 of a standard deviation in magnitude and, again a, larger impact for boys compared to girls. However, there is no or mixed evidence of an effect of the intervention on beliefs or effort in years 2 and 3. This suggests that the treatment effect on graduation outcomes is mostly driven by improvement in basic course knowledge in the first year, which lays the foundation for successful learning in the second and third year.

A valid concern with any type of intervention is its replicability (Nosek *et al.*, 2015). To deal with this, we implemented the same intervention at another university where students are from a different socio-economic background on average than in our main study site. Our fourth key finding is that the treatment effect on beliefs about effort and first-year academic achievement, as well as the differences by gender, are strikingly similar in this different setting.[3] This replication exercise gives us confidence that our results could be replicated at

[3] We do not have data on academic inputs in this other university so cannot compare on this dimension.

scale in different types of Higher Education institutions.

Our paper sheds light on a possible new avenue to reduce the gender gap in educational attainment by enhancing boys' academic effort through a change in beliefs about the returns to effort. There is a growing public concern about the under-performance of boys in educational attainment (Goldin *et al.*, 2006; Bertrand & Pan, 2013; Lundberg, 2020), but surprisingly little evidence on what type of policies can mitigate it.[4] Although women have been found to be endowed with better non-cognitive skills (Gensowski *et al.*, 2021), most interventions fostering these skills have paid attention to the socio-economic or ethnic minority gap in achievement (Broda *et al.*, 2018; Yeager *et al.*, 2019). Some work using the concept of growth mindset has sought to evaluate whether one can increase girls' participation in STEM, with mixed success (Dar-Nimrod & Heine, 2006; Burnette *et al.*, 2018), but little is known on how to boost boys' outcomes. Our study is therefore of great policy importance as it shows that relatively light-touch interventions aimed at improving some non-cognitive skills can help young men to succeed at university.

By focusing on early adulthood, this paper also complements the literature on non-cognitive skills interventions in childhood discussed earlier. A meta-analysis of school-based universal interventions focusing on social and emotional learning from kindergarten to high-school reports a positive effect on a range of non-cognitive skills, behaviors and attitudes, and an average effect of 0.33 of a standard deviation on grades (Durlak *et al.*, 2011). Recent studies have also focused specifically on fostering a growth mindset among students, mostly in high school (Paunesku *et al.*, 2015; Yeager *et al.*, 2016; Bettinger *et al.*, 2018; Yeager *et al.*, 2019) and at university (Broda *et al.*, 2018) with evidence of positive short-term ef-

[4]Using PISA test scores and cross-country variations in educational policies, Hermann & Kopasz (2021) suggest that early tracking and student-oriented teaching practices benefit girls relative to boys. Some intensive multi-year non-cognitive skills programs targeting boys with behavioral issues had a positive impact on educational and adult outcomes as in Algan *et al.* (2014), but detrimental effects in other contexts as in McCord (1978), possibly because it did not create a sense of autonomy among the participating boys.

fects mainly concentrated in at-risk or disadvantaged groups.[5]

Our intervention delivers new information to university students to improve their educational outcomes, and such a low-cost approach has been successful in other contexts. For example, providing information about financial aid (Dinkelman & Martínez A, 2014), university cost (Hoxby & Turner, 2015) and earnings (Jensen, 2010; Wiswall & Zafar, 2015) has an impact on enrollment and university and major choices. Our intervention is also "light-touch" and, by focusing on effort, is similar to other light-touch interventions delivered to enhance university students' effort and performance, such as goal-setting, text-messages coaching or scheduling help (Lavecchia *et al.*, 2016). The results of these studies are overall mixed, with limited effect on academic outcomes in some contexts (Oreopoulos & Petronijevic, 2019; Oreopoulos *et al.*, 2020) and more positive in others (Clark *et al.*, 2020; Ersoy, 2021). Our reading of the evidence in those studies and our own work suggests that there might be some important factors which predict success. The targeted students must be exerting low effort prior to the intervention (like male students in our context), they must be relatively unconstrained to be able to increase it (e.g. financial constraint may force low SES students to work and reduce their ability to increase study time), and the increase in effort must be directed toward specific and productive activities, like focusing effort on where students are doing worst in our context, or study task completion as in Clark *et al.* (2020).

An important feature of our work is that we use subjective expectations to measure non-cognitive skills. Increasingly, economists rely on subjective expectations data from survey respondents to better understand how individuals make decisions under uncertainty (Manski, 2004; Delavande, 2008). Closely related to our approach is work that elicit beliefs about

[5]Existing growth mindset interventions focus typically on immediate or shorter-term outcomes (less than 4 months) (Sisk *et al.*, 2018), with some exceptions such as Alan *et al.* (2019) that includes growth mindset in their interventions? content and measures treatment effects 2.5 years after their intervention.

earnings and non-pecuniary outcomes associated with counterfactual choices of high school tracks (Giustinelli, 2016), college majors (Arcidiacono *et al.*, 2020; Wiswall & Zafar, 2021) and university (Delavande & Zafar, 2019). As in these studies, we collect data on expectations for a number of possible alternative choices, with the innovation that these choices represent different effort levels (hours of study and attendance), which is a central input in education. This allows us to construct for each individual the expected grade and ability return to choosing one particular level of effort over another. We believe this approach could be used more broadly to measure other non-cognitive skills which have proved to be relevant in predicting a range of education and adult outcomes and link them better to more traditional economic constructs and models. This includes for example self-efficacy (i.e., expectation in one's ability to perform tasks to reach a goal, Bandura, 1977), and locus of control (beliefs about the causal relationship between own behavior and its consequences, as in Rotter, 1966). Although not using expectations directly to measure non-cognitive skills, Caliendo *et al.* (2020) find a positive relationship between expected future wage growth and internal locus of control among workers who have undertaken training.[6]

1.2 Our Data

1.2.1 The BOOST2018 Study

The BOOST2018 Study is a longitudinal survey of undergraduate students who enrolled at one UK university in the academic year 2015/16, and for the vast majority completed their degree in 2017/18. The institutional features of this university are typical of other

[6]Interestingly, Bandura (1977) describes how participants' efficacy expectation was measured by asking them to rate the strength of their expectations for being able to complete a task on a 100-point probability scale ranging, in 10-unit intervals, from great uncertainty to complete certainty. However, many recent work uses the self-generalized efficacy scale based on Schwarzer *et al.* (1995) in which respondents are asked whether they agree, on a four-point scale, with 10 different statements about themselves.

Higher Education institutions in England. Students choose their major and institution jointly at the time of application, which is usually one year before enrollment, so they arrive at university to study a specific degree program and there is very limited scope to switch subject. Undergraduate degrees typically last three years. Students are required to pass their first year in order to progress into the second. Performance in the second and third years is used to calculate the "degree class" for the level of Honors with which the student graduates.

The sampling frame of the BOOST2018 Study comprised *all* undergraduate students enrolling in the first year of an undergraduate (Bachelor's) course in October 2015. The target population consists of 2,621 subjects, and includes Home (UK resident) students as well as EU and Overseas students. In order to participate in the study, each student was required to sign a consent form. To ensure that the sample was representative of the target population, the study was widely advertised across the main university campus and all students who enrolled received £5 as an incentive. By the end of the Autumn term of the academic year 2015/16, when the participation register was closed, 1,978 students had given their consent (about 75% of the target sample).

Participants were interviewed 4 times a year for the 3 years of their university course. Specifically, each year they were invited to reply to a long online survey in November and March (60 min), a short online survey during the revision period (April), and to attend a session at the Social Science Experimental Laboratory in January. Participation in the surveys was incentivized using monetary rewards – between £8 and £20 for online surveys and on average £30 for the laboratory sessions. The online surveys were designed to collect information on students' academic investments (hours of study, attendance), study habits, their expectations about future academic achievement and labor market outcomes. The randomized information intervention we analyze in this paper was implemented during the lab session of the first year (between January 2015 and February 2016). Figure 1.1 presents the data collection timeline for the first year of the study.

Due to the presence of monetary incentives and the fact that the study was frequently advertised using flyers, banners and social media posts, participation to the surveys was consistently high throughout the first year. Between 1,029 and 1,276 students took part in the surveys at different points in time in the first year, with higher response rates for the long online surveys (above 62%), and lower rates for the laboratory session (52%). The survey data was subsequently linked to administrative records held by the university. Specifically, we use here information on the student demographics (gender and age), socio-economic status (SES) as measured by parental occupation and the university participation rate in their neighborhood of domicile, and grades from coursework and exams. Importantly, we also have access to weekly records of attendance obtained through a swipe-card electronic system.

1.2.2 Our Sample

Our analysis focuses on Home or UK resident students, who represent 72% of the overall target population (N=1,893). We apply this restriction for two reasons. First, this is to be consistent with our analysis plan which focused on Home students to analyze the effect of the intervention by gender and socio-economic status (SES). Information on the latter is only available for Home students.[7] The second reason is that the intervention was delivered through a video, which was recorded only in English. Therefore we think it is appropriate to focus the analysis on the population for whom English is most likely to be the first language

[7] Our funding proposal which acts as our pre-analysis plan and focused on explaining difference in academic achievement by SES. For a description of the project see here https://www.iser.essex.ac.uk/research/projects/inequality-in-higher-education-outcomes-in-the-uk-subjective-expectations-preferences-and-access-to-information. This project was funded by the UK Economic and Social Research Council grant number ES/M008622/1 with a start date of March 2015.

spoken. For transparency, we will present results for the whole sample in the Appendix, and we will see that these are qualitatively similar to the results on the Home student sample.

We summarize the demographic characteristics of our sample in Table 1.1. We first show the overall student population enrolled in the academic year 2015/16 in any UK university in column 1. We compare this to the student population in the university where the study took place (column 2) and then to the sample of students who enroll in the study (column 3). All numbers refer to Home students only. The table shows that there are some important differences between the student population at the study university and the overall UK student population. First, we see that the percentage of female students at the study university is 48%, while at the UK-level we see a higher participation of women with respect to men (55%). The second aspect that differs is the percentage of mature students (i.e. aged 22 or above at enrollment); this is 14% nationally but only 9% at the study university. Finally, we see that the students who enroll at the study university are on average negatively selected with respect to previous academic achievement in that their mean tariff score is lower than that of the population of all UK university entrants, but they are also concentrated towards the middle of the national distribution. 32% of the national population have a tariff score that would place them in the bottom quintile at the study university, and 29% in the top quintile.[8] The students at our institution are similar to UK students as a whole in terms of SES, with about a third of them qualifying as low SES.

Comparing columns 2 and 3, we see very small differences between the student population at the study university and the sample of study participants. The main difference we notice

[8]The tariff points are available through the linkage with the university administrative data and come from the Universities and Colleges Admissions Service (UCAS). The UCAS Tariff points are a way of comparing the value of all post-16 qualifications in the UK, as students can access university by gaining academic qualifications, vocational qualifications or a mixture of the two. The total score is obtained by assigning a numerical value to each grade and qualification and summing these up. The higher the grade the student achieves per each qualification, the higher the number of points awarded. The standardized tariff score and quintiles shown are derived with respect to the population of students at the study university who have a non-missing tariff score. This includes non-British students who took UCAS-recognized qualifications.

here is in relation to the higher percentage of high and low SES students (vs. students with missing SES information) in the BOOST2018 sample as compared to the target sample. Other characteristics are remarkably similar, including the tariff scores. This suggests that recruitment into the study was very successful, with the enrolled sample reflecting well the characteristics of the underlying population.

In columns 4 to 8 we present the different respondent samples used throughout our analysis. For example, the wave 1 sample includes all respondents to the initial survey, while the wave 2 sample refers to those who attended the session in the laboratory, when the intervention took place. The waves 1&2&3 sample is used to derive the treatment effects of the intervention, as it includes respondents at wave 1 (pre-intervention), 2 (intervention), and 3 (post-intervention). Some pre-intervention variables are only collected shortly before the intervention takes place, i.e. during the laboratory session at wave 2, so we also use the subsample of participants at waves 2&3 to calculate some of the treatment effects of interest. The waves 1&3 sample compares pre- and post-intervention outcomes for the larger sample that replies to wave 1 and 3, but does not necessarily attend the laboratory session; we use this sample to calculate intention-to-treat effects. The different respondent samples vary based on individual participation to different combinations of surveys but are generally representative of the study participants. The main difference is that we observe a higher percentage of female students in all the respondent samples, but this is not unusual in a longitudinal study (Lynn & Borkowska, 2018).

1.3 The Intervention

1.3.1 Intervention Design

The students enrolled in the study were stratified by sex, age (whether a mature student or not), department, parental socio-economic status, and tariff quintile. Within these strata, the subjects were randomized into groups A and B with equal probability. When email invitations to sign up for the laboratory session (wave 2) were issued, each group was offered a different set of sessions, such that each session was attended by students from the same group.[9] Each group was offered a menu of sessions on different days of the week and different times of the day for a period of three weeks. The day and time of the sessions were randomized between treated and control groups and there were always at least 2 control and 2 treatment sessions per day.[10]

Students who came to the lab sat in individual partitioned booths with their own computer screen and noise-canceling headphones. All students were asked to complete a set of incentivized tasks designed to elicit several cognitive and non-cognitive traits for about 35 minutes. These tasks were identical for the treated and control groups and the average payoff was very similar, at £24 and £22 respectively. All students were then shown a 10-minute video containing the information intervention or an alternative for the control group. After the video, the students were asked to answer three multiple choice questions about the video and to write a short text summarizing its main message. Students were prevented from skipping ahead until they had spent 10 minutes on the page containing the video, though they

[9]There were 63 sessions in total, with 31 for each group and one session where both control and treatment participants took part.

[10]Students asking to take part in a session they were not offered (but available to their friends) were told that this was because the session included a competitiveness task where individual were asked to compete against other participants and we wanted to minimize the chance of people who knew each other well being paired together. This explanation was always accepted. Five students out of 1,025 participants managed to defy their original allocation and take part in the wrong session. They are included in the sample using their ex-post allocation to treatment and control group. Our results are robust to the exclusion of these observations.

could spend longer if they wished. They, then, were given 1 minute for each of three multiple choice questions, and rewarded with £1 per correct answer. Finally, students were asked to spend at least two minutes, and up to 10 minutes, on a writing task. They were rewarded with £1 per 200 characters (2 lines in the box they were shown to write in) of coherent text up to a maximum of £10. These essays were reviewed by a member of the team before the payoffs were calculated. The videos, questions, and writing tasks were different for the treated and control groups.

The Treatment Group – The students in the treatment group were asked to watch a video entitled "What your brain can do". The video lasted about 10 minutes and comprised images, visual text prompts, and short academic presentations, featuring three academic psychologists explaining evidence from a series of studies showing: (i) the structure of and purpose of neurons, dendrites and synapses; (ii) how neural connections develop in the presence of stimuli or after a learning experience; (iii) that training one area of the brain leads to improvements in other cognitive domains and that the effects persist in the long run; and (iv) that brain activity is highest after the occurrence of mistakes especially for those who believe that ability is not fixed. The messages from these scientific studies were reinforced with simple, summary statements such as "Your brain is like a muscle, it grows with exercise" and "Receiving a poor grade is not an indication of low ability". The video then provided practical suggestions about the most effective ways of studying, which was presented as a way to exercise one's brain. Specifically, four study tips were given relating to: (a) *Testing*, including writing notes from memory, using flashcards, completing past papers, or using textbook questions, all of which are forms of active learning; (b) *Spacing*, with the message that study time on a particular topic is better distributed among several sessions, it lasts longer and more brain connections get formed; (c) *Attending lectures and classes* is effective especially complemented with other active ways of studying, such as note-taking and completing reading assignments; (d) *Avoiding bad situations*, such as stress and lack of sleep, as they inhibit formation of new brain cells and encoding of new information, while exercise was presented as beneficial as it improves blood flow to the brain. In the writing task that followed the video the students were asked to write a letter to a friend to explain that "ability is not fixed and what implications this has for how he or she should study."[11]

The Control Group – Control students were also asked to watch a video of 10 minutes in duration. Like the treatment video, it was entitled "What your brain can do", featured the same three academic psychologists, and had the same visual style. Unlike the treatment video, it focused on the specialties of different regions of the brain (frontal, parietal, temporal and occipital), with evidence from studies showing the implications of damage to these regions. The video contained no study tips, only information about which parts of the brain are being used when undertaking certain activities. The writing task was presented as follows: "The brain is divided into different areas called lobes. Each lobe has several specific functions. Describe some of these functions and tell us where in the brain they are located. What happens when damage to the brain occurs? Give some examples by using the content of the video you have just watched or from other studies you might have come across." The similarities between the control and treatment video in terms of general topic (i.e. the brain), style, and format were intentional. We intended to minimize students' awareness of being exposed to different information and thus reduce externalities from information sharing by treated students to control students. Note that if information sharing occurred, our estimated treatment effects will represent a lower bound of the actual treatment effects.

[11] Screenshots from the treatment video are shown in Appendix C. For the full transcript of the intervention, see Appendix B.

1.3.2 Comparison with Other Interventions

The main message of the first part of the intervention is very similar to interventions in psychology that convey to students the notion of "growth mindset" (Dweck, 2008). Students endowed with a growth mindset believe that intelligence can grow with effort, and academic challenge is not seen as a threat to one's ability but rather an opportunity to learn. This is in contrast with students with a fixed mindset, who believe that their intelligence cannot change over time. Those students will not embrace difficulty and may see a bad academic result as a reflection of their low level of ability.

There is evidence that a student's mindset can be changed. For example, praising students for their effort rather than their intelligence can encourage them to adopt a growth mindset (Mueller & Dweck, 1998). More closely related to our specific intervention, several recent studies have used neuroscience and the idea that the brain is a muscle that needs to be trained to communicate the growth mindset message to high school and university students through online sessions (Paunesku *et al.*, 2015; Yeager *et al.*, 2016; Bettinger *et al.*, 2018; Broda *et al.*, 2018; Yeager *et al.*, 2019). In contrast to these studies, our intervention took place in one sitting, and had a shorter duration.[12] To deliver the content in a way that may appeal to university students, we used a video, presented evidence from different scientific studies, and relied on experts (psychology scholars) to deliver the content. In comparison, Paunesku *et al.* (2015) asked participants to read a scientific article. With the exceptions of Yeager *et al.* (2019), all these other studies ask students to write an essay/letter as we do. Providing advice to others is a "saying-is-believing" tactic which makes the content more self-relevant and can help to internalize it (Aronson *et al.*, 2002).

[12]For example, Paunesku *et al.* (2015); Yeager *et al.* (2016) and Bettinger *et al.* (2018) all use similar interventions delivered in two 45-minute sessions, while Yeager *et al.* (2019) had two 25-minute sessions.

The second part of the intervention provides students with suggestions on how to study, based on some of the most effective methods as identified in the relevant educational literature (Dunlosky *et al.*, 2013). The primary motivation for providing these suggestions is that, while the first part of the video may convince students that they need to exert effort to grow their brain, they may be unsure about what precise type of activities might be more productive. Indeed and relatedly, there is evidence that students are not well informed about which academic inputs may increase academic performance as incentivizing (or setting goal for) academic input has more effect on academic performance than incentivizing academic performance directly (Fryer Jr, 2011; Hirshleifer, 2017; Clark *et al.*, 2020). This may be particularly the case for university students, whose inputs are richer and more multidimensional than primary or high school students. Note that while the specific study advice we provide may not be new to students, their link to neuroscientific studies evidence could make it more powerful.

Motivated by existing evidence that many students have poor study skills and study little, other light-touch interventions have delivered suggestions on how to study or encouraged planning and test preparation exercises. The effects of these interventions on academic performance tend to be null, or small and limited to subgroups (Angrist *et al.*, 2009; Oreopoulos *et al.*, 2018; Oreopoulos & Petronijevic, 2019), although more comprehensive programs have been found to increase college completion rates (van der Steeg *et al.*, 2015; Weiss *et al.*, 2019).

1.4 Conceptual Framework

The way the intervention was designed is consistent with a simple conceptual framework that highlights the relationship between individuals' beliefs about ability, study effort, and academic achievement.

Consider a university student whose utility depends on grades g and effort e.[13] Before deciding how much effort to exert, the student is endowed with individual-specific subjective expectations about (i) their ability, (ii) how effort influences ability, and (iii) how ability and effort influence grades. Their subjective expected utility can be written as follows:

$$U(g; e) = g(e, a(e)) - c(e),$$

where $a(e)$ denotes the student's perceived ability conditional on exerting effort e, $g(e, a(e))$ is their expected grade conditional on effort e and perceived ability $a(e)$, $c(e)$ is a strictly increasing convex cost function for exerting effort e ($e \in [0, E]$, $c(e) > 0$, $c'(e) > 0$ and $c''(e) \geq 0$). We further assume that $g(.)$ and $a(.)$ are twice differentiable and concave, and that $\frac{\partial g}{\partial a} \geq 0$, $\frac{\partial g}{\partial e} \geq 0$ and $\frac{\partial a}{\partial e} \geq 0$.

The student will chose the level of effort e that maximizes their subjective expected utility. The optimal level of effort e^* satisfies the following First Order Condition:

$$\frac{\partial g(e^*, a(e^*))}{\partial e} + \frac{\partial g(e^*, a(e^*))}{\partial a} \frac{\partial a(e^*)}{\partial e} = c'(e^*). \tag{1.1}$$

From equation (1), we note that an increase in either $\frac{\partial a(e)}{\partial e}$ or $\frac{\partial g(e,a(e))}{\partial e}$ will increase the optimal level of effort e^*. The objective of our information intervention is to increase effort by changing individuals' beliefs about the functions $g(.)$ and $a(.)$.

In other words, we anticipate the information intervention will lead to a change in students' subjective expectations about effort and ability. In particular, we make the following

[13]We acknowledge that students care about future consumption and labor market outcomes in addition to academic achievement, but we make this simplification for tractability. In our data, students are aware that a higher grade increases future earnings and non-pecuniary labor market outcomes (Delavande *et al.*, 2020a).

hypotheses:

H1: The intervention increases the perceived direct effect of effort on grades $\frac{\partial g(e,a(e))}{\partial e}$. This is because students were told that they can improve their grades by training their brain and were provided suggestions on how to study more effectively.

H2: The intervention increases the perceived return of effort on ability $\frac{\partial a(e)}{\partial e}$. This is because the video contains the message that the brain is a muscle and can grow with effort.

H3: The intervention increases students' effort. An increase in either $\frac{\partial a(e)}{\partial e}$ or $\frac{\partial g(e,a(e))}{\partial e}$ will increase the optimal level of effort e^* (equation 1).

H4: The intervention increases academic performance. This will be the case if effort has a positive effect on grades.

In our empirical analysis, we will test these hypotheses using unusual rich data on subjective expectations, effort, and grades.

1.5 Measuring Academic Outputs and Inputs

In this section, we present our measures for academic achievement, effort, beliefs about ability and the production function of grades, as well as other potentially relevant inputs. We discuss different sets of variables in turn, and provide descriptive statistics of the way in which they are distributed in our sample, drawing attention to differences by gender, SES, and prior achievement. The section concludes with checks on the balance of the stratifying and baseline variables between the treated and control groups.

1.5.1 Academic Achievement

At the university where the study took place, all teaching and assessments are organized in a modular structure. Students take between 4 and 8 modules each year, depending on their program of study, and receive an overall grade for each module, which is a weighted average of their coursework assessments and exam results obtained during the summer term. All grades are awarded on a scale between 0 and 100, with a minimum grade of 40 required for a pass. Grades in different modules are moderated by external examiners, with the intention that grading standards are comparable within subjects and across universities (Naylor *et al.*, 2016).

Our primary outcome of interest is the average grade at the end of the first year (GPA), which is a credit-value weighted average of module grades because different modules are associated with a different number of credits. We also consider the exam grade, calculated as a credit-value weighted average of exam results. We analyze the continuous score, as well as specific thresholds, and look at students who obtain a first (above or equal to 70%), a good (above or equal to 60%), and a pass (above or equal to 40%) grade at the end of their first year.[14] Panel A of Table 1.2 shows that students get on average a GPA of 60 (standard deviation 12), with females, high SES and high tariff (i.e., those above median tariff score) students doing significantly better than their counterparts.

We combine the various measures of academic outcomes (GPA, exam grade, getting a first, a good or a pass) to create an overall Attainment Index. We apply the method suggested by Anderson (2008) to generate a summary index of these variables through an inverse covariance weighting scheme designed to put less weight on highly correlated outcomes. This index shows mainly differences in attainment by gender and prior achievement (e.g. tariff)

[14] In the first year most modules are compulsory for the specific degree program the student has registered on.

of about 18-19% of a standard deviation.[15]

We then consider graduation outcomes, i.e. students' educational attainment at the end of their course of study, which could last 3 or 4 years depending on the subject and whether or not a student has chosen to spend a year abroad or on a job placement scheme. The GPA is here calculated using module-based grades from the second and third year exams only and, as before, we consider specific thresholds representing a first (above 70%) or good (above 60%) grade. These thresholds, which define a "degree class", play an important role in the UK system as they are used as the main measure of performance by prospective employers.[16] The next measure is an indicator variable for graduating on time, which we use to discriminate between students who graduate regularly at the end of their course of study and those who fail to do so (although they might still graduate after resitting some exams or going through an appeal process). As before, we also create a weighted average of all these variables, the Graduation Index. Table 1.2 shows that 52% of students graduate on time and that the average final GPA is 63, with 25% of students graduating with a first class degree. As in the first year, we see that female students and those with higher tariff at entry have significantly better outcomes, whereas there are no significant differences by SES.

1.5.2 Effort

We collect various measures of academic effort to reflect the variety of activities students can choose to engage in while at university. Some of these measure are meant to capture quantitative aspects (i.e. hours of study), others reflect the qualitative dimension, such as

[15] We also look at whether at the end of the first year students *fail to progress* because for example they dropout, fail some or all their modules, repeat the year or restart. We do not show these results, but we notice here that about 16% of student fail to progress and this affects slightly more male and low SES students.

[16] There is a well-established and significant degree class premium on earnings. This is estimated around 6 percentage points for a first class degree (70 or more) over an upper second (60-69), and a further 5 percentage points over a lower second (50-59) (Walker & Zhu, 2011). These differentials are also thought to be increasing over time (Smith *et al.*, 2000).

variables capturing differences in study methods and habits.

Study Quantity – We consider two measures of quantity of study: (i) attendance to classes and lectures (in hours and %) and (ii) hours of study.[17] As mentioned before, we obtained administrative records of students' timetables as well as weekly records of their attendance from a swipe-card electronic system, which allows us to derive measures of attendance that are not affected by self-reporting.[18] We compute the average weekly hours of attendance to lectures and classes for each student over the Autumn term (October to November) and Spring term (January to March), each of which was 10 weeks in duration. As hours of attendance vary significantly according to subject studied, we also measure attendance in percentage of scheduled hours by dividing hours of attendance by the number of hours a student is expected to attend according the course she is enrolled in. Hours of study are self-reported from the question "Not counting hours spent in class and lectures, how many hours in a typical week during term time do you usually study?". This question is asked in the Autumn term (wave 1) and Spring term (wave 3).[19]

Panel B of Table 1.2 provides descriptive statistics for these variables for the Autumn term, i.e. at baseline. Each week students attend lectures and classes for about 10 hours, which is 64% of their scheduled events, while they study for 12.5 hours. The gender difference in effort is consistent with the discussion in the introduction. Female students attend a higher proportion of lectures (65% versus 63%) and study substantially more (13.9 hours versus 10.9 hours per week) than male students. Students with higher tariff at entry attend significantly more lectures and classes (68% versus 63%) than lower tariff students but have similar study

[17] It is important to note that attendance is not compulsory in this institution, and in general in all UK universities. However some departments might monitor attendance much more closely than others and can make attendance to some classes effectively compulsory. This is why in all our analysis we take into account of department fixed-effects.

[18] The swipe-card system was put in place to record non-EU students' compliance with their visa and immigration requirements. The measures of attendance obtained using administrative records are not error-free (e.g. students may forget their swiping card), but they are such that it is much more unlikely that the errors in measurement are correlated to individual characteristics.

[19] We cap self-reported hours of study to 35 hours per week.

hours. There is no difference in the quantity of study by SES instead. We also construct a Study Quantity Index, using the inverse covariance weighting method employed by Anderson (2008). This index exhibits similar heterogeneity patterns as the underlying variables, with females scoring 0.17 of a standard deviation higher than the males, and a difference of 0.15 of a standard deviation between high and low tariff students.

Study Quality – We consider two sets of measures of study quality, which we label Study Methods and Study Habits.

We obtain measures of *Study Methods* by asking students about how they spend their hours of study outside lectures and classes. We ask them to allocate the total amount of study into the 5 following categories: (i) compulsory homework (essays, exercises, etc.), (ii) reading or re-reading textbooks or course materials, (iii) paraphrasing or making notes, copies, outlines, or annotations from textbooks or course materials, (iv) testing themselves with questions, practice problems, past exams or flash cards, and (v) other. We then calculate the percentage of study hours spent on each of these activities. Panel B of Table 1.2 shows the situation in the Autumn (wave 1). We see that students spend 45% of their study time on compulsory homework, 22% on reading, 19% on note-taking and 9% on testing. There are some differences by gender, with female students being more likely to take notes and less likely to test themselves, but no significant differences in study methods by SES or tariff at entry. The Study Method Index (constructed using all these variables) shows no significant differences across any of the sub-groups.

We use a measure of *Study Habits* from Kornell & Bjork (2007) which ask students how they plan what to study next. The question includes 5 items: (i) whatever is due soonest/overdue; (ii) whatever I haven't studied for the longest time; (iii) whatever I find interesting; (iv) whatever I feel I'm doing the worst in; (v) I plan my study schedule ahead of time, and I study whatever I've scheduled. Students can indicate how often they adopt the related approach using a 4-point frequency scale (Never, Sometimes, Often and Always). We construct a binary indicator for each category with 1 for Often and Always, and 0 otherwise. We are particularly interested in whether the students decide the order of their topics according to "whatever they are doing worst at", as this is related to the message about the importance of making mistakes and embracing challenges discussed in the intervention, and "whatever they have not studied for the longest time", which is related to the practice of spacing out studies, also emphasized in the intervention video.

Panel B of Table 1.2 shows that students tend to prioritize what is overdue, with 86% of students reporting that they often or always focus on this when deciding what to study next. We also see that 56% percent often or always study the topics in which they are doing worst, and 34% the topics they have not studied for the longest period of time. There are some gender differences, with female students less likely to study "whatever they find interesting" than their male counterparts, but generally differences by subgroups are small, as also shown by the Study Habits Index which aggregates across all these measures.

We also construct a Study Quality Index as a more concise summary measure by considering a weighted average of all the variables which reflect the quality of study time. This index, shown at the bottom of Panel B of Table 1.2 shows no significant heterogeneity across different sub-groups.

1.5.3 Beliefs

We use different measures to capture students' subjective beliefs about how effort influences ability and academic performance. We first consider a measure of *growth mindset*, as proposed in many psychological studies. We elicit individual growth mindset at baseline (wave 1) and in the post-intervention survey (wave 3). We also elicit respondents' *subjective expectations* about: (i) grades conditional on different levels of effort and ability, and (ii) ability conditional on different levels of effort. The former represent the extent to which students perceive that grades might increase with attendance, study or ability, or $g(e, a(e))$, as shown in eq.(1), while the latter are meant to capture the production function of ability w.r.t. effort, or $a(e)$. These expectations are first measured at wave 2, just before students are shown the video, and are elicited again at wave 3, about two months after the intervention.

Growth Mindset – We consider the growth mindset instrument that has been validated and is widely used in many psychological studies (Dweck, 2008). Specifically, students were presented with four statements about whether ability could be changed or improved, and expressed their agreement or disagreement using a 7-point Likert-scale which ranged from "strongly disagree" to "strongly agree". Using the answers to these questions, we derive a growth mindset score that varies from 0 to 60.[20] Panel C of Table 1.2 shows that our sample has a mean growth mindset score of 36.7 out of 60 at baseline (wave 1). Female students have a higher growth mindset score than male students. This difference is large (26% of a standard deviation) and statistically significant at the 1% level. By contrast, we do not see any differences by SES or previous achievement.

Grade Expectations – Subjective expectations about how grades change with different levels of effort and ability are elicited as follows. During the lab session, students were asked to complete a Raven-style test, which is usually used to measure IQ. The test was presented to them as a problem-solving exercise and students received no feedback on their performance.

[20] Table A1.11 reports the exact statements and the scores associated with each item on the Likert-scale. Notice that the total score is calculated by taking the sum of scores across statements and multiplying this by 5 (Dweck, 2008).

We told the students that the questions they answered were from a problem-solving task which measured their capacity for analyzing problems, abstract reasoning, and ability to learn. We then asked students to think about how their expected grade would change conditional on different levels of effort (as measured by study hours and attendance to classes and lectures), and ability (as measured by ranking on the Raven-style test). Specifically, we asked the following question:

"We would like you to think again about your final degree class, and what your average final grade (between 0 and 100) might be depending on:

- How many hours you study per week during term time (outside of lectures and classes).
- The proportion of lectures and classes you attend this year.
- Your rank when answering a problem-solving task similar to the one you just did.

When answering your questions, assume that you will study and attend lectures and classes during 2nd and 3rd years as you have just answered before."

Each respondent was asked to provide the expected grade for 8 different scenarios that included 2 levels of study hours, 2 levels of attendance and 2 level of ability. One scenario for example was 15 hours of study per week, 60% of attendance to lectures and classes, and a rank of 500 out of 1000 in the IQ task.[21] The top panel of Figure 1.2 shows the average expected grade for all scenarios. Here we see that on average students perceive positive returns to study hours, attendance, and ability on grades. For example, holding attendance and study hours at the high level, an ability rank improvement of 300 out of 1000 is perceived as leading to an average increase in grade from 60 to 74. Similarly, holding ability and study hours at their highest levels, an increase in attendance from 60% to 95% is perceived to

[21] See Appendix Figure A1.1 for details of all the scenarios.

increase grades from 64 to 74.

To make the analysis of these expectations data more tractable, we assume that students use a production function of grades that has a Cobb-Douglas functional form, where the inputs are attendance, study hours, and ability:

$$\ln(g) = \alpha + \alpha_{att} \ln(attendance) + \alpha_s \ln(study) + \alpha_{ab} \ln(ability) \tag{1.2}$$

where g is expected grade, *attendance* is weekly hours of attendance, *study* is weekly hours of study, and *ability* is a transformation of the rank into a z-score. In particular, we assume that ability is normally distributed with a mean of 100 and a standard deviation of 15 (as are IQ scores) and that students report their percentile in that distribution.[22]

As a way to describe the baseline expectations, we first estimate eq.(2) using an individual fixed-effect regression by pooling all respondents and scenarios. Here, the dependent variable is the expected grade, and we exploit variation in the level of effort and ability generated by the 8 scenarios, i.e. the independent variables are the hours of study, hours of attendance, and ability scores in the associated scenario.[23] The results are presented in column 1 of Appendix Table A1.1 and, in line with the evidence from Figure 1.2, we see a positive expected return to all three inputs. Specifically, we see that attendance is perceived as the most productive form of effort with a 10% increase in attendance increasing expected grades by about 3%, whereas increasing study hours by 10% leads to an increase in expected grades of 1.9%. Appendix Table A1.1 also shows that a 10% increase in ability score is expected to increase grades by 7% on average.

[22]Specifically, for a student who report a rank of R we compute ability as $ability = invnormal([(1000 - R)/1000]) * 15 + 100$.

[23]The scenarios present attendance in percentages, however we transform this variable in hours of attendance by multiplying it by the modal number of hours students are scheduled to attend, which is 12 (2 hours of lectures and 1 hour of classes/seminars per module, for an average of 4 modules per term). This allows us to compare more directly the effect of hours of study and attendance.

Next, we use these data to estimate an individual-level production function. Given that we have 8 observations per student, we can estimate eq.(2) for each respondent, as in (Blass *et al.*, 2010), and recover the individual-specific parameters $\{\alpha, \alpha_{att}, \alpha_s, \alpha_{ab}\}$ of the production function of grades. Panel B of Table 1.2 shows that the average of these individual-level coefficients is similar to the coefficients from the fixed-effect regression shown in Appendix Table A1.1, as we would expect, but it also reveals interesting heterogeneity by gender. Female students perceive that attendance and study hours have a higher productivity for grades than male students (by a magnitude of 18 to 28% of a standard deviation), and at the same time attribute a smaller weight to ability (although the difference is not statistically significant in this case).

Ability Expectations – We elicit students' expectations about the role of effort on ability. We do so by asking the following question:

"Now, suppose that you and 1,000 students from all UK universities were doing a similar problem-solving task with 50 questions again this time next year. We would like now to ask you to think what your next year rank on this problem-solving task might be depending on:

- How many hours you study per week
- The proportion of lectures and classes you attend."

Each respondent was asked to provide their expected ability rank for 4 different scenarios that included 2 levels of study hours and 2 levels of attendance (see Appendix Figure A1.2). The bottom panel of Figure 1.2 shows the average expected rank for all scenarios. On average, students perceive study hours and attendance to be productive in terms of ability performance.

As before, we assume that students believe that the production function of ability has a

Cobb-Douglas functional form and is given by:

$$\ln(ability) = \beta + \beta_{att} \ln(attendance) + \beta_s \ln(study), \tag{1.3}$$

where *ability* is the ability score as defined earlier, *attendance* is the weekly hours of attendance, and *study* is the weekly hours of study as before.

Again, we first estimate eq.(3) using an individual fixed-effect regression pooling all respondents and scenarios. The results are presented in column 2 of Appendix Table A1.1 and show that there is a positive expected return to both attendance and study. Specifically, increasing attendance by 10% would increase ability score by 1.3% on average, while the effect is 0.8% for study hours.

We then use the same data to estimate individual-level production functions. Specifically, given that we have 4 observations per person, we can estimate eq.(3) for each respondent and recover the individual-specific parameters $\{\beta, \beta_{att}, \beta_s\}$. Panel C of Table 1.2 shows the average values of these individual parameters.[24] These averages are consistent with the fixed-effect coefficients, and indicate that females believe that effort, in particular hours of study, is more productive at increasing ability than their male counterparts.

Overall, this indicates that students on average expect effort to have a direct effect on grades as well as an indirect effect by increasing ability, and that these effects are larger for women. This gender gap in beliefs is also clearly seen when we combine all the measures of beliefs (including the growth mindset measures and the subjective expectations measures) into an overall Belief Index, as shown at the bottom of Panel C of Table 1.2.

Ability expectations from eq.(3) are closely related to the concept of growth mindset.

[24] We censor the top and bottom 1% of the distribution of the individual-specific parameters.

Indeed, in Appendix Table A1.2 we see that the expectation about the effect of study hours on ability, or β_s, is significantly correlated with the growth mindset score. By contrast, there is no significant correlation between the growth mindset score and grade expectations, represented by the estimated $\{\alpha_{att}, \alpha_s, \alpha_{ab}\}$. The table also indicates that there is only a weak correlation between the perceived productivity of effort on ability from eq.(3) and on grades from eq.(2). This suggests that expectations about the productivity of effort on grades and on ability are conceptually different in the respondents' mind.

Finally, to evaluate the potential of our intervention, which aims to change beliefs in order to change effort, we consider the association between inputs and different measures of beliefs at baseline. Appendix Table A1.3 shows coefficients obtained by regressing several inputs on each of our measures of beliefs. We see here that beliefs measured by the growth mindset score are not correlated with attendance and only weakly correlated with study time. By contrast, there is a strong association between subjective expectations about the productivity of study on grades (α_s) and hours of study. Attendance is mainly associated with subjective expectations about the productivity of attendance on grades (α_{att}). Those who believe that there is a higher return to study in terms of ability (β_s) are also more likely to study additional hours. The Study Quality Index, which is our overall indicator for the quality of study, also shows a positive association with several measures of beliefs, specifically ability expectations and growth mindset. Although these are just associations, this exercise suggests that changing beliefs about returns to effort has the potential to affect students' effort.

1.5.4 Other Inputs

We look at other inputs in the education production function. In particular, we measure sleep and exercising, which were both mentioned in the last part of the intervention video. Here we use data from a time diary module of the surveys.[25] Table A1.4 shows that students sleep on average almost 8 hours per day and exercise a bit less than half an hour per day. Once again we see some gender differences, with female students sleeping on average more and exercising less than male students.

In the survey, we collected measures of other non-cognitive skills which may also be correlated with students' academic outcomes and could be affected by the intervention. We consider here *grit*, i.e. having passion and perseverance for long-term goals (Duckworth *et al.*, 2007; Duckworth & Quinn, 2009), and *learning orientation* (Mueller & Dweck, 1997), designed to distinguish between individuals who enjoy the process of learning while achieving their goals from those who care exclusively about results (Elliot & McGregor, 2001; Ames, 1992; Dweck, 1986).[26] As Table A1.4 shows, we find some significant gender differences in all these non-cognitive skills measures. Specifically, female students exhibit higher levels of grit, and are more likely to be interested in learning as an objective.

1.5.5 Balance at Baseline

Our identification strategy is based on the randomization of students into treatment and control groups. We pursue a stratified randomization, with the strata defined by gender, age, SES, department and tariff quintiles. Table 1.3 shows the mean of the stratification variables among all BOOST2018 participants. As we can see from columns 1 and 2, the

[25]The time diary measure time allocation in hourly intervals on a non-weekend day of the week. For each of these hourly windows students are asked to report what they generally do by considering the following categories: sleeping, exercising, student clubs, shopping, recreation alone, recreation with friends, class, lecture, commuting, leisure, and other.

[26]We describe these scales (based on self-report) in greater detail in Appendix Table A1.12 and Appendix Table A1.13.

samples are perfectly balanced. In columns 4 and 5 we condition on participation at wave 2, i.e. on receiving or not the treatment information. Again, there is good balance across all variables, which suggests that participation in the laboratory session was random with respect to treatment assignment.

In Appendix Table A1.5, we consider whether there is balance across the range of beliefs and inputs that we observe at baseline, which is wave 1 for most variables and wave 2 for the subjective expectations measures. As we can see, there is no difference in growth mindset or subjective expectations measures across groups, and this holds whether we consider initial assignment or actual treatment. The next set of variables represent measures of effort, both in terms of quantity and quality. Once again, we do not see statistically significant differences by treatment status. The main exception is when we look at Study Habits, where we notice that the percentage of students choosing to focus on what they are most "interested" in is higher in the assignment group. However, this difference is only significant at the 10% level, and it becomes not statistically significant when we compare the control and treated groups. The sample appears to be perfectly balanced also in respect to other inputs, like sleep and exercise, and non-cognitive skills, such as grit and learning orientation.

1.6 Empirical Results

1.6.1 The Empirical Strategy

We investigate the effect of the information intervention on beliefs, academic achievement, effort and other inputs. We do so by estimating the following regression:

$$y_{it} = \alpha + \delta T_i + \beta y_{i,t-1} + \gamma X_i + \epsilon_{it}, \tag{1.4}$$

where y_{it} is the post-treatment outcome of interest for student i and T_i is treatment dummy variable. In our analysis, we use both treatment assignment, in which case δ measures the intention-to-treat effect (ITT), as well as actual treatment exposure, in which case δ measures the treatment effect on the treated (TE). We control for the baseline outcome, y_{it-1} for student i, and the vector X_i of stratifying variables in order to improve precision (McKenzie, 2012; Bruhn & McKenzie, 2009).

As our focus is on gender, for each outcome we also estimate a fully-interacted regression using the female dummy, F_i:

$$y_{it} = \alpha + \zeta T_i + \delta T_i \times F_i + \eta y_{i,t-1} + \beta y_{i,t-1} \times F_i + \theta X_i + \gamma X_i \times F_i + \lambda F_i + \epsilon_{it}. \qquad (1.5)$$

Panel B of each Table 4-10 reports the TE for females and males separately and the p-value of the difference. The ITT effects will be discussed in Further Analysis section and presented in the Appendix.

As shown in Figure 1.1, the intervention took place during wave 2, i.e. at the beginning of the Spring term. For most variables (e.g., study hours, study habits) the baseline value was measured at wave 1, during the Autumn term. For the subjective expectations measures, the baseline was obtained at wave 2, just before the video was shown. All survey-elicited post-treatment measures were obtained at wave 3, during the last part of the Spring term. Academic achievement is measured by first year grades, obtained during exams that take place in the Summer term (Table 1.6); and graduation outcomes determined by performance in the second and third years (Table 1.9). Our baseline measure for achievement is given by the tariff points, which reflect the students' performance in qualifications taken at school prior to enrollment into university.

When we estimate the effect of treatment on the treated, we condition on participation in wave 2. For variables measured in waves 1 and 3, this means using a balanced panel of respondents who participated in waves 1, 2 and 3. To measure the intention to treat effect of the intervention, we consider respondents who took part in waves 1 and 3, except when considering administrative outcomes such as attendance and grades, where we use all available observations.

1.6.2 Effect on Beliefs

We start by analysing treatment effect on beliefs, which were the primary target of the intervention. Panel A of Table 1.4 presents the treatment effect on the treated for the growth mindset score. We start from a regression with no additional controls (column 1), then we add the baseline measure (column 2), and finally all the stratifying variables (column 3). The results are very stable across all specifications and show that the information intervention had a positive and statistically significant effect on the most commonly used measure of the growth mindset (Dweck, 2008). In terms of magnitude, the effect is quite large, at about 25% of a standard deviation. Previous studies which have implemented growth mindset interventions usually find larger effects, of about 30 or 35% of a standard deviation, but there the effects are measured immediately after the treatment whereas we observe them after a lag of about 8 weeks (Paunesku *et al.*, 2015; Yeager *et al.*, 2016, 2019).

We next evaluate the treatment effect on the subjective expectations about the productivity of effort and ability. For this analysis, we use as post-treatment outcomes the individual-specific preference parameters of the education production functions measured at wave 3 - the $\{\alpha_{att}, \alpha_s, \alpha_{ab}\}$ estimated from eq.(2) and the $\{\beta_{att}, \beta_s\}$ estimated from eq.(3) - while the baseline outcomes are the same parameters estimated at wave 2. Note that each time we control for all the parameters at baseline, as they were jointly estimated.

Panel A of Table 1.5 shows that the intervention changed beliefs about the productivity of effort (attendance and study hours) on grades. Specifically, we see that the perceived productivity of attendance increases by 0.067 or 15% of a standard deviation while the productivity of study time increases by 0.048 or 18% of a standard deviation. The coefficient associated with the treatment dummy for the productivity of ability (column 3) is instead negative. This coefficient is not precisely estimated, and the magnitude is relatively small (4% of a standard deviation), but it points to a less important role of ability in the subjective production function of grades for treated students. Overall, these results are consistent with the message that effort can increase academic achievement, which was conveyed in the video, and with hypothesis **H1**. Columns 4 and 5 show the TE on expectations about the effects of effort on ability. The coefficients here are much smaller (between 0.5 and 5% of a standard deviation), and in all cases not statistically different from zero. This indicates that the intervention had no effect on the beliefs that ability increases with effort and is not consistent with hypothesis **H2**. Column 6 shows the effect of the intervention on the Belief Index and indicates a positive overall effect of about 22% of a standard deviation. Panel B of Table 1.5 reports separate treatment effects by gender. Consistently with what we saw for the more commonly used measures of growth mindset beliefs, we see no statistically different effects of the intervention on men and women.

The observed treatment effects on expectations indicate that the intervention has changed students' beliefs about the productivity of effort in relation to grades but not in relation to ability. The null result on ability expectations is in contrast to the positive treatment effect on the growth mindset score. This is perhaps not so surprising as the two measures of beliefs are different. Our subjective expectations measure is based on a very specific representation of the relationship between inputs (study time, attendance) and outputs (ability), while the wording of the items which yield the growth mindset score (see Appendix Table A1.11) are much looser in this sense. The various statements used to derive the growth mindset score never mention any of the inputs (e.g. "You can learn new things, but you can't really change your basic intelligence"), and do not give a clear definition of "intelligence", whereas we adopted a specific definition of ability (i.e. ranking in an IQ test score) in designing our expectations questions. We saw that the two measures are correlated at baseline (Appendix Table A1.2), but this does not guarantee that they would be equally affected by the intervention.

There are three reasons that lead us to think that our expectation measures might be better at capturing the effects of our intervention. The first is that the intervention itself was designed to have two components: the first part focused on the message that ability was malleable and could increase with effort, while the second part emphasized the importance of specific types of effort (study, attendance, testing. etc.) for achieving better grades. So, it makes sense to use precise measures of beliefs that decompose the effect of effort on grades into an indirect effect through ability and a direct effect. Indeed, it would appear that the main change occurred in terms of the direct effect. The second reason is that due to ambiguity in the wording, it is possible that the growth mindset score suffers from interviewer-demand effects (Zizzo, 2010), as the questions used to derive the score resonate closely with the messages from the intervention, and this may bias upward the treatment effect on the score. Finally, in a recent meta-analysis, Sisk *et al.* (2018) noted that the effectiveness of growth mindset interventions on academic achievement is only statistically significant in studies with no effect on growth mindset, and not significant in studies where there is an effect on growth mindset, suggesting that the effect on academic achievement might be driven by something else, possibly the perception that effort will yield better grade as we identify here.

Overall, our expectations results suggest that not all beliefs are equally malleable in light of new information, and that this type of interventions may not be able to yield positive effects in domains other than education.

1.6.3 Effect on First-Year Academic Achievement

In Panel A of Table 1.6, we consider the effects of the intervention on various measures of academic achievement at the end of the first year. All the specifications condition on tariff score at entry expressed as a continuous variable as a measure of baseline attainment.

A key result is that there is a positive and precisely estimated effect of the intervention on average grades (column 1). This is in the order of about 1.7 GPA units on a scale of 0-100, which represents an almost 3% increase on the mean, and equates to 14% of a standard deviation. This can be described as a *medium* effect in the education literature if we consider that in terms of magnitude it sits between the 50th and 60th percentile of the distribution of effects found in a number of education intervention recently analyzed by Kraft (2020).[27] Alternatively, we can consider that an effect size of 20% of a standard deviation broadly represents the impact of having a high-quality teacher (vs. an average teacher) on GPA scores (Hanushek, 2011), or prohibiting computers in the classroom at university (Carter *et al.*, 2017). In terms of later outcomes, a 20% improvement in education outcomes has been found to increase annual lifetime earnings by as much as 2% (Chetty *et al.*, 2014). This effect is also within the range of the effects on attainment found in comparable growth

[27] Kraft (2020) proposes new benchmarks based on the distribution of 1,942 effect sizes from 747 RCTs evaluating education interventions with standardized test outcomes.

mindset interventions. For example, Yeager *et al.* (2019) and Paunesku *et al.* (2015) find an improvement of GPA between 11% and 13% of a standard deviation in core classes for low achievers or those at risk of dropping out in 9th grade, while Broda *et al.* (2018) find an improvement of 42% of a standard deviation in first year cumulative GPA at university for Latino students (but no effect for other subgroups). In a meta-analysis of growth mindset interventions, Sisk *et al.* (2018) report an average treatment effect of 8% of a standard deviation.

Table 1.6 further shows that the intervention had an effect on exam grades (column 2), and not only on coursework (included in the GPA). This is interesting, as all exams are taken at the end of the Summer term, several weeks (14 weeks on average to be precise) after the intervention took place and this suggests that the effects persist at least until the end of the academic year. In relation to the distribution of scores, we see that the effect is concentrated at the top. The proportion of students that achieves a First grade (70% or above) increases by almost 8ppt (an increase of 44% on the mean), whereas there is no significant effect in other parts of the distribution or on pass scores. Column 6 shows the treatment effect on the Attainment Index which takes a weighted average of the previous attainment measures (Anderson, 2008). Here again we see a treatment effect of about 14% of a standard deviation.

In Panel B of Table 1.6, we describe how the treatment effect varies by gender. We clearly see here that the effect is nearly twice as large for men compared to women, and only statistically significant for the former group. For example, the effect on GPA is 20% of a standard deviation for men compared to 12% for women, and treated men see a 13ppt increase in the probability of obtaining a first class degree compared to controlled men, while the effects for treated female is only 4ppt. When considering the overall Attainment index, the effect is 32% for men and 2% of a standard deviation for women.

1.6.4 Effect on Effort

We next consider the impact of the intervention on different measures of effort which take into account both the quantity and quality dimensions.

Panel A of Table 1.7 reports the results on attendance, in hours and as a percentage of scheduled events, and on weekly study time. As we see, the coefficient on attendance is positive and for the percentage measure is also significant, although only marginally so. The effect size is quite small though, implying that for the treated group attendance rates in the Spring term increase only by 1.6ppt, or 2.5% on the mean, with respect to the Autumn term. We also look at measures of attendance according to type of events (i.e. classes or lectures), but the results are similar to those reported here. There is no significant effect on hours of study, or on the overall Study Quantity Index.

Panel B investigates how these treatment effects vary by gender. Here, we clearly see a larger treatment effect on the quantity of study for men. Treated men attend about 1/2 hour more of weekly classes and lectures or 10% of a standard deviations. This is an interesting finding as attendance is not self-reported but derived using administrative records. Weekly study time also increases for male students, by about 1.8 hours per week, which is equivalent to a 17% increase with respect to the mean or 25% of a standard deviation. These gender differences are economically large and statistically significant in some cases.

In Table 1.8, we consider other aspects of effort which are more qualitative. In our survey, we ask students about their *study methods*, or how they allocate their study time across compulsory assignments, reading, taking notes, self-testing, or other activities (Panel A and B). We also ask about *study habits*, i.e. how students decide how to schedule and space out their topics (Panel C and D). Some of these concepts, in particular "testing" and "spacing out", were mentioned clearly in the intervention video as ways in which students could increase the productivity of study time.

Panel A shows that students exposed to the intervention report more time spent testing themselves, possibly at the expense of time spent on compulsory assignments and other activities (although here the coefficients are not significantly different from zero). In Panel C, we see a statistically significant effect of the intervention on the probability that a student focuses on topics they have neglected for a longer period of time or that they have found more difficult. These results are clearly in line with the messages of the intervention, and indicate that the information video might have had an impact on the way in which students approach and organize their study time.

Panel B and D present treatment effects by gender. In terms of study methods, the effects tend to be similar although men exposed to the interventions are less likely to spend their time on other activities compared to men in the control group (and more likely to spend time on compulsory activities and on testing themselves). These differences are more apparent when we look at the weighted average of all these variables, which we label Study Methods Index. Here we see a strong and positive treatment effect for men (equivalent to a third of a standard deviation) and a much smaller effect for women, with the difference by gender being statistically significant at the 11 percent level. In terms of study habits, the effect for men and women are similar, but again when considering the overall Study Habits Index, there is evidence of a more marked impact of the intervention on men (Panel D).

Overall, these findings suggest that the intervention has increased the effort of men more than that of women, both in terms of quantity as well as in terms of the specific activities conducted while studying. This is consistent with the larger effect of the intervention on academic achievements for men seen earlier.

It is useful to compare the size of these effects to what has been observed in other contexts. For example, Oreopoulos *et al.* (2018) analyze a college support program specifically designed to target study time. The program included information about the recommended amount of study, it required students to plan their weekly schedule in advance, and offered them the opportunity to receive follow-ups and reminders during the course of the term. That intervention was more intensive than the one we analyze here, but it focused only on the quantitative aspects of effort, i.e. hours of study. The authors find positive treatment effects on weekly study of about 1.6 hours, which represent 10% of the mean or 13% of a standard deviation, but no significant effects on grades, either overall or by gender (or indeed any other sub-groups). In quantitative terms, the results of that intervention are smaller than the one we find here for male students, and we additionally find significant changes in several qualitative measures of study time. It is therefore possible that the combination of the quantity and quality effects we see as a result of our intervention explain why we find in our case a small but significant impact on grades.

1.6.5 Other Inputs

In order to understand the mechanisms through which the intervention had an effect on effort and academic achievement, we also look more widely at its effects on other uses of time. In particular, we check whether the intervention changed students' sleeping time or time spent exercising. These activities were mentioned in the intervention video as potentially important factors contributing to better academic achievement and where measured in wave 1 and wave 3 using time diaries. The results are reported in Panel A of Appendix Table A1.6

which shows no evidence of a significant treatment effect on these variables. Panel B shows a positive treatment effect of sleep and a negative one on exercise for women, with no precise effect for men, which reinforces the baseline differences (Table 1.2).

We also consider whether the intervention had an impact on other non-cognitive skills which are also usually associated with better academic outcomes as well as with growth mindset beliefs (Dweck, 2013). Columns 3 and 4 in Appendix Table A1.6 show the effect on grit and learning orientation. Interestingly, we see no effect on these skills, either in the overall sample or by gender.

1.6.6 Graduation Outcomes

As part of the BOOST2018 study, we follow students until their graduation. This gives us the opportunity to look at their academic achievement about 2.5 years after the intervention (for most students). Panel A of Table 1.9 shows that the intervention had no effect on the probability to graduate on time. However, we see a clear indication that final GPA is improved by 1.6 points, which represents 2.5% on the mean or 18% of a standard deviation. There is also a positive but not statistically significant effect on the probability to graduate with a first or a good degree. As a consequence, the overall Graduation Index indicates a sustained effect on academic achievement of about 13% of a standard deviation. Panel B reports the results separately by gender. Here, once again, we see larger effect for males compared to females (22.5% vs. 3% looking at the Graduation Index) and when considering the probability of getting a good degree (i.e. a score of 60 or above), this gender difference is statistically significant. Longer-term effects on test scores are rarely recorded in relation to education interventions, so this result is an important finding.[28]

To understand the drivers of the treatment effect on graduation outcomes, we investigate the long-term effects of the intervention on beliefs and effort as measured in year 2 and 3. These are shown in Appendix Table A1.7.[29] In Panel A we present estimates of the treatment effects using both OLS and Inverse Probability Weighting (IPW) regressions to account for survey attrition in years 2 and 3.[30] Note that we do not find attrition to be related to the treatment, and indeed the two sets of estimates are nearly identical. The results mostly reveal no long-term effect of the intervention on beliefs, whether they are represented by the growth mindset measures or the overall Belief Index which includes also subjective expectations. In terms of academic inputs, again we find mostly no significant differences between treated and control groups, although the magnitude of the treatment effect on the Study Methods Index in year 2 is similar to that in year 1 (10% of a standard deviation). When looking at the difference by gender in Panel B, we see a sustained effect on the quantity of effort for men in year 3, which is very much in line in terms of magnitude with the results we obtain in the first year.

Overall, these results suggest that the effect on graduation outcomes are not driven by long-term changes in beliefs. We see however an indication that male students might have increased their study effort, especially in the run up to the third year exams and this could be a potential explanation for the longer term effects on grades. Alternatively, the graduation impacts might be due to the existence of dynamic complementarities generated by improve-

[28]There are some noticeable exceptions of course, for example Alan *et al.* (2019) find a 20% on math test scores 2.5 years after implementing an intervention on grit in elementary schools in Turkey.

[29]We measure growth mindset twice a year and take the average of the two measures. Grade and ability expectations were measured again only in the Autumn of the second year. So, our Belief Index is constructed only for year 2. We capture only some qualitative measures of study time, as the module on study habits was not fielded beyond the first year. We report instead the Study Quantity Index, as composed by attendance (in % and hours) and study time (in hours), and the Study Methods Index, reflecting the composition of study time.

[30]We use stratifying variables to derive probability of non-attrition. We, then, run the regressions where we weight our estimates by this probability of non-attrition.

ment in basic course knowledge in the first year.

1.7 Replication Results

When it comes to randomized control trials one important consideration is replicability. In order to understand whether our findings would hold on a different sample of students, in the academic year 2017/18, we conducted a replication study at another UK university. The main characteristics of this other university are not very different from the one in which we implemented the main study. Both are state-funded universities and both offer a wide range of programs across different subjects of study. However, the second institution is larger in size (with 5,585 target students as compared to 1,893 in the main setting) and is part of the Russell Group, a group of UK universities that rank high according to indicators of research outputs. Its students therefore tend to be more positively selected in terms of initial tariff scores and to be from a more privileged family background (see Appendix Table A1.8).

The recruitment of participants was done in a similar way to the main study.[31] There are however three main differences. First, while our main study allocated participants to the treatment and control groups using a stratified sampling scheme, the replication study used simple random allocation. This is because the replication study was a one-wave study, which was conducted entirely through an online survey, and the researchers did not have prior access to information on participants' characteristics. Second, students were exposed to the intervention online rather than in a laboratory setting. Finally, the control group did not receive an intervention video.

More specifically, during the online survey the treatment group was asked to watch the

[31] The eligibility requirements were similar to those of the main study, except for the fact that mature students were not in the target group.

same intervention video we used for our main study. At the end of the video, the students were presented with multiple choice questions and were asked to write a short essay about the video, as per the main study. All the participants who wrote at least 10 lines of coherent text (1000 words) were entered into a prize raffle. At the end of the survey (and after the video for the treatment group) we measured participants' growth mindset scores. We later on obtained their first-year academic outcomes from administrative records and linked these to the survey records. Appendix Table A1.8 reports the main descriptive statistics of the participants in the replication study and the balancing checks.

In Table 1.10, we report the results of the replication study. The analysis shows that the intervention increased participants' growth mindset scores by 7.16 points. The effect is much larger in magnitude than the effect we observe in the BOOST2018 study. This can be easily explained by the fact that in the replication study growth mindset was measured right after the intervention, while in the main study this was obtained several weeks afterwards.

The positive effects of the intervention also extend to participants' academic outcomes with results that are strikingly similar to our main study. The intervention increased first-year GPA by 1.6 points, or 17% of a standard deviation, (compared to 1.74 GPA or 14% of a standard deviation in the main study); and their probability of obtaining a first class honors degree by 7.8ppt (compared to 7.6ppt in the main study). Finally, Panel B of Table 1.10 shows that the treatment had a similar impact on the beliefs of men and women, but a greater impact on the academic performance of men (e.g., 2.99 GPA for men compared to 1.23 for women), although these differences are slightly less precisely estimated than in the main study.[32] These results suggest that our intervention would likely yield similar results on different groups of students across different institutions.

[32]In the replication study, we cannot differentiate those who received a grade below 40 from those who dropped out. That is why, we use "no fail to progress" as a measure of pass.

1.8 Further Analysis

In this section we address some important issues for our analysis and provide a series of checks and additional validation of our results.

Multiple Hypothesis Testing – We estimate the effect of the intervention on many different outcomes and we recognize this may raise concerns related to multiple hypothesis testing. One approach to deal with this problem is to adjust the p-values corresponding to each statistical test used to investigate the impact of the intervention. Many adjustments have been proposed including the Bonferroni (Bonferroni, 1936), Holm (Holm, 1979), or Benjamini-Hochberg (Benjamini & Hochberg, 1995) corrections. The problem with these types of procedures is that they tend to be very conservative in that they assume that each test is independent of each other, which would be the case if the outcomes were uncorrelated.[33]

An alternative approach is to create summary indexes using different combinations of variables through an inverse covariance weighting scheme which puts less weight on highly correlated outcomes, as suggested in Anderson (2008). This effectively reduces the number of outcomes, and therefore the number of tests performed. We follow here this approach and rely on summary indexes for (i) Beliefs, (ii) Attainment (at the end of the first year and at graduation), (iii) Study Quantity, and (iv) Study Quality. We have already discussed some of these indexes, but we now further aggregate the Study Methods and Study Habits indexes into one single measure for Study Quality (see Appendix 1.2).

Estimates of the effect of the intervention on these indexes are reported in Figure 1.3. Panel A shows that the intervention had a positive and significant effect on beliefs, attainment, and quality of effort, but estimates for the quantity of effort are not statistically significant. Panel

[33] The Bonferroni correction divides the unadjusted p-values by the total number of tests, i.e. it assumes that the tests are independent of one another. The Holm and the Benjamini-Hochberg corrections are slightly less extreme and use the order to the p-values (in terms of magnitude) to take into account that there is some correlation across outcomes.

B shows the effects for male and females separately. Here we clearly see that the effects are stronger for males, and for the Study Quantity, index these differences are also statistically significant. By contrast, we cannot detect gender differences in the effects of the intervention on the Beliefs Index.

Heterogeneity – Although we have focused on gender differences throughout our analysis, it is also interesting to consider differences by SES and previous academic achievement. We describe this heterogeneity using the summary indexes, as this allows us a more parsimonious representation of the results. Figure 1.4 Panel A shows heterogeneity by SES. We see no statistically significant differences in the treatment effect by this indicator of disadvantage. This is not very surprising in our context as low and high SES students exhibit similar level of beliefs and effort to begin with (see Table 1.2).

In the second part of the figure, we show differences by previous academic achievement or tariff score. We see a larger effect on beliefs for low tariff students (defined as those who are not in the highest two tariff quintiles), but this is not statistically different for the two groups. The evidence on other outcomes is more mixed, with some suggestion that outcomes at graduation are in fact better for high tariff students. Ultimately, however, none of these differences are statistically significant. Once again, this is consistent with the fact that differences in measures of beliefs and effort are very small even at baseline.

It is interesting to compare these heterogeneity results with findings from other studies. The previous literature on growth mindset has generally found stronger effects on disadvantaged or low-ability students. Indeed, these interventions have often been advocated on the ground that they can reduce socio-economic inequalities in educational outcomes (Yeager *et al.*, 2016; Yeager & Dweck, 2020). By contrast, many of these studies are silent about gender difference. When they do report results by gender, they usually show no differential impact (Broda *et al.*, 2018; Outes-Leon *et al.*, 2020). Only a few studies, which focus very specifically on achievement in mathematics or STEM subjects report sometimes larger effect for women (Good *et al.*, 2003; Dar-Nimrod & Heine, 2006)), but not always (Burnette *et al.*, 2018).

Our analysis shows clear differential effects by gender, but not by SES or previous achievement. One possible explanation is that heterogeneity in the effects of these interventions is context-dependent. In other words, the effects are likely to be stronger for groups that exert less effort, or have less strong beliefs about the productivity of effort at baseline. In our case, the most striking differences are seen between male and female students. It is also possible that differences will only emerge where individuals are relatively unconstrained in terms of their time allocation (Delavande & Zafar, 2019). So, for example, it might be harder for these interventions to affect SES differences among university students if low-SES students are more likely to hold a part time job.

Intention to Treat Effects – The intention-to-treat effects corresponding to the TE effects shown in Tables 4-8 are presented in Appendix Table A1.9. These shows similar results as in the TE estimates, although in general the effects are smaller and less precisely estimated, as one would expect. For example, the effect on the first-year GPA is 1.195 or 10% of a standard deviation (against a TE of 1.7 or 14% of a standard deviation), while the effect on the first-year attainment index is only 7% and not precisely estimated (against a TE of 14%). Once again, we see clear gender differences, with the ITT effects being generally larger and more significant for male students than females. In some cases, as for the Study Quantity Index and the effect on exam scores, these gender differences are also significantly different from zero.

Different Analytical Samples – Our main analysis is conducted on the sample of Home student. We present results for the whole sample, including Overseas and European Union students, in Appendix Table A1.10. The results are qualitatively very similar in most cases. There is, for example, a treatment effect of 2.71 points for the growth mindset score, which is remarkably close to effect of 2.23 points estimated on the Home sample in Table 1.4. Similarly, we see an effect of 20% of a standard deviation for the beliefs index (compared to 22% in our main sample). There is also an increase of 13% of a standard deviation in the first year Attainment Index and Graduation Index, which are comparable to what we saw for the Home sample in Table 1.6 and Table 1.9, respectively. The differences by gender also follow the same patterns we observed in our main analysis, with little or no heterogeneity in relation to the beliefs measures, but a stronger indication that the intervention had a larger impacts on male study time and academic achievement.

1.9 Conclusion

In this paper we implement a new randomized intervention on a cohort of first year university students at a UK Higher Education institution. The main aim of the intervention is to change individual beliefs about the productivity of effort - specifically, study time, attendance to lecture and classes, and different study methods and techniques - in order to improve general ability and grades. A second objective of the intervention is to reduce the large and significant gender differences in beliefs and effort observed at baseline, with a consequent reduction in male disadvantage in terms of attainment.

We find significant and positive treatment effects on students' beliefs, measured through a validated and widely adopted psychological instrument, the growth mindset, but also through subjective expectations about the effect of study and attendance on grades. We also find positive treatment effects on first-year and graduation attainment, with significant differences by gender. In exploring the mechanisms which could explain these effects, we are able to identify significant changes in quantitative as well as qualitative aspects of study time, with treated students being for example more likely to test themselves or revise topics they find more difficult. All our results indicate a stronger impact of the intervention on male students, to the extent that some of the gender differences we observe at baseline in terms of attainment, quantity, and quality of study time are significantly reduced by the end of the first year (see Figure 1.5).

Our findings extend the existing literature on education interventions in several ways. First of all, this is one of the few studies that targets non-cognitive skills, in this case beliefs about the productivity of effort, on a population of young adults. By contrast, most of the literature focuses on school-aged children. Second, we propose new ways to measure individual beliefs about the productivity of effort. Specifically, we measure these beliefs through subjective expectations about the effect of effort and ability on grades, and about the effect of effort on ability, where the latter is the concept most widely used in the psychological literature. Our study highlights that grade expectations, or the beliefs that effort can affect grades, are much more malleable than ability expectations, or the beliefs that effort can affect general ability. Third, we demonstrate that our intervention is able to significantly reduce gender differences in attainment by inducing male students to exert more effort and change their study methods.

Figures

Figure 1.1: Timeline

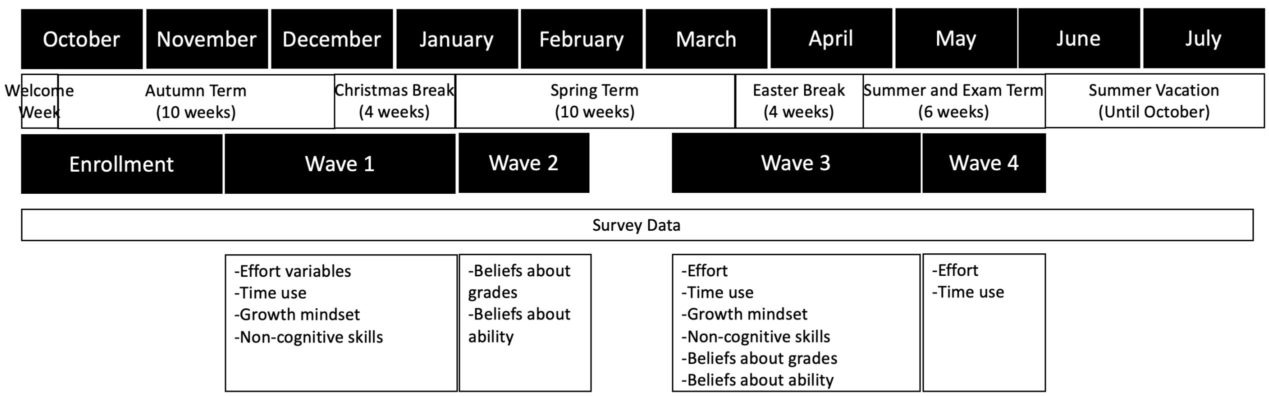
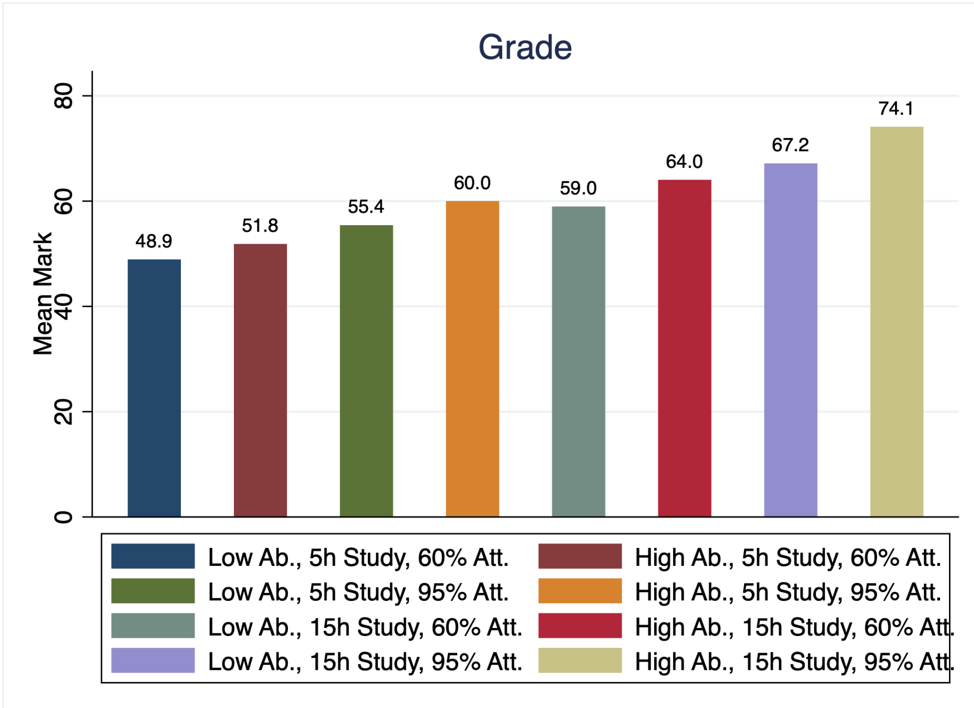


Figure 1.2: Average Grade and Ability in Each Scenario



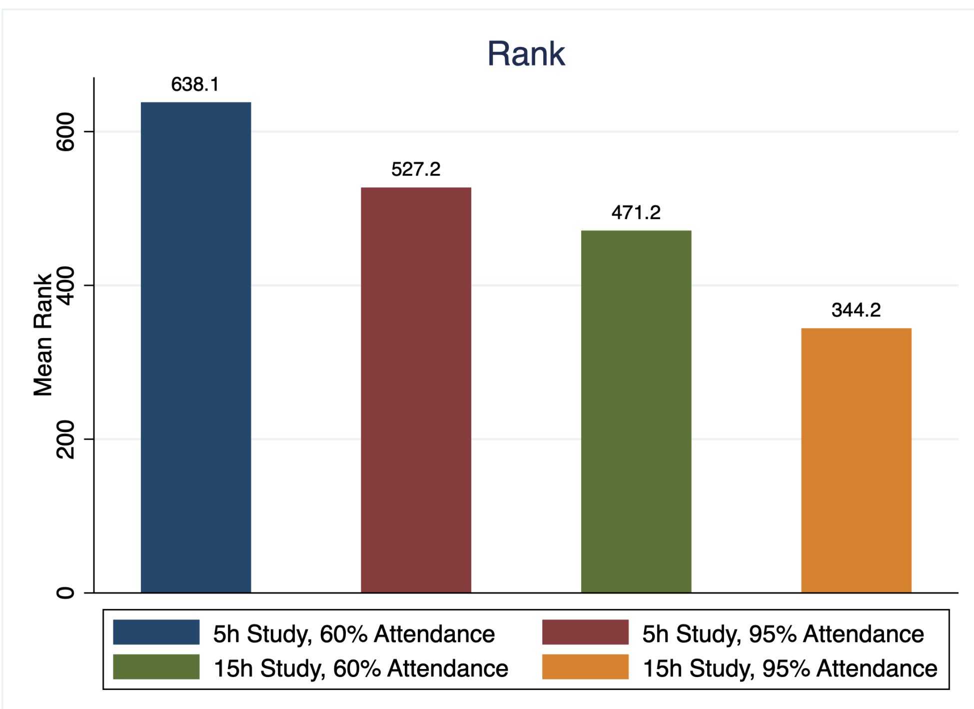
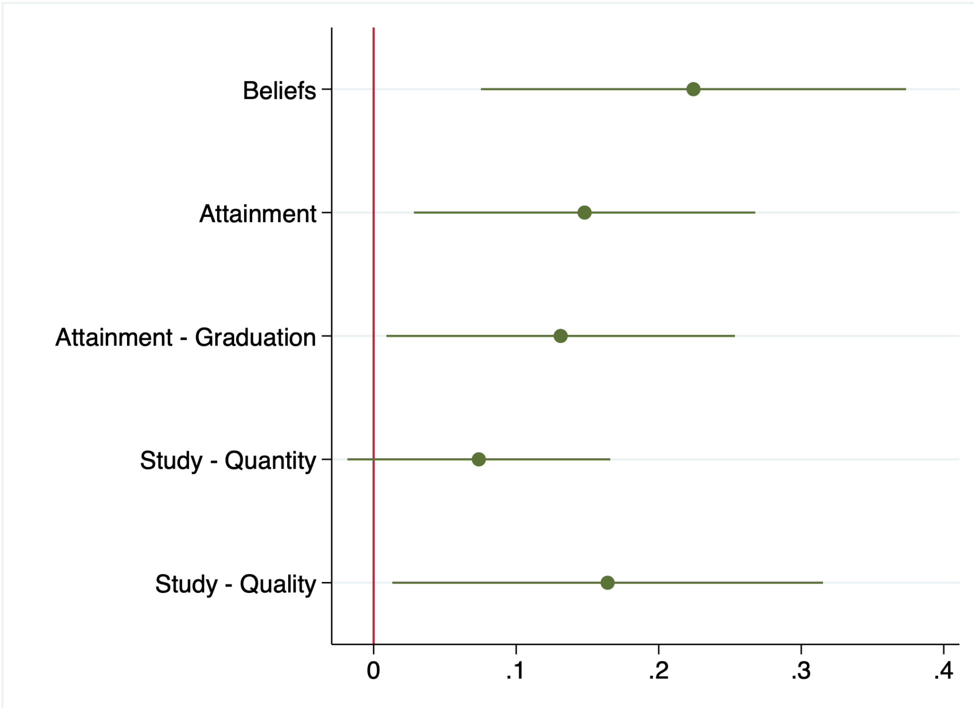
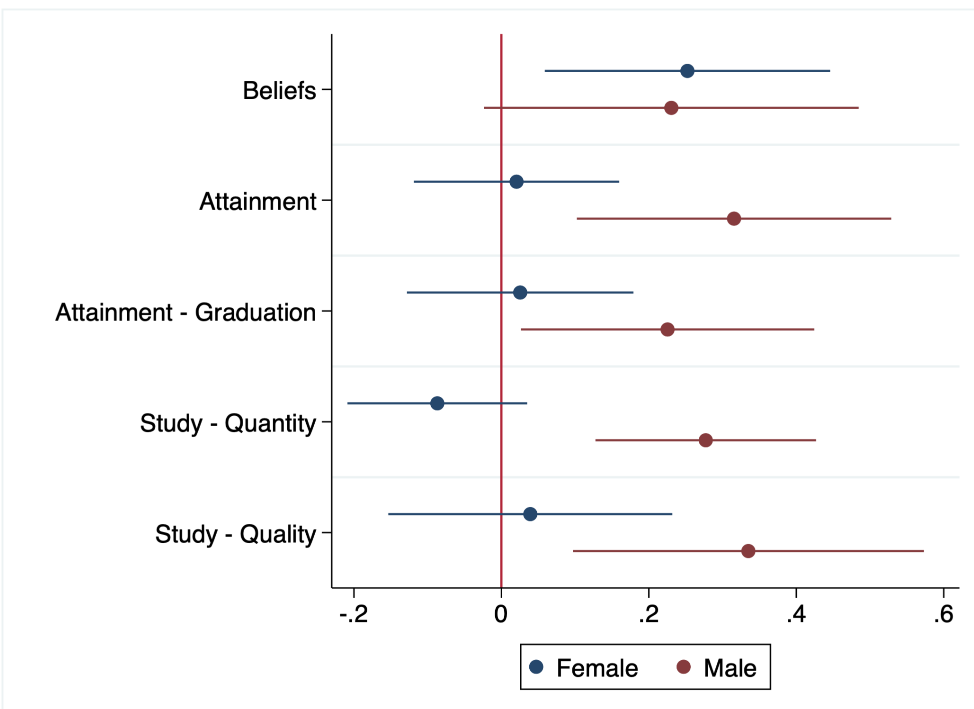


Figure 1.3: Heterogeneity of Treatment Effect

Panel A: TE for Home Students



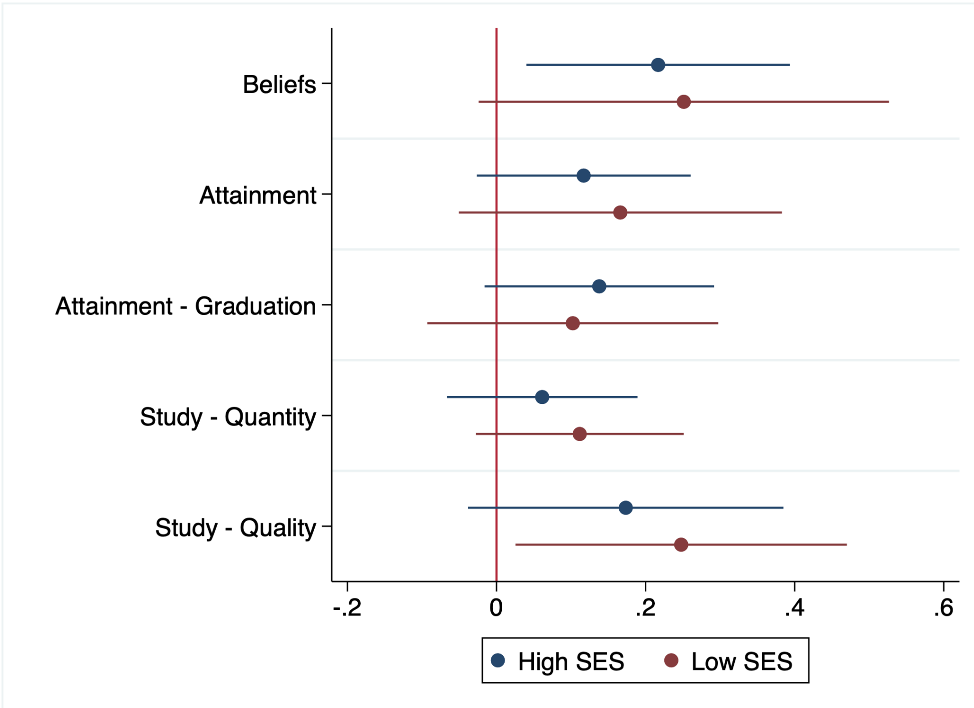
Panel B: TE for Home Students by Gender



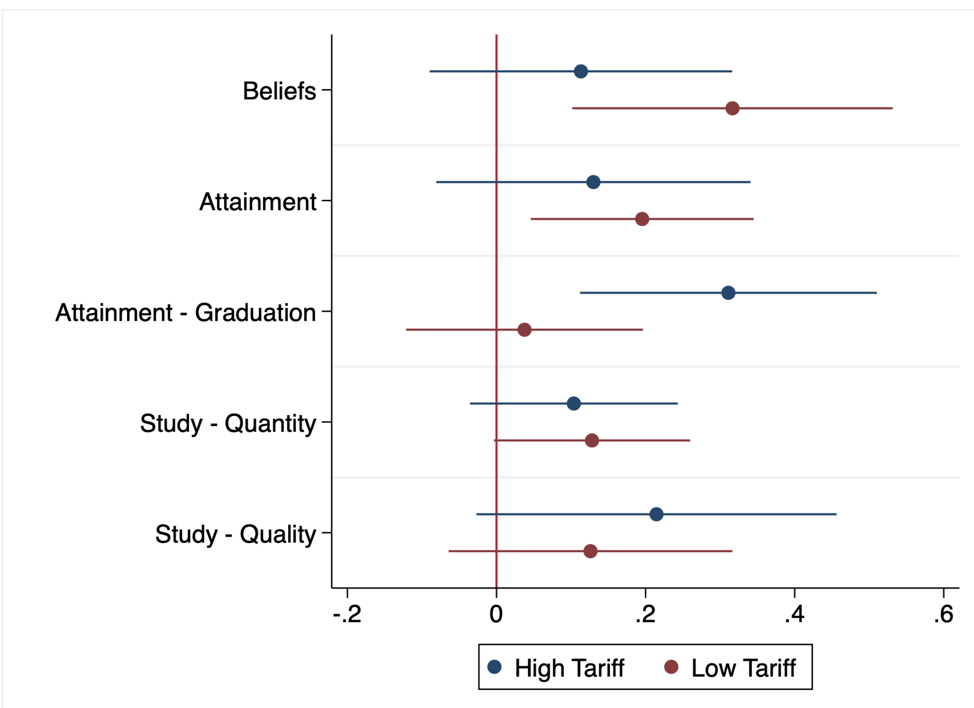
Notes: We create these indexes using the method described in Anderson (2008). Thus the results are in standard deviation terms.

Figure 1.4: Heterogeneity of Treatment Effect

Panel A: TE on Home Students by SES

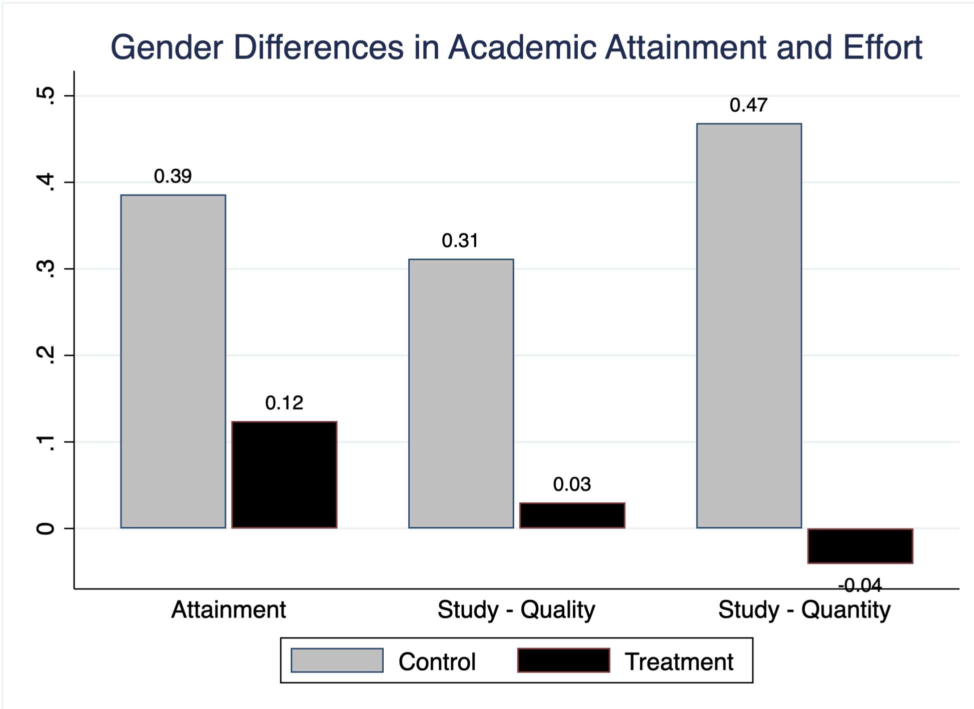


Panel B: TE on Home Students by Tariff



Notes: We create these indexes using the method described in Anderson (2008). Thus the results are in standard deviation terms.

Figure 1.5: Gender Gap



Notes: We create these indexes using the method described in Anderson (2008). Thus the results are in standard deviation terms.

Tables

Table 1.1: Characteristics of the population and study samples of BOOST2018

	All UK universities	Study university	Study participants	Waves 1	2	1&2&3	2&3	1&3
Female	0.55	0.48	0.49	0.54	0.56	0.56	0.56	0.55
High SES	0.50	0.49	0.53	0.53	0.52	0.54	0.53	0.55
Low SES	0.26	0.29	0.32	0.32	0.33	0.32	0.33	0.32
SES Missing	0.24	0.21	0.16	0.15	0.16	0.14	0.14	0.14
Mature (> 21)	0.14	0.09	0.08	0.07	0.07	0.07	0.08	0.07
Tariff (std.)	0.32	0.08	0.10	0.14	0.10	0.12	0.10	0.11
Tariff quintiles								
First (Lowest)	0.32	0.16	0.16	0.17	0.17	0.17	0.17	0.18
Second	0.11	0.20	0.21	0.19	0.21	0.19	0.20	0.18
Third	0.11	0.16	0.16	0.17	0.16	0.16	0.16	0.17
Fourth	0.17	0.19	0.21	0.22	0.21	0.21	0.21	0.22
Fifth (Highest)	0.29	0.18	0.20	0.21	0.21	0.21	0.21	0.20
Observations	327,685	1,893	1,380	883	688	522	599	688

Notes: Column 1 shows the characteristics of all students enrolled at any UK university, column 2 shows those who enrol at the university where the study took place, column 3 shows those who enrol in the study. Columns 4-8 show the different samples used in our analysis: Columns 4 and 5 restrict the sample to those who participated in wave 1 and 2, respectively; column 6 restricts the sample to those who participated in waves 1, 2 and 3; columns 7 and 8 refer to those who participated in wave 2 and 3, and waves 1 and 3, respectively. All columns show only Home (i.e. UK resident) students enrolled during the academic year 2015/16. Socio-economic status is derived from parental occupation. Mature students are those who start their undergraduate education at the age of 21 or older. The tariff score is obtained by assigning a numerical value to all the post-16 qualifications that a student holds, according to the grade achieved. This variable is standardised with respect to the population of all school leavers, whether they enrol at university or not.

Table 1.2: Descriptive Statistics

	Panel A - Academic Outcomes						
	All	Female	Male	High SES	Low SES	H Tariff	L Tariff
First Year Outcomes							
GPA	59.76	61.04	58.49***	60.23	58.77*	61.24	58.75***
	[11.84]	[10.30]	[13.07]	[12.03]	[11.52]	[12.45]	[11.13]
Exam Grade	58.73	60.47	57.02***	58.99	57.66***	59.27	58.10*
	[12.44]	[11.27]	[13.25]	[12.23]	[11.92]	[13.28]	[11.06]
First ($\geq$ 70%)	0.17	0.17	0.18	0.18	0.15*	0.23	0.13***
	[0.38]	[0.38]	[0.38]	[0.39]	[0.35]	[0.42]	[0.34]
Good ($\geq$ 60%)	0.55	0.61	0.49	0.57	0.53	0.62	0.50
	[0.50]	[0.49]	[0.50]	[0.50]	[0.50]	[0.49]	[0.50]
Pass ($\geq$ 40%)	0.94	0.97	0.92	0.95	0.93	0.95	0.94
	[0.23]	[0.17]	[0.27]	[0.22]	[0.25]	[0.22]	[0.23]
Attainment Index	0.07	0.16	-0.02***	0.09	0.00	0.17	-0.02***
	[1.00]	[0.90]	[1.08]	[0.97]	[1.04]	[1.03]	[0.97]
Graduation Outcomes							
GPA	63.23	63.94	62.47	63.34	63.02	64.68	62.23***
	[8.97]	[8.19]	[9.70]	[9.21]	[8.56]	[8.74]	[8.89]
First ($\geq$ 70%)	0.25	0.25	0.25	0.27	0.23	0.33	0.20***
	[0.43]	[0.43]	[0.43]	[0.44]	[0.42]	[0.47]	[0.40]
Good ($\geq$ 60%)	0.74	0.78	0.70***	0.74	0.75	0.79	0.71***
	[0.44]	[0.41]	[0.46]	[0.44]	[0.44]	[0.41]	[0.46]
Graduated on Time	0.52	0.58	0.47***	0.56	0.55	0.56	0.55
	[0.50]	[0.49]	[0.50]	[0.50]	[0.50]	[0.50]	[0.50]
Graduation Index	0.07	0.13	0.02**	0.09	0.05	0.22	-0.02***
	[0.98]	[0.94]	[1.03]	[1.00]	[0.97]	[0.99]	[0.97]

Notes: Means and standard deviations (in square brackets) of variables observed before enrollment and after 1st and 3rd year. Differences are tested using t-test. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 2: Descriptive Statistics (cont.d)

	Panel B - Inputs at Baseline						
	All	Female	Male	High SES	Low SES	H Tariff	L Tariff
Quantity							
Attendance (%)	0.64	0.65	0.63**	0.65	0.64	0.68	0.63***
	[0.21]	[0.21]	[0.21]	[0.20]	[0.20]	[0.19]	[0.21]
Attendance (Hours)	9.97	9.84	10.10	10.05	10.14	10.50	9.71***
	[4.68]	[4.80]	[4.56]	[4.63]	[4.57]	[4.55]	[4.64]
Study (Hours)	11.98	13.25	10.48***	12.17	11.61	12.07	11.58
	[8.57]	[9.05]	[7.72]	[8.66]	[8.49]	[8.90]	[8.02]
Study Quantity Index	0.04	0.14	-0.07***	0.10	0.00	0.13	-0.02**
	[1.01]	[1.05]	[0.96]	[0.99]	[1.02]	[1.03]	[0.97]
Study Methods							
Compulsory	0.45	0.45	0.44	0.45	0.45	0.46	0.44
	[0.23]	[0.23]	[0.24]	[0.23]	[0.23]	[0.24]	[0.22]
Reading	0.22	0.23	0.22	0.22	0.22	0.22	0.22
	[0.17]	[0.16]	[0.17]	[0.17]	[0.16]	[0.18]	[0.16]
Note Taking	0.19	0.20	0.17***	0.19	0.18	0.18	0.20
	[0.16]	[0.15]	[0.17]	[0.16]	[0.17]	[0.16]	[0.17]
Testing	0.09	0.07	0.11***	0.09	0.09	0.09	0.09
	[0.13]	[0.10]	[0.15]	[0.12]	[0.14]	[0.14]	[0.11]
Study Methods Index	0.00	0.03	-0.02	-0.00	0.01	0.04	-0.03
	[0.97]	[0.89]	[1.06]	[0.97]	[0.97]	[0.93]	[1.01]
Study Habits							
Overdue	0.86	0.87	0.84	0.86	0.84	0.88	0.83*
	[0.35]	[0.34]	[0.36]	[0.34]	[0.36]	[0.33]	[0.37]
Longest Since	0.34	0.36	0.31	0.34	0.34	0.35	0.34
	[0.47]	[0.48]	[0.46]	[0.47]	[0.47]	[0.48]	[0.48]
Interested	0.46	0.42	0.50**	0.46	0.46	0.48	0.45
	[0.50]	[0.49]	[0.50]	[0.50]	[0.50]	[0.50]	[0.50]
Doing Worst	0.56	0.57	0.56	0.58	0.54	0.55	0.58
	[0.50]	[0.50]	[0.50]	[0.49]	[0.50]	[0.50]	[0.49]
Scheduled	0.24	0.25	0.23	0.25	0.24	0.24	0.24
	[0.43]	[0.44]	[0.42]	[0.43]	[0.43]	[0.43]	[0.43]
Study Habits Index	-0.03	-0.02	-0.04	0.01	-0.09	-0.03	-0.02
	[1.00]	[1.00]	[0.99]	[1.00]	[0.99]	[1.02]	[0.99]
Study Quality Index	-0.01	0.02	-0.03	-0.00	-0.02	0.02	-0.03
	[0.97]	[0.89]	[1.06]	[0.96]	[1.01]	[0.96]	[1.00]

Notes: Means and standard deviations (in square brackets) of variables observed before enrollment and after 1st and 3rd year. Differences are tested using t-test. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 2: Descriptive Statistics (cont.d)

	Panel C - Beliefs at Baseline						
	All	Female	Male	High SES	Low SES	H Tariff	L Tariff
Growth Mindset Score	36.70	37.82	35.38***	36.96	36.20	36.37	36.68
	[9.07]	[8.87]	[9.13]	[9.08]	[9.06]	[9.04]	[9.10]
Grade Expectations[a]							
α_{att}	0.31	0.34	0.26**	0.32	0.28	0.31	0.30
	[0.45]	[0.47]	[0.41	[0.43]	[0.47]	[0.45]	[0.44]
α_{s}	0.20	0.21	0.18*	0.20	0.18	0.18	0.21
	[0.26]	[0.29]	[0.22]	[0.25]	[0.27]	[0.26]	[0.27]
α_{ab}	0.70	0.61	0.80	0.67	0.74	0.81	0.64
	[1.77]	[1.70]	[1.86]	[1.80]	[1.73]	[1.74]	[1.85]
Ability Expectations[a]							
β_{att}	0.15	0.16	0.14	0.16	0.15	0.14	0.17*
	[0.22]	[0.21]	[0.23]	[0.22]	[0.21]	[0.20]	[0.24]
β_{s}	0.09	0.10	0.07***	0.09	0.09	0.08	0.10*
	[0.11]	[0.12]	[0.10]	[0.11]	[0.11]	[0.09]	[0.12]
Beliefs Index	-0.01	0.13	-0.19***	0.04	-0.07	-0.10	0.06*
	[1.00]	[0.98]	[1.00]	[1.02]	[0.96]	[1.04]	[1.04]

Notes: Means and standard deviations (in square brackets) of variables observed at the 1st and 2nd wave. Growth Mindset is measured in Wave 1 and Beliefs about Grades and Ability are measured at the 2nd wave. Differences are tested using t-test. * p<0.1, ** p<0.05, *** p<0.01

Table 1.3: Balancing

	Assignment			Treatment		
	Control	Assignment	p-value	Control	Treatment	p-value
Female	0.50	0.49	0.96	0.56	0.56	0.92
High SES	0.52	0.53	0.85	0.49	0.55	0.12
Low SES	0.32	0.32	0.97	0.35	0.30	0.17
SES Missing	0.16	0.16	0.76	0.16	0.15	0.73
Mature (> 21)	0.08	0.08	0.98	0.07	0.08	0.50
Tariff	0.10	0.10	0.93	0.11	0.10	0.88
Tariff Quintiles						
Lowest	0.17	0.16	0.90	0.16	0.17	0.61
Second	0.21	0.21	0.85	0.21	0.21	0.97
Third	0.16	0.17	0.70	0.16	0.16	0.82
Forth	0.21	0.20	0.90	0.22	0.20	0.44
Fifth	0.20	0.20	0.96	0.20	0.21	0.89
Observations	692	688		326	362	

Notes: Mean of individual characteristics according to assignment and participation to the intervention.Socio-economic status is derived from parental occupation. Mature students are those who start their undergraduate education at the age of 21 or older.

Table 1.4: Treatment Effect on Growth Mindset

Panel A: TE on All Students

	Growth Mindset Score		
Treatment	2.235***	2.051***	2.234***
	(0.811)	(0.698)	(0.698)
Baseline		0.510***	0.515***
		(0.050)	(0.051)
Controls	No	No	Yes
Observations	520	520	520

Panel B: TE by Gender

	Growth Mindset Score		
TE on Females	2.242**	2.176**	2.120**
	(1.017)	(0.875)	(0.863)
TE on Males	2.196*	1.964*	2.033*
	(1.309)	(1.129)	(1.169)
p-value difference	0.98	0.88	0.95

Table 1.5: Treatment Effect on Subjective Expectations

Panel A: TE on All Students

	Grade Expectations			Ability Expectations		Beliefs Index
	Attendance	Study	Ability	Attendance	Study	
Treatment	0.067*	0.048**	-0.076	-0.013	0.001	0.220**
	(0.034)	(0.022)	(0.213)	(0.013)	(0.008)	(0.091)
Wave 2 - α_{att}	0.221***	0.029	-0.221			
	(0.080)	(0.040)	(0.411)			
Wave 2 - α_s	-0.183	0.062	0.100			
	(0.122)	(0.074)	(0.651)			
Wave 2 - α_{ab}	-0.018	-0.007	0.116			
	(0.011)	(0.006)	(0.095)			
Wave 2 - β_{att}				0.138**	0.079**	
				(0.065)	(0.037)	
Wave 2 - β_s				0.018	0.015	
				(0.106)	(0.066)	
Baseline Index						0.405***
						(0.057)
Observations	511	511	511	590	590	446

Panel B: TE by Gender

	Grade Expectations			Ability Expectations		Beliefs Index
	Attendance	Study	Ability	Attendance	Study	
TE on Females	0.094**	0.038	-0.122	-0.017	-0.006	0.252**
	(0.043)	(0.029)	(0.247)	(0.018)	(0.011)	(0.118)
TE on Males	0.037	0.059*	-0.120	-0.001	0.010	0.231
	(0.056)	(0.033)	(0.247)	(0.014)	(0.011)	(0.153)
p-value difference	0.41	0.64	1.00	0.52	0.35	0.91

Notes: All regressions control for gender, socio-economic status, mature student status, tariff quintiles and include department fixed effects. The estimation sample consists of individuals who attended wave 1, 2 and 3. Standard errors in parentheses. * p <0.1, ** p <0.05, *** p <0.01.

Table 1.6: Treatment Effect on First-Year Academic Outcomes

Panel A: TE on All Students

	(1) GPA	(2) Exam	(3) First (≥ 70)	(4) Good (≥ 60)	(5) Pass (≥ 40)	(6) Attainment Index
Treatment	1.744**	1.522*	0.076***	0.044	0.017	0.138*
	(0.786)	(0.828)	(0.029)	(0.036)	(0.015)	(0.072)
Tariff(Std)	1.830***	1.476**	0.083***	0.060***	-0.001	0.089
	(0.526)	(0.680)	(0.017)	(0.021)	(0.013)	(0.064)
Observations	677	672	677	677	677	670

Panel B: TE by Gender

	GPA	Exam	First (≥ 70)	Good (≥ 60)	Pass (≥ 40)	Attainment Index
TE on Females	1.407	0.916	0.041	-0.012	0.022	0.024
	(0.989)	(1.011)	(0.038)	(0.047)	(0.016)	(0.085)
TE on Males	2.385*	2.662*	0.126***	0.123**	0.013	0.321**
	(1.332)	(1.424)	(0.047)	(0.057)	(0.029)	(0.127)
p-value difference	0.56	0.32	0.16	0.07	0.80	0.05

Notes: All regressions control for gender, socio-economic status and mature student statuss and include department fixed effects. TE sample consists of individuals who attended wave 2. Standard errors in parentheses. * p <0.1, ** p <0.05, *** p <0.01

Table 1.7: Treatment Effect on Study - Quantity

Panel A: TE on All Students

	(1) Attendance (Hours)	(2) Attendance (Percentage)	(3) Weekly Study (Hours)	(4) Quantity Index
Treatment	0.245	0.016*	0.034	0.074
	(0.169)	(0.009)	(0.556)	(0.056)
Baseline	0.781***	0.965***	0.492***	0.698***
	(0.034)	(0.032)	(0.043)	(0.034)
Observations	672	672	520	512

Panel B: TE by Gender

	Attendance (Hours)	Attendance (Percentage)	Weekly Study (Hours)	Quantity Index
TE on Females	0.123	0.015	-1.259	-0.087
	(0.218)	(0.013)	(0.821)	(0.074)
TE on Males	0.459*	0.014	1.754**	0.277***
	(0.265)	(0.014)	(0.771)	(0.090)
p-value difference	0.33	0.94	0.01	0.00

Notes: All regressions control for gender, socio-economic status, mature student status, tariff quintiles and include department fixed effects. The estimation sample consists of individuals who attended wave 1, 2 and 3. Standard errors in parentheses. * p <0.1, ** p <0.05, *** p <0.01

Table 1.8: Treatment Effect on Study - Quality

Panel A: TE on Study Methods on All Students

	Compulsory	Reading	Note Taking	Testing	Methods Other	Study Index
Treatment	-0.018	0.000	0.008	0.021**	-0.010	0.131
	(0.020)	(0.014)	(0.014)	(0.010)	(0.010)	(0.090)
Baseline	0.399***	0.101	0.214**	0.157*	0.000	0.079*
	(0.112)	(0.073)	(0.096)	(0.081)	(.)	(0.041)
Observations	502	502	502	502	502	502

Panel B: TE by Gender

	Compulsory	Reading	Note Taking	Testing	Other	Study Methods Index
TE on Females	-0.042	0.003	0.010	0.025*	0.004	0.007
	(0.028)	(0.017)	(0.019)	(0.013)	(0.013)	(0.113)
TE on Males	0.012	0.000	0.001	0.017	-0.030*	0.303**
	(0.030)	(0.025)	(0.021)	(0.016)	(0.016)	(0.143)
p-value difference	0.18	0.94	0.75	0.69	0.10	0.11

Panel C: TE on Study Next on All Students

	Overdue	Longest	Interested	Doing Worst	Scheduled	Study Habits Index
Treatment	0.035	0.100**	0.074*	0.158***	0.028	0.174**
	(0.031)	(0.043)	(0.042)	(0.042)	(0.038)	(0.080)
Baseline	0.226***	0.165***	0.339***	0.361***	0.385***	0.359***
	(0.055)	(0.047)	(0.043)	(0.042)	(0.050)	(0.046)
Observations	520	519	520	520	520	519

Panel B: TE by Gender

	Overdue	Longest	Interested	Doing Worst	Scheduled	Study Habits Index
TE on Females	0.021	0.081	0.062	0.138***	0.003	0.114
	(0.038)	(0.058)	(0.054)	(0.056)	(0.050)	(0.111)
TE on Males	0.055	0.101	0.082	0.187***	0.058	0.230***
	(0.052)	(0.068)	(0.070)	(0.063)	(0.058)	(0.113)
p-value difference	0.60	0.82	0.81	0.56	0.47	0.46

Notes: All regressions control for gender, socio-economic status, mature student status, tariff quintiles and include department fixed effects. Panel A & B control for all study methods, compulsory, reading, note taking, testing and other. Panel C & D show the marginal effects results from probit regressions. The estimation sample consists of individuals who attended wave 1, 2 and 3. Standard errors in parentheses. * p <0.1, ** p <0.05, *** p <0.01

Table 1.9: Treatment Effect on Graduation Outcomes

Panel A: TE on All Students

	Graduated on Time	GPA	First (≥ 70)	Good (≥ 60)	Graduation Index
Treatment	0.003	1.616**	0.050	0.046	0.132*
	(0.029)	(0.646)	(0.035)	(0.033)	(0.074)
Baseline	0.012	2.216***	0.102***	0.076***	0.192***
	(0.017)	(0.344)	(0.021)	(0.017)	(0.042)
Observations	685	613	613	613	613

Panel B: TE by Gender

	Graduated on Time	GPA	First (≥ 70)	Good (≥ 60)	Graduation Index
TE on Females	-0.005	0.774	0.013	-0.019	0.027
	(0.039)	(0.784)	(0.046)	(0.043)	(0.094)
TE on Males	0.014	2.241**	0.078	0.112**	0.225*
	(0.046)	(1.131)	(0.058)	(0.051)	(0.117)
p-value difference	0.75	0.29	0.38	0.05	0.19

Notes: All regressions control for gender, socio-economic status, mature student status, tariff quintiles, and department fixed effects. The estimation sample consists of individuals who attended wave 1, 2 and 3. Standard errors in parentheses. * p <0.1, ** p <0.05, *** p <0.01

Table 1.10: Replication Study

Panel A: TE on All Students

	Growth Mindset	GPA	First (≥ 70)	Good (≥ 60)	Attainment Index
Treatment	7.164***	1.637***	0.078**	0.025	0.115**
	(0.824)	(0.610)	(0.036)	(0.022)	(0.049)
Baseline		2.787***	0.137***	0.057**	0.162***
		(0.721)	(0.033)	(0.025)	(0.057)
Observations	805	775	775	775	775

Panel B: TE by Gender

	Growth Mindset	GPA	First (≥ 70)	Good (≥ 60)	Attainment Index
TE on Females	7.728***	1.235	0.074	0.023	0.124**
	(0.971)	(0.768)	(0.044)	(0.027)	(0.060)
TE on Males	6.633***	2.986*	0.092	0.093	0.172*
	(1.695)	(1.671)	(0.067)	(0.048)	(0.093)
p-value difference	0.58	0.29	0.82	0.20	0.66

Notes: All regressions control for gender, socio-economic status, and department fixed effects. The sample consists of individuals who participated in the replication study. Standard errors in parentheses. * p <0.1, ** p <0.05, *** p <0.01.

Chapter 2

SES-Based Affirmative Action and Academic and Labor Market Outcomes: Evidence from UK's Contextualized Admissions

2.1 Introduction

It is now a well-known fact that education has a positive impact on many domains such as labor market (Angrist & Keueger, 1991; Kane & Rouse, 1995; Card, 1999; Oreopoulos, 2006), health (De Walque, 2007; Silles, 2009; Buckles *et al.*, 2016), non-cognitive outcomes (Cornelissen & Dustmann, 2019), test scores (Cornelissen *et al.*, 2018) and immigration (Malamud & Wozniak, 2012).[1] In particular, Higher Education (HE) received special attention from economists due to its impact on many later life outcomes. Perhaps not surprising, holding an undergraduate degree leads to higher earnings and better employment (Maurin & McNally,

[1] See also Oreopoulos & Salvanes (2011) and Grossman (2006) for non-pecuniary, Black *et al.* (2008) for fertility, Lafortune (2013) for marriage market, Lleras-Muney (2005) for mortality and Lochner & Moretti (2004) for crime effects of education.

2008; Walker & Zhu, 2011). It also increases voter participation and support for free speech (Dee, 2004a) while reducing the probability of smoking (De Walque, 2007). The impact of HE is not only limited to those who acquire it but it persists to the next generations, leading better academic and health outcomes while increasing social mobility (Currie & Moretti, 2003; Blanden & Macmillan, 2016; Oreopoulos *et al.*, 2006; Suhonen & Karhunen, 2019).

While education has such an impact on many domains, HE participation in the United Kingdom remains low among people from disadvantaged backgrounds (Blanden & Machin, 2004). A strand of literature has focused on why individuals choose not to attend university (Carneiro & Heckman, 2002; Chowdry *et al.*, 2013). From a policy perspective, Widening Participation has long been an important part of the policy agenda in the UK. A government white paper on the future of Higher Education by Department for Education & Skills (2003) outlined the steps to make HE admissions fair in the UK. The government paper stated that education should not be a signal of privilege but a force for social justice and opportunity. The paper also announced that a new regulator will be established in the UK to oversee the admission process of the universities and make sure that the process is fair and same chances are given to all the students regardless of their background. Later in 2009, the government announced a target to double the number of students from disadvantaged backgrounds in the universities by 2020 with respect to 2009 numbers but this target is yet to be achieved.

HE in the England is costly to the students with a current tuition fee cap of £9250 per year for UK citizens, with most universities charging this amount for their undergraduate degrees. There have been several HE funding reforms, that changed the grant and loan availability and eligibility criteria. Research shows that the 2012 reform that increased the tuition fee caps in the England coupled with the increase in the loan and scholarship availability reduced the socio-economic gaps in university enrollment but it was slow on making progress on the government's target (Azmat & Simion, 2020). One way that universities are working on this target is to use contextualized admissions. Contextualized admission policies take applicants' socio-economic background information into account in addition to their academic background to assess their potential when making admission decisions. This is, in a sense, similar to the affirmative action in the context of US but in England, this type of admission policy does not rely on race (as this was the case in US) but several disadvantage factors such as being the first in the family to go to university, coming from an area where HE attainment is low, receiving free school meals, or graduating from a school with lower average exam scores. So, this is a more comprehensive version of the US-based affirmative action that is based on socio-economic status.

Universities started applying contextualized admissions in 2000s. While this admission policy is applied by the universities in each of the devolved nations of the UK, for this paper, I focus on England. This is because the tuition fee reforms in 2006 and 2012 made HE funding different in each devolved nations (HE is free in Scotland for students domiciled in Scotland while HE in England is costly regardless of student domicile). Among English universities, nearly 60% of them use contextualized admissions in 2019. While the earliest known year for the implementation of this policy is 2006, the universities implemented this policy at different years. Of those universities that apply contextualized admissions, 10% of them implemented this policy prior to 2012, 40% implemented in 2012 and the remaining universities implemented after 2012. While one might expect the universities that have a lower proportion of students from disadvantaged backgrounds to implement this policy earlier, an in-depth analysis of policy implementation timing shows that this is not the case.

Current evidence, focusing on a small group of universities, looking at the average academic outcomes of the degree programs finds that there are no differences in the proportion of students graduating with a first class honors degree or dropping out between the programs that use contextualized admissions and those that do not (Boliver *et al.*, 2017).

In this paper, using linked administrative and survey data, I study the effect of the introduction of contextualized admissions on applications that the universities receive, student composition at universities, and academic and labor market outcomes of the graduates. The rich administrative and survey data let me analyze several aspects of this policy change. I also collect data on the timing of this policy change and link this to the administrative and survey data. In order to collect data on the timing of the policy change, I use universities' Access and Participation Plans that are freely available on the Office for Students' (the above mentioned regulator) website. As these plans include information about the admission process of each university for each and every year, these plans serve as evidence on the use of contextualized admissions and the first year the universities mention that they use contextualized admissions serve as the year that the policy was implemented. On applications, I focus on the applications that the universities receive from their prospective students. On student composition, I focus on student characteristics and their entry scores. Then, I focus academic and labor market outcomes of the students. The data that is currently available allows me to study the effect of implementation of contextualized admissions for the cohorts that started their undergraduate study between 2001/2 and 2015/16 academic years since 2017/18 graduates are the ones who enrolled to the universities in the academic year 2015/16 (HE programs in the England generally take 3 years to complete as opposed to US programs which take 4 years). Of the universities that implement contextualized admissions, 71% of them did so in this period.

In order to study the effect of being recruited under this policy, I use differences-in-difference method. While this method is most commonly used to study the effect of a policy change that happens at a given point in time, it can also be used to understand the effect of the staggered implementation of a new policy, as it is the case here. In order to control for the changes that happened in different years at different universities, I control for university and cohort fixed effects, following two-way fixed effects approach. Thus, the empirical strategy is similar to the ones adopted in seminal papers such as Stevenson & Wolfers (2006) and Stevenson (2007) and more recent papers (Bailey & Goodman-Bacon, 2015; Gentzkow, 2006; Gentzkow *et al.*, 2011; Prager & Schmitt, 2021). A strand of the literature shows that when there are multiple time periods, the two-way fixed effects differences-in-differences approach may assign negative weights to the earlier periods (De Chaisemartin & d'Haultfoeuille, 2020; Callaway & SantAnna, 2020; Goodman-Bacon, 2021). In order to understand whether this is the case and whether the results are biased because of this, I follow Prager & Schmitt (2021) and first estimate the effects year-by-year and then use the number of students in treated universities in each of these years as the weights and calculate the weighted differences-in-differences results which show that the results obtained from the two-way fixed effects model hold.

One typical worry with policies that are implemented at different times is the exogeneity of timing. There can be some student characteristics that the universities keep track of and changes in these characteristics might encourage universities to implement policies to mitigate these changes. Before moving on to results, I present evidence on the exogeneity of the timing of this policy change. In order to check whether changes in the universities' student characteristics predict whether universities use contextualized admissions or not, I run a survival model. I find that changes in student characteristics (especially disadvantage factors) do not predict the implementation of this policy. This ensures that the changes in the student population at a given university do not predict whether a university uses contextualized admissions or not.

I find that introduction of this policy results in students with lower high school grades being more likely to apply to universities that adopt contextualized admissions. Universities' responses to students' applications results in students with lower entry scores to be admitted to the universities and an increase in the enrolled students' probability of coming from a state school and coming from low HE attainment areas. On the academic outcomes, I find that the introduction of this policy has a negative effect. The policy reduces the probability of getting a first class honors degree (an average mark of 70 or above) by 2.22 percentage points and getting a good honors degree (a first or upper second class honors degree, an average mark of 60 or above) by 4.44 percentage points. Although the effect on the probability of getting a good honors degree is not relatively high as most of the students get a good honors degree, the effect on the probability of getting a first class honors degree is quite high, 25 percent of the standard deviation. While the policy does not increase the likelihood of dropping out which is consistent with affirmative action literature, students take longer to graduate. On the labor market outcomes, contextualized admissions does not affect graduates' employment outcomes. However, graduates are less likely to go on to further study after completing their undergraduate degree. In terms of job characteristics, the results show that there is a slight increase in the likelihood of holding a permanent job and a slight decrease in the likelihood of holding a job where subject studied at the university is important for. These results show that while the policy negatively affects students' academic outcomes, there is little to no effect on graduates' labor market outcomes.

One of the advantages of the data that I use in this paper is to have detailed information about the students. This allows me to do heterogeneity analysis by several disadvantage factors. This is an important aspect because contextualized admissions targets disadvantaged students but the definition of disadvantage can be different for each university. In order to study the effect of this policy on sub-groups, I look at the effects by school type as private school students are the subgroup that is definitely not targeted by this policy and by the POLAR quintiles of the areas that the students come from, as those coming from POLAR quintile 1 & 2 areas would be the students that are targeted by this policy. In terms of academic outcomes, I find that students coming private schools and state schools are negatively affected by this policy. However, the effects are stronger for students coming from private schools, the group that is definitely not treated. On the top of that, I also find that private school students are more likely to dropout as a result of this policy. Considering, the students are also less likely to graduate on time and graduate with a first or a good degree as a result of this policy, there is triple negative effect for this particular group of students. While the effects are stronger for those coming from private schools in the context of academic outcomes, I do not find any heterogeneous effects for the labor market outcomes. Looking at the results by the POLAR quintile of the area that the students come from, I find that the effect of this policy is similar for those coming from low HE attainment areas and those coming from other areas. The results also show that students that are not coming from low HE attainment areas are less likely to have a job where subject studied at the university is important. This shows that while the policy does not affect the overall student population in terms of labor market outcomes, those coming from the most disadvantaged neighborhoods are more likely to have worse labor market outcomes when they enroll into universities while this policy was in effect. Considering these students are the main target group of this policy, these negative effects on the labor market outcomes show that students do not receive additional help that prepares them for the labor market once they enroll into an undergraduate program.

This paper closely relates to the affirmative action literature. The affirmative action literature relies on the bans on the affirmative action at state levels in the US although there are papers studying similar policies in other countries too (such as Estevan *et al.* (2019); Francis & Tannuri-Pianto (2012) for Brazil, Bagde *et al.* (2016); Frisancho & Krishna (2016) for India and Alon & Malamud (2014) for Israel). The literature studies the effect of affirmative action both for under-represented minorities and for the non-minority students. Hinrichs (2012) shows that affirmative action did not affect the enrollment or graduation rates for the under-represented minority individuals. Arcidiacono *et al.* (2016) find that less prepared minority students who get into universities because of affirmative action have lower persistence in STEM majors and take longer to graduate. On the labor market outcomes, Arcidiacono (2005) uses a sequential model that includes application, admission, major choice steps where the admission decisions vary for Black and White students and shows that eliminating the variation in the admissions decision would reduce the labor market outcomes for Black students but this reduction would be small.

On the non-minority students' side, Hinrichs (2014) shows that the share of the Black students at a university does not have any predictive power on the labor market outcomes for the White students. Arcidiacono & Vigdor (2010) show that there is a negative but insignificant relationship between under-represented minority student share and the future income of White students. They also show that the estimated negative effects are driven by the under-represented minority students that are at the bottom of the academic performance distribution.

The contribution of this paper is fourfold. Previous studies that analyze the effect of affirmative action rely on policies that are based on race (in American and Brazilian case) and on caste (in Indian case). Although Alon & Malamud (2014) study the effect of an SES based admission policy in Israel, they explain that the socio-economic classes are correlated with the ethnicity and where the individuals immigrated from making it a policy on the combination of ethnicity and immigration background. However, in the UK, race cannot be used in university admissions as it would be discriminatory which is why affirmative action was banned in the US (and race is a protected characteristic in the UK according to Equality Act (2010)). This paper brings new insights to the Widening Participation literature by studying the effects of an admission policy that is based entirely on socio-economic status.

This paper extends the unit of analysis to all the universities in England. Previous studies such as Arcidiacono (2005), Arcidiacono *et al.* (2014) and Hinrichs (2014) study the effect of admission policies in a given state or at a group of universities. However, it is likely that different admission policies would change the prospective students' application behavior. Students who might benefit from a change in the admission policy may be more likely to apply to a specific university while others who might be worse off by it might shy away from those universities. This might have an effect on the equilibrium behavior if some students choose to study out of state. By studying all the universities in England, my analysis also accounts for the equilibrium effects. Although fee reforms that happened in the UK in 2012 made university fees differential in devolved nations of the UK (such as HE being free in Scotland while English universities could charge up to £9000 in 2012 and currently this cap is £9250), the effect of this change would be minimal as the crucial factor in the university fees is the domicile rather than the place of study (meaning if a student living in England applied to a Scottish university, they would still need to pay fees).

Previous papers mostly use data from enrolled students to understand the effects of affirmative action policies. It is likely that this policy will change the applications that the universities receive. As this is a policy focusing on improving access from disadvantaged backgrounds and that it offers lower admission requirements for those coming from disadvantaged backgrounds, it is possible that the universities receive more applications from students from these backgrounds and from students with lower high school test scores. As to my knowledge, this is the first paper that studies how an affirmative action policy affects the applications a university receives. I study the effect of this admission policy on the high school test scores and personal characteristics of the students that apply, that receive a positive response and that are accepted into their choices from the universities' perspective.

The literature on the effect of affirmative action on labor market outcomes relies on simulation methods. Arcidiacono (2005) shows that removal of race-based admission policy would lead to little change on labor market outcomes such as earnings and employment. However, there are more aspects of the labor market outcomes that affirmative action policies might affect such as the job characteristics. The survey data used in this paper has a rich set of questions to understand the job characteristics of the graduates. I make use of this data to study the effect of this admission policy on the graduates' job characteristics such as type of contract and importance of different elements for the jobs that the graduates hold in addition to further study after graduation. As to my knowledge, this is the first study that analyze the causal effects of an SES-based affirmative action policy on labor market outcomes empirically.

The rest of the paper is organized as follows: Section 2 describes the institutional framework, Section 3 presents data and the descriptive statistics, Section 4 explains empirical strategy, Section 5 discusses results, Section 6 presents the robustness check and Section 7 concludes.

2.2 Institutional Framework

2.2.1 Higher Education in England

Education system in England is divided into stages named Key Stage (KS). The first 4 KS are compulsory (until the age of 16) and after KS4, students need to continue to their formal education in KS5 or start working as an apprentice as part of their education until the age of 18. Those who aspire to go to university mostly continue to KS5 where students take advanced subjects in preparation to university, although there are alternative routes to go to university too. KS5 consists of year 12 and year 13 and students take exams called Advanced Subsidiary Level (AS Level) and Advanced Level (A Level) exams, respectively. Although AS Level grades do not play a role in university admissions, they are important for students to get feedback on their progress and for their teachers to use AS Level grades to predict students' A Level exam grades which students use for university applications.

UK university admissions system is quite different than other admissions systems around the world. While in most countries, students apply to universities after knowing the grades they receive from the university entrance exams, in the UK, students apply before taking their exams and they receive offers from universities based on their expected grades predicted by their teachers. The universities can give the students unconditional or conditional offers or they can invite the students for an interview. The conditional offers normally require the students to achieve a specific minimum grade from their A Level exams. After receiving offers from the universities, students select their firm and insurance choices and this is also done before taking their exams so both parties are involved in an imperfect information setting. While there are previous exams to predict the grades, this admission system also has problems. For example, if a particular group of students (such as disadvantaged students) apply to universities with much more over- (or under) predicted grades than their peers, this particular group of students might mismatch or they might miss a place at a university.[2] Once the students take their exams and get their grades, if they achieve the minimum grade requirement that is specified on their admission letter, then the students are accepted into their choices. If they do not get the grades required for their firm or insurance choice, then the students can use universities' clearing round during which they contact the universities directly. If they achieve better grades than their expected grades, they can also use adjustment round where they apply to universities that are generally more demanding in terms of minimum entry scores.

Higher Education in England, as opposed to most OECD countries is costly to the students. Currently, the tuition fee caps are £9250 per year for students categorized as Home students (those who are UK citizens or those who have settled status) and most of the universities charge this amount. In 2006, tuition fee loans were introduced. These loans cover the full tuition fee and the repayment is due after graduation. They are not means-tested

[2] Murphy & Wyness (2020) show that 75% of the students apply to universities with over-predicted grades while only 9% apply with under-predicted grades. They also show that high achieving students from lower socio-economic backgrounds receive lower predictions than their peers from higher socio-economic backgrounds.

and all UK citizens (and those who have settled status) are eligible to apply. Currently the minimum gross income required for the start of repayment of these loans is £1657 a month (or £2274 a month if they started their course after September 2012). So, even though these loans are payable, the current structure of these loans is aimed at ensuring credit constraints do not play a significant role in obtaining a university degree. In addition to tuition fee loans, there are also maintenance loans and maintenance grants that are available to students but different conditions such as low family income apply for these.

Undergraduate degrees in English universities typically take 3 years to complete. There are exceptions to this such as degrees including a component of studying abroad or placement year or combined undergraduate/ postgraduate degrees which generally take 4 years to complete. If students are studying in a program with study abroad or placement year, these additional years are generally spent as the 3rd year of the program. Students arrive to the universities to study a specific subject. As opposed to US where students declare their majors after starting university, students make this decision before coming to university. However, most of the students normally need to decide what they would like to study 1-2 years before coming to university as some courses need specific A Level subject requirements. English undergraduate programs are very specialized and students take courses mostly in their field of study. Free elective courses are rare but students can have area elective courses depending on their degree program and university. Students cannot switch programs without losing their accumulated credits as they normally start from the beginning of the new program except in some rare cases (such as transferring from BSc in Economics to BA in Economics or unless they have already gained credits of the program that they would like to switch). Double major or minor programs do not exist, except in the cases where a program has a component from a different course of study and the students applied to these programs when applying to university (for example BA in Economics & Politics is similar to a double major in Economics and Politics however students do not take all the required courses in Economics and Politics degree courses but only a composition of them while BA in Economics with Mathematics is similar to an Economics degree with a minor in Mathematics).

The students' grades are measured on a 0-100 scale for each course and the passing grade for undergraduate level courses is generally 40. Marks are moderated by examiners from different universities so that the marks are comparable between subjects and between universities. At the end of their study, students may be awarded one of the 4 different honors classes. These are first class honors (for those achieving an average mark of 70 or above), upper second class honors (between 60 and 69) lower second class honors (between 50 and 59) and third class honors (between 40 and 49). If a student has an average passing mark but do not qualify to receive an honors degree, the student is awarded a "pass". Most employers in the UK use first class honors or upper second class honors as their criteria for hiring and these two combined is mostly referred as good honors degree.

2.2.2 Contextualized Admissions

In the last years, the UK government targeted to double the number of university entrants from disadvantaged backgrounds by 2020 relative to the numbers in 2009. This progress has been slow but universities started applying new strategies to attract disadvantaged students. One such policy is contextualized admissions. Some universities started applying contextualized admissions, using applicants' characteristics to bring context to their application and to determine their potential, rather than using their exam scores alone to increase the number of students' coming from disadvantaged backgrounds. With contextualized admissions, universities aim to accept more students whose potential did not or could not materialize in their high school test scores due to the circumstances that surround their life.

When students make their university choices on Universities and Colleges Admissions Service (UCAS), they are asked to fill a form about themselves that includes questions about their parents' occupation, parental education, free school meals (FSM) status, where they live, whether they have been in care and information about the school that they went to in addition to their basic demographic information. Universities can choose to use this data to inform their admission decisions and prioritize disadvantaged students in different ways.

Universities are free to choose what type of information they use on their admission policies. They, however, cannot discriminate based on the characteristics of the applicants that are protected by the law, such as gender and race. This freedom gives the universities an option to include contextual information about the applicants on their admission process to increase the number of students from disadvantaged backgrounds. This autonomy also gives the universities freedom to choose the type of information that they would like to include on their admission policy. For example, some universities use care-leaving status or coming from an area where HE attainment rate is low, while others use whether the students' graduated from a secondary school where average attainment is low. Similar to the criteria, the universities also offer different opportunities to students from disadvantaged backgrounds. While some universities offer lower entry requirements for students that are eligible for contextualized admissions, others offer guaranteed interviews (see Boliver *et al.* (2017) for a list of factors used by the universities and the offers made by them). While there are these differences between universities, all the universities aim to attract more students from low socio-economic backgrounds.

Universities inform the prospective students about their admission policies through their Access and Participation Plans (APP). These plans include information about how universities ensure equality of opportunity in HE. The Office for Students (OfS) is the regulatory body of HE in England and they ensure that the universities provide equal opportunities to all students. OfS requires all universities to provide fair access to HE and universities agree their APPs with OfS. This is required for universities to be able to charge students and to receive the tuition fees of the students who take government loans to pay for their education. The need for approval from OfS gives an incentive for universities to implement contextualized admissions to ensure equality of opportunity. In addition to this, universities clearly state whether they use contextualized admissions or not and if they do, they state the requirements to be eligible and how it works on their university websites. Some universities also include the minimum grade required for specific courses on their websites if a student is eligible for contextualized admissions.

In addition to the criteria and the offers of contextualized admissions, the timing of policy implementation also varies across universities. While some universities started applying contextualized admissions as early as 2006, some universities have chosen not to implement it. There are also universities that clearly states in their APPs that they do not plan to use contextualized admissions. In 2015, the last year that we can follow the students, of the 106 universities, 46 of them included contextual information on their admission policies. While it is expected that most of the universities that use this admission policy to have different characteristics than those that choose not to implement, the data shows that the number of universities using contextualized admissions is very similar across different tariff and mission groups. Figure 1 shows the year that universities started applying contextualized admissions by 3 groups: before 2012, in 2012, after 2012. 2012 is an important year because in 2012, the maximum tuition fee a university in England can charge has increased from £3000 to £9000. It is also the same year that most of the universities started applying contextualized admission policy. Of the 46 universities that have implemented contextualized admissions between 2006-2015, 26 of them started in in 2012.[3]

2.3 Data and Descriptive Statistics

In this section, I first describe the main data sources used in the analysis and then present some descriptive statistics. For this paper, I focus on England-domiciled, UK citizen students studying at English institutions because Higher Education funding reforms, including tuition fee and loan/maintenance policies have been different in Wales, Scotland and Northern Ireland (see Azmat & Simion (2020) for a review).

2.3.1 Data

I use data from four sources. The first is the universe of university applications in the UK that comes from UCAS which is the UK's university applications service, covering all the applications after 2007. The records include detailed information about applicant characteristics, their qualifications (both previously achieved and expected), their previously achieved and expected grades and the university-programs that they applied to. It also includes whether the students were accepted to their choices making it possible to understand where they would be eligible to enroll. However, it does not include information about the grades they actually achieved from their expected qualifications. This presents an obstacle as the stu-

[3] It is important to note that the universities might implement this policy as they might forecast that the number of disadvantaged students coming to HE would see a reduction as a result of the increasing tuition fees.

dents apply to the universities before actually taking A Level exams which means that data from UCAS only includes predicted grades from the students' A Level exams.

The second data source that I use is the universe of university students in the UK. This data comes from Higher Education Statistics Agency (HESA) Student Records. HESA is the regulatory body in the UK that collects individual level student data from all of the universities in the UK for all of the students enrolled, no matter where they come from or what course they are studying for. HESA Student Records include highly detailed administrative data on students' characteristics and progress over the time. The information includes students' previous outcomes such as achieved A Level exam grades, their domicile, whether they come from an area where HE participation rate is low (POLAR measure) and other characteristics. It also includes detailed information about students' academic progress over time, courses that students take and whether they pass or fail the course and students' final degree outcome.

The third data source is HESA's Destinations of Leavers from Higher Education (DLHE) survey. DLHE is a survey that is sent to all the graduates that graduate from a degree program from a university in the UK. DLHE is sent 6 months after students graduate and it includes questions about the employment outcomes of the graduates, whether they are in further study and if so what type of qualification they are studying for, their employment conditions and their perceptions of HE's usefulness for finding a job, starting a business and studying for a further degree. This dataset can be linked to HESA Student Records making it possible to see how students progress over time during university and their outcomes in labor market. It is worth noting that as the survey is sent only 6 months after they graduate from a degree program, so it includes information about the graduates' *short-term* labor market outcomes.

The last data source is a dataset that includes information about when the universities changed their admission policies to include contextualized admissions. I collected this dataset using universities' APPs that are freely available online. As mentioned before, APPs include information about how universities recruit their students. I collected information about the timing of the policy change as follows: If a university does not mention contextualized admissions (with or without the name by implying) on APP in year t but mentions in year *t+1*, then I have recorded the university as the policy change occurred at year *t+1* APPs are published online before the students apply to universities so the students are aware of the universities' admission policies when applying to universities.

These four data sources allow me to have two set of linkages. First, I link UCAS Applications dataset to contextualized admissions dataset. This linkage allows me to study whether the implementation of this study had an effect on students' applications that the universities received. Second, I link HESA Student Records to DLHE survey data and to contextualized admissions dataset. This linkage allows me to understand how contextualized admissions changed student composition at the university and what is the effect of this admission policy on students' academic and labor market outcomes. While it is currently not possible to link UCAS Applications dataset to HESA Student Records, the current linkages that I perform allow me to understand the effect of this policy on applications, student composition, and academic and labor market outcomes.

2.3.2 Descriptive Statistics

Table 2.1 presents the main characteristics of the students 2 years before ($t-2$ and $t-1$) and 2 years after ($t+1$ and $t+2$) the universities started applying contextualized admissions. While creating this table, I took $t = 0$ for the year that the universities implemented contextualized admissions at a year until 2019. For universities that did not change their admission policies at any year, I took $t = 0$ in 2012 as most of the universities that changed their admission policies did so in 2012. The top panel of Table 1 presents the controls that I use in this research while the bottom panels present the variables of interest.

The table shows that at the time of the policy change, the universities have seen an increase in proportion of students with no parents with university education, in proportion of students coming from the areas that belong to the lowest two quintiles of HE attainment and a slight increase in proportion of students coming from state school. The table also shows the the proportion of high SES students had a slight decrease. The biggest change is seen on the proportion of students coming from areas where HE attainment belongs to the lowest two quintiles. In the first year of the policy implication, this proportion has increased from 24.88% to 26.03%. Table 2.1 also shows that the universities had a lower increase in average tariff scores (a continuous measure of the grades received from A Level exams or BTEC exams that are required to gain admission to undergraduate programs) compared to the year before. As the universities can offer lower entry requirements for disadvantaged students, this is an expected finding alongside the increase in proportion of students with a disadvantage factor.

When it comes to variables of interest, Table 2.1 shows that with the introduction of contextualized admissions at time t, there is a slight increase in the proportion of students dropping out and a slight decrease on the proportion of students graduating on time while there are slight increases in proportion of students graduating with a first class honors degree or a good degree. However, for these two outcomes, the increase from $t-1$ to t is lower than the increase from $t-2$ to $t-1$. While the increase in proportion of students dropping out continues to grow, proportion of students graduating on time recovers to its pre-contextualized admission levels. The table shows little to no effect on employment outcomes and job characteristics.

When interpreting this table, one needs to keep in mind that the universities started applying contextualized admissions in different years. I use data from cohorts that start their undergraduate education between 2001 and 2015. During this period, there have been several changes in the university admissions, applications, and the labor market conditions. Thus, the changes over time might be because of the trends in the UK university admissions or UK labor market changes due to having data for a long period of time. During this period, there has also been an increase in the proportion of students graduating with a first or a good degree. This grade inflation might also play a role in the increase in proportion of students that graduate with better outcomes. Another thing to keep in mind is that in 2006 and 2012, there have been HE funding reforms that increased the cost of attending university in the UK. The reforms increased the tuition fee caps and most universities charge the maximum amount they can charge. Most universities in the data have changed their admission policies in 2012, the year the tuition fee cap has tripled. Thus, we need to carefully consider the changes over time and looking at this table is not enough to get an idea of the effects of contextualized admissions.

2.4 Empirical Strategy

I estimate the effect of contextualized admissions first on the applications that universities received, characteristics of enrolled university students, then their academic outcomes, and finally on the labor market outcomes. I restrict the sample of analysis to England-domiciled UK citizen students who are studying at an English university. Then in order to eliminate the effect of previous labor market experience, I exclude those who are classified as mature student (those older than 21 at the time of starting their undergraduate degree). I also exclude those who are younger than 17 (there are less than 20 cases) as the earliest a student can start studying at the university in the UK is at the age of 18 (in Scotland it is the year that the students turn 18 but as the sample only consists of England-domiciled students, this would not bias the results).

For the labor market outcomes, I exclude those who are working outside the UK for two reasons: i) It would be hard to compare the labor market outcomes for other countries as the unemployment rate and labor market conditions vary quite a lot, even within the European Union, ii) People who move to other countries to work might face different labor market conditions because they have a foreign qualification such as some countries not acknowledging diplomas for some specific subjects (for example, law or medicine).

In order to study the effect of contextualized admissions on universities' responses to applicants, the characteristics of university students and students' academic and labor market outcomes, I use differences-in-differences method. The common differences-in-differences method does not account for the policy changes that happen in different years. Since universities started applying contextualized admissions in different academic years, this is an important feature of this study. In order to account for the timing of the policy change, I include university and cohort dummies following Stevenson & Wolfers (2006) and Stevenson (2007). Equation 1 shows the empirical specification.

$$y_i = \beta_1 Post_u + \beta_2 Contextual_u + \beta_3 \mathbf{X}_i + \beta_4 \gamma_u + \beta_5 \theta_c + \beta_6 \delta_s + \epsilon_{iu} \tag{2.1}$$

Here in Equation 1, $Post$ is a dummy that takes the value of 1 if a student enrolls (or applies for) the year or after the year that a university started applying contextualized admission and 0 otherwise. If student enrolls to (or applies to) a university that does not change its admission policy during the period that I study, then the dummy $Post$ is defined as 1 if the year is 2012 or later, and 0 otherwise. The threshold for $Post$ is defined as 2012 because this is the year when most of the universities changed their admission policies to include contextualized admissions. In two-way fixed effects settings, normally there is no need for a $Post$ dummy. However, 40% of the universities that implemented this policy in the period that I study implemented this policy in 2012. In order to account for this concentration in 2012, I include $Post$ dummy as well (the results are similar and not statistically different than the ones presented in the main tables when $Post$ is excluded from the empirical specification). $Contextual$ is the interaction of the dummy variable $Post$ and the dummy variable for ever-treated, so it takes the value of 1 if a student applies to or enrolls into a university that ever uses contextualized admissions after the university implemented this policy and 0 otherwise. $\mathbf{X}$ is a vector of student characteristics that includes gender, socio-economic status, ethnicity, and being from an area where HE attainment rate is low. γ represents university dummies, θ represents entry or application for entry cohort dummies, δ represents subject dummies (see Table A2.14 and Table A2.15 for the list of subjects) and ϵ is unknown to the econometrician. The subscript i stands for individual, u for university studied and s for subject studied and c for entry cohort. For academic and labor market outcomes, I also run additional set of regressions that control for previous academic achievement. I use the type of qualification that a student comes to university with and the grades that they achieved from them as previous academic achievement for academic outcomes and students' degree classes for labor market outcomes. Degree class is a measure of achievement that signals the job market about students' achievements. The regressions are estimated with Ordinary Least Squares (OLS) even though the outcome variables are binary. The analysis uses population data and the proportions are well interior of the margins so the use of OLS is appropriate.

A few recent papers on the effectiveness of differences-in-differences have pointed out that when there is time and group variation, the groups that implement the policy early are more likely to be assigned a negative weight when the estimation is run with two-way fixed effects method (Callaway & SantAnna (2020); De Chaisemartin & d'Haultfoeuille (2020); Goodman-Bacon (2021)). In order to check whether two-way fixed effects model assigns negative weights and whether the results are sensitive to this, I follow Prager & Schmitt (2021) and first run differences-in-differences for each period following Goodman-Bacon (2021). Then following Callaway & SantAnna (2020), I use the number of observations "treated" in each period as the weights and calculate weighted differences-in-differences results. Here, treated means students studying at treated universities so the number of treated individuals is the number of students studying at contextualized admissions universities. The results in most cases are identical to the two-way fixed effects method, and where different, differences are small and not statistically significant.

It is likely that the policy will result in heterogeneous results since this policy aims to attract and accept more students coming from disadvantaged backgrounds. In order to understand the heterogeneous effects, I run triple differences-in-differences model. This model interacts $Post$, $Contextual$ and university dummies with the disadvantage factors. I check heterogeneous effects by school type and by coming from an area with low HE attainment in the main text but heterogeneity results by other disadvantage factors, gender and previous achievement are presented in Appendix.

2.5 Results

2.5.1 Parallel Trend Assumption and Exogeneity of Timing of the Policy Change

Before moving on to results, I present evidence on the two assumptions of the differences-in-differences method: parallel trend assumption and exogeneity of the timing of the policy change. Figure 2.2 and 2.3 show tariff scores for ever-treated and never-treated groups both by the time of policy change and by year. I create these graphs for years $t-2$ to $t+2$ to show the changes 2 years before and after the policy implementation. However, it is important to note that for the universities that never use contextualized admissions, 2012 is imputed as t=0.

Figure 2.2 shows that universities have increasing trend in terms of students' tariff scores but with the introduction of contextualized admissions, this upward trend slows down and Figure 2.3 shows that this slowdown mainly comes from students from low SES backgrounds.

One worry is that universities might not start applying this policy randomly. As some universities implement contextualized admissions earlier than others and while some universities never implement, it is important to understand whether some universities change their admission policies to increase participation from disadvantaged backgrounds in a specific year. In order to study whether this is the case I run a survival analysis model. OfS requires universities to submit their APPs 1.5 years before the plans are implemented. For example for students starting in 2022/23 academic year, the plans need to be submitted in May 2021.

This shows that the universities wont be able to know the average student characteristics at time $t-1$ before they submit their plans. This ensures that the universities will not be able to implement policies in a short notice. However, there is also a possibility that the universities implement this policy as a result of a change that happens between $t-2$ and $t-3$ or $t-4$ and $t-3$. In order to understand whether changes in the characteristics of student population predict whether a university starts to use contextualized admissions or not, I run survival analysis. While running this model, I drop the years after the year that the policy is implemented for universities that use contextualized admissions. One typical worry here is whether the universities can opt-out of using this policy after implementing it. According to the most current APPs of the universities, no university that implemented this policy have opted out at any point.

Appendix Table A2.1 regresses the changes in student characteristics, namely proportion of students from state schools, proportion of students from low HE participation areas and proportion of low SES students from $t-4$ to $t-3$ and from $t-3$ to $t-2$. In Appendix Table A2.1, I regress these changes first separately for each of the changes, then together for each years, and then all together. The results show that none of the changes from $t-4$ to $t-3$ or $t-3$ to $t-2$ predict whether the universities start to apply contextualized admissions. This ensures that the timing of the policy change is random.

2.5.2 Student Composition and Entry Qualifications

The main aim of this policy is to increase HE participation from disadvantaged backgrounds by looking at their potential rather than just their exam scores. As this is the case, we would expect the policy to result in either a higher proportion of students from disadvantaged background or a lower entry score for those students. We might also have a case where we have these two situations simultaneously. When analyzing the effect of an admissions policy, the first thing to look at is whether the changes affect the students' and universities' behavior. In Table 2.2, I look at the characteristics of student who applied, who received a positive response to their applications, and of those who were accepted into their choices as well as those who are enrolled into the university. While the Panel A and B pool all the applications (so that there can be more than 1 application per student), Panel C only use data from the applications that students' ended up placing with Panel D showing those who enrolled into those universities.[4] Panel A shows that when the policy is implemented, universities are 1.11 percentage points more likely to receive an application from students from state schools. The effect size is similar for those that receive a positive response[5] from the university but is higher for those who end up being placed into their choices and is 1.12 percentage points while the effect for those enrolling into university is even higher, 1.7 percentage points. When we look at probability of receiving an application from students coming from a low SES families or coming from an area with low HE attainment (POLAR Quintiles 1 & 2), we do not see any effect for those who apply, for those who receive a positive response and for those who are placed.[6] On the other hand, when we look at those who end up enrolling, we see that the policy increases the probability of a student coming from an area with low HE attainment by 0.8 percentage points.[7]

One aspect of contextualized admissions is to evaluate students not just by their exam scores but also taking into account the disadvantages that they faced before coming to uni-

[4]The difference in sample sizes of Panel C and Panel D is due to students who have enrolled after the main application period is over. Students who fail to gain a place at a university can use universities' clearing round where they apply to the universities directly. Similarly those that achieved better than their predicted grades can apply to adjustment rounds of the universities. While this is not the main route to apply to university, each year several thousand of students enroll into universities via this route.

[5]Positive response corresponds to receiving a conditional offer, unconditional offer or invitation for interview.

[6]Keep in mind that these only include mainstream applications and adjustment/clearing applications made through UCAS but it is also possible for students to make these applications directly to the universities.

[7]Applications dataset is only available for applicants applying for 2006/7 onward while student records are available from 2001/2 academic year for POLAR Quintiles.

versity. Since some universities offer lower entry requirements for students who can benefit from contextualized admissions, it is important to look at the effect of contextualized admissions on newcomers' entry scores. In Table 2.3, I analyze the effect of this admission policy on applicants' *predicted* and actual tariff scores. The first three panels show the results for predicted tariff scores while the last panel is for the scores actually received from the exams. The table shows that there is a decrease in applicants' and students' tariff scores. This is true both for *predicted* and actual tariff scores of the students. The first two panel of the table shows that there is no heterogeneity in terms of tariff scores of the applicants by the type of school they come from and interestingly, for those coming from low SES families and from areas with low HE attainment, the effect of the policy is less pronounced. Panel B shows that the positive heterogeneity by SES is similar for those receiving a positive response while the positive heterogeneity by coming from an area with low HE attainment is low diminishes. Panel C, on the other hand, shows that this positive heterogeneity diminishes when we look at those who placed into the universities and those coming from state schools are placed with lower *predicted* tariff scores as a result of this admission policy. And lastly, Panel D shows that those who are enrolled into universities do so with lower *achieved* tariff scores. The negative effect on the tariff scores are entirely driven by the state school students while there are also heterogeneity by coming from an area with low HE attainment. While the results between the first two panels and the last panel might seem like a contradiction, it is important to note that *predicted* grades are generally over-predicted with 76% of students applying to universities with over-predicted grades while only 16% of the applicants achieve the exact grades as in their predicted grades (Murphy & Wyness, 2020). As previously mentioned, universities can have different entry requirements for students coming from disadvantaged backgrounds as part of contextualized admissions.

In order to put this into perspective, consider two students, J and K. Both of them have the same predicted grades but J is disadvantaged while K is non-disadvantaged. Contextualized admissions results in minimum grade requirement received by the disadvantaged student to be lower than the minimum grade requirement received by the non-disadvantaged student K, $C_J < C_K$. This is because J is someone who cannot show their true potential due to the circumstances surrounding their lives. Both J and K receive the same grade G. Then their acceptance is

$$Accept_i = \begin{cases} Both & \text{if } G \geq C_K \\ J & \text{if } C_K > G \geq C_J \\ None & \text{if } C_J > G \end{cases} \tag{2.2}$$

Table 2.3 shows that while we do not see any heterogeneous results on predicted continuous measure of high school test scores by disadvantage factors, we see that disadvantaged students have lower achieved test scores than non-disadvantaged students. This provides evidence that the universities do in fact offer lower entry requirements for students coming from disadvantaged backgrounds.[8]

Introduction of the policy may also affect the student characteristics such as gender, ethnicity, disability or entry qualifications being more vocational oriented. Appendix Table A2.2 shows the results for these other student characteristics. It shows that contextualized admissions reduces the probability that an enrolled student is female by 1.2 percentage points. This might be because female students come to universities with much better entry qualifications

[8]University applications data does not have information about the minimum grade requirement of conditional offers but the differences between the first three panels and the last panel provide evidence for this.

and they might be less likely to benefit from the contextualized admissions. It also shows that students are less likely to hold vocational (BTEC) diplomas. Contextualized admissions normally targets students coming with A Level exams. Most universities include information about their contextualized admission policies on their website and BTEC is rarely mentioned, although the term "alternative routes" is normally included. This might discourage students holding BTEC qualifications to apply to universities that apply contextualized admissions if they believe that they cannot benefit from this admission policy.

2.5.3 Academic Outcomes

I analyze the effect of this admission policy on four academic outcomes: graduating with a first class honors degree (achieving an average of 70), graduation with a good degree, defined as graduating with either a first or an upper second class honors degree (achieving an average of 60), dropping out, and graduation on time. HESA Student Records do not have students' grades on 0-100 scale but this is not something the employers look for when they hire new graduates. Graduating with a first class honors degree or an upper second class honors degree is generally considered as a requirement for applying for graduate level jobs. It has also been shown that there are significant earnings differences across different degree classes. Walker & Zhu (2011) show that those graduating with a first class honors degree earn 6 percent more than those graduating with an upper second, and there is an additional 5 percent premium over lower second class honors degree.

Table 2.4 presents the results for the academic outcomes. Odd columns show the results when the regressions do not control for the previous achievement while the even columns do. The table shows that students who were recruited while this policy was in place are 2.2 percentage points less likely to graduate with a first class honors degree. This effect gets even higher when regressions also control for the previous academic achievement, the results show that this effect is 6.6 percentage points. This shows that the reduced outcomes are not due to lower quality of the entrants implying that the evidence does not support mismatch hypothesis due to lower high school test scores. Similarly, the admission policy reduces the probability of graduating with a good degree class by 4.4 percentage points and this effect, again, gets higher when tariff is included among controls. In terms of dropout, the results show that the policy has little to no effect but when previous academic achievement is included alongside other controls, the results show that the policy increases the probability of dropping out by 1.3 percentage points but this effect is weakly estimated. While the students do not drop out, the last two columns of Table 2.4 show that they take longer to graduate. On average, the policy reduces the students' probability of graduating on time by 2.3 percentage points. While students have lower academic outcomes on graduation, they are also less likely to graduate on time.

The findings on the academic outcomes are important. Although the effect on achieving a good degree is small, the effect on achieving a first class honors degree is important. There is a grade inflation in the UK universities resulting more and more students graduating with a good degree class. Currently, most employers require a good degree class from the applicants on their job openings. However, in the future, grade inflation may cause employers to change the degree requirements for their job openings to having achieved a first class honors degree. Although the effect of contextualized admissions on the likelihood of getting a good degree is low, having found a decrease of 25 percent of the standard deviation in the likelihood of achieving a first class honors degree might have strong impact on the future labor market outcomes if the strong effects continue alongside the grade inflation.

2.5.4 Labor Market Outcomes

Table 2.5 presents the effects of contextualized admissions on the labor market outcomes. The results show that conditional on not being in study, contextualized admissions does not have any effect on the full-time employment or unemployment in general. However, columns (7) and (8) show that the policy reduces the graduates' likelihood of studying for a further degree by 2.9 percentage points which decreases only to 2.5 percentage points when the regression controls for the degree class. Considering only 23 percent of the graduates continue their study after graduation from their undergraduate degree, this effect size is not negligible. As previous studies show that there is a graduate premium which is increasing over time (Lindley & Machin, 2016). This reduction in the likelihood of studying for a further degree may result in long-term negative effects on employment outcomes.

While the results show that there is no effect on the employment, it is possible that the quality of the job that the graduates hold might change as a result of contextualized admissions. In Table 2.6, I present the results on the effect of the introduction of contextualized admissions on salary and job characteristics. The results show that conditional on being in full-time employment, contextualized admissions does not affect graduates' salary. While there is no effect on the salary, it positively affects the probability of holding a permanent contract. While these type of contracts give graduates a safe job, it is worth noting that graduates can gain permanent employment even in low-skilled job or job that require no skills (such as retail jobs). As this is the case, one should be careful about interpreting the results on the likelihood of holding a permanent contract as a signal of job quality. In order to see if the policy changes the quality of the job that the graduates hold, I study the effect of the policy on the probability that subject and level studied at the university being important for the job that the graduates hold. Column (3) shows that contextualized admissions reduces the probability that a graduate holds a job where subject studied is important by 2.5 percentage points although the effect is weakly significant. Controlling for degree class, however, decreases the effect only slightly but diminishes the significance which shows that this negative effect is due to the reduced academic outcomes of the students. It is also likely that students might be willing to study a different subject at university as a result of this policy and if they are studying for subjects that are more specialized (such as STEM courses) and go for jobs that are not relevant for their undergraduate degree, then this can also be considered a negative outcome. Appendix Table A2.12 shows that this is not the case. When I examine whether this admission policy changes students' course choices, I find no effect. Table 2.6 also shows that the policy does not have any effect on the probability of holding a job where level of study is important, where qualifications are required or holding a professional job.

While students do not have lower labor market outcomes due to contextualized admissions, it is possible that some students take some extra steps to secure their job. For example, this policy might encourage non-disadvantaged students to find their graduate jobs using their connections. If non-disadvantaged students have personal connections that would provide them opportunities to gain employment at a graduate level job, then it is expected for this policy to not have any effect on the labor market outcomes. On the other hand, those who get into university while this admission policy is in place might need to secure employment to pay for their personal expenses and they might start working while at the university. This might result in students gaining experience at a job and they might go on to do this job after university. Similarly, students who come from disadvantaged backgrounds might be more willing to apply to programs that have an additional component such as study abroad or placement year. If employers value these additional opportunities undertaken by the students during their university years, then it is likely that these students can cover up negative effects of this admission policy, if there is any. In Appendix Table A2.12 and Appendix Table A2.13, I present the results on the effect of contextualized admissions on taking an additional year as study abroad or placement year, working during university as part of a placement year program and how the graduates found their job. As the tables suggest, contextualized admissions do not make the students more likely to study for a program with an additional component but they are more likely to work during university as part of a placement program. The policy increases students' likelihood of working during university as part of a placement program by 3.6 percentage points. Although this is only weakly significant, it provides some evidence that students might gain work experience while at the university as a result of this policy and that this might be one of the reasons why we do not see any negative effect on the labor market outcomes even though there are negative effects on the students' academic outcomes because the students improve their chances of getting a graduate level work by taking additional in-job training. The last columns of the Appendix Table A2.13 show that the admission policy does not change how graduates' find their job. This shows using personal connections to secure employment cannot be a possible reason why there is no effect on labor market outcomes.

Finding no negative effect on employment with little effect on the employment conditions is important but it is also worth noting that these are graduate outcomes that are measured only 6 months after graduation. It is possible that in the long-term, those who were recruited to the universities while contextualized admissions were in effect might have lower outcomes than the previous cohorts. If low ability individuals who were admitted to the university because of contextualized admissions graduate with lower skills from university, they might show their skills to their employers while working and this might result in these graduates having worse labor market outcomes. Additionally, there is a strand of literature showing that the labor market rewards a graduate degree Lindley & Machin (2016). If the graduates that were moved from further study to labor market as a result of this policy do not go on to study for a further degree in the future, these graduates may also face worse long-term labor market outcomes.

2.5.5 Potential Mechanisms

The main aim of contextualized admissions is to widen the HE participation of disadvantaged students by considering their potential rather than just the merit measured by the exam grades. One thing to keep in mind is that the universities apply different criteria for the contextualized admissions but the common thing among universities is that they are looking for students from low socio-economic backgrounds. The criteria that the universities use vary and include several items such as being from a family where the parents do not have university education (first in the family), coming from an area where the HE attainment is low, coming from a school where the average exam grades are low, free school meals status etc. All these items proxy one thing in common, low SES.

In the affirmative action context, there are 2 important hypotheses: i) the mismatch hypothesis and ii) the peer effects hypothesis (Arcidiacono *et al.*, 2015). Mismatch hypothesis states that affirmative action allows students with low ability (not necessarily grades) who would not be in the HE without affirmative action into universities or it allows students to place at better universities than the ones that they would attend without affirmative action and this results in lower outcomes for the target group. Peer effects hypothesis, on the other hand, states that students with low university readiness who are admitted to the university due to affirmative action would reduce the outcomes of the students who would be in the university even without affirmative action.

Looking at the academic outcomes, Table 2.7 shows the effect of the introduction of contextualized admissions by school type and coming from an area with low HE attainment. The table shows that the policy reduces the probability of achieving a first class honors degree by 5.2 percentage points for private and 1.9 percentage points for state school students, and the probability of achieving a good degree by 9.5 percentage points for private and 4.1 percentage points for state school students. In terms of dropout, the results show that the effects are entirely driven by those coming from private schools while the effect on graduation on time is driven by both disadvantaged and non-disadvantaged students. Looking at this table, one of the possible mechanisms of these negative effects could be that students come to universities with lower grades as a result of contextualized admissions. However, Table 2.4 shows that when the regressions control for the high school test score of the students, the effect sizes do not decrease but increase. Table 2.7 provides some evidence on why this can be the case. Table 2.3 shows that contextualized admissions results in students to arrive to universities with lower grades. In fact, it shows that the negative effects are only applicable to state school students when we look at heterogenous effects by the type of school that the students come from. While these negative results are applicable to only non-advantaged students, Table 2.7 shows that the negative effects on academic outcomes are more pronounced for students from private schools. Similarly, they are more pronounced for those coming from areas where HE attainment is not low. As these groups of students are the ones less affected from the policy in terms of entry scores but more affected in terms of academic outcomes, it is expected that inclusion of entry scores to increase magnitude of the effects in Table 2.4 because the effects are concentrated on those that are less affected by the additional control that we include, tariff. This provides evidence that the negative effect on the academic outcomes of the disadvantaged students is not entirely driven by the students' lower test scores.

In Table 2.8, I present the heterogeneity results on employment outcomes. The results show that in terms of employment outcomes there is no heterogeneity by the type of school that the students come from. However, the results also show that those coming from areas where HE attainment is low are now 2.1 percentage points less likely to be in full-time employment. In terms of study, the results show that the negative effects are applicable both for state and private school students and for students coming from areas with low HE attainment and students coming from other areas. The negative results on the students from areas where HE attainment is low are important. These students are negatively affected by this policy both in terms of being in full-time employment and in terms of being in further study. If these effects persist, it means that these students would spend longer periods as NEET (Not in education, employment or training). This might affect their not only short-term outcomes but also long-term outcomes.

Table 2.9 shows the heterogeneous effects of the admission policy on graduates job characteristics. The table shows that the positive effect of the policy on the probability of holding a permanent contract comes from the disadvantaged group. Those coming from state schools are 2.1 percentage points more likely to hold a permanent contract as a result of this admission policy while this effect is 2.4 percentage point for those coming from low HE attainment areas. As previously stated, while these types of contracts give higher level of job security, they do not guarantee a high quality job. There is a strand of literature that studies the long-term effects of graduating in a bad economy with a focus on how early employment conditions affect later labor market outcomes (Genda *et al.*, 2010; Kahn, 2010; Oreopoulos *et al.*, 2012). If those state school students are more likely to hold a permanent contract for non-graduate level job, the effect of these early labor market outcome might persist until the late stages of work life and this might result in lower outcomes throughout the graduates' entire career. Column (6) shows that the effect is driven by those coming from state schools while column (5) shows that the negative effects of the policy on subject studied at the university being important is driven by both those coming from low HE attainment areas and those from other areas.

While the results show that the effects exist both for target and non-target groups and that the effects are more pronounced for non-target students than target students, we need to understand why this is happening. One possible explanation for private school students being more affected could be that private school students are less used to having a heterogeneous peer group. They are more likely to have peers like themselves prior to coming to university. Contextualized admissions introduces more heterogeneity into their peer groups. If those new students that get into university due to contextualized admissions lower the outcomes of others, then it is expected that those who are more "vulnerable" to peer group effects to be affected more. The second possible explanation is about the allocation of university sources. If universities reallocate their student support resources to improve the outcomes of the students that arrive to the universities due to contextualized admissions, then students from non-target group would be the ones to be affected. While the universities use their resources to improve the outcomes of target students, non-target students may be left behind.

When it comes to the mismatch hypothesis, one needs to think about mismatch in two different contexts: mismatch due to grades and mismatch due to readiness to university. The results on the academic outcomes show that when the regressions control for the tariff scores of the students, the effects do not diminish or decrease but in fact, they increase. This rules out the possibility of mismatch due to grades. However, one still cannot rule out the possibility of mismatch due to lower readiness to university. If students from disadvantaged backgrounds who get into university due to contextualized admissions have less knowledge about the skills and ways to be successful at the university, then we would expect these students to have lower academic and labor market outcomes. As the results suggest, the effects do exist for disadvantaged students as well as non-disadvantaged students, albeit lower. When I study where the effects are concentrated on the "ability" distribution (see Appendix Table A2.4), I find that the effects are concentrated at the bottom of the "ability" distribution but the differences between the quintile groups are not statistically different in most cases. This shows that there is evidence for the mismatch hypothesis but this evidence is not based only on the tariff scores of the students, rather on their unobservable ability ie. study skills, etc.

2.5.6 Heterogeneity

While the main results show that the effects exists both for target and non-target students, it is also important to study whether the results hold by other heterogeneity factors such as gender and degree subject. In Appendix Table A2.3, the last column shows the results by gender. The table shows that the effects are more pronounce for female students. It shows that on average, female students are 1 percentage point and 1.4 percentage points more affected in terms of their likelihood of achieving a first and good degree class. They are also more likely to dropout than their male peers as a result of this policy and less likely to graduate on time. While the effects are more pronounced for female students in terms of academic outcomes, the table shows a different picture for labor market outcomes. It shows that females are in fact more positively affected than male students in terms of their likelihood of being employed while they are more negatively affected in terms of their likelihood of being unemployed and of their likelihood of holding a permanent contract. These results are not surprising. Female students outperform male students in university and as female students have more to lose from this policy, it is also expected that they are the ones who are more affected from this policy. In terms of labor market outcomes, male university graduates generally have better labor market outcomes than female university graduates. As females underperform males, it is expected that males are less positively affected than the females.

When we look at the results separately by the degree subject group, we see another interesting set of results. In terms of academic outcomes, students studying for a degree in Allied to Health Sciences, Social Sciences and Humanities are negatively affected from this policy but the effect on STEM students are not statistically significant and their magnitudes are very close to 0. When we look at the employment and study outcomes, we see that the negative effect of this policy on the probability of further study comes from STEM, Social Science and Humanities graduates. When we look at job characteristics, we see a similar pattern: STEM, Social Science and Humanities graduates are less likely to hold a job where subject studied at the university is important while Social Science and Humanities graduates are more likely to hold a permanent contract. Additionally, we see that STEM graduates are less likely to hold a job where level of study is important. The findings on STEM graduates are important. While there is no effect of contextualized admissions on these students' academic outcomes, they are less likely to be in further study and at the same time, their job characteristics are negatively affected. The negative results on the likelihood of holding a job where subject of study and level of study are important for the job are important because they show that STEM graduates who enter the university while contextualized admissions are in place are a lot less likely to work for jobs that they were trained for. Considering the amount of investment from students and from the government on these subjects, this signals inefficiency of this investment.

2.7 Robustness Check

When studying the effects of a policy on different outcomes, one must make sure that there are no other changes happening at the same time that might bias the results. In 2012, with the increase of tuition fee caps, the student number caps for students achieving AAB or above from their A Level exams (or equivalent from an alternative qualification) have been lifted. With this change, universities were able to recruit as many students who achieved AAB grades or above as they want without any control. The removal of student quotas has been expanded in 2013 to include students with ABB results (or equivalent from an alternative qualification). As previously mentioned, 2012 is also the year when most of the universities started using contextualized admissions. Prior to this reform, most selective universities might have needed to choose among successful students due to the student number caps but with this reform, they could recruit as many successful students as they could. This might bias the result in a way that those successful and disadvantaged students previously being turned down by the most selective universities now can be admitted, resulting less selective universities to lose disadvantaged students. This might be picked up as a result of contextualized admissions for the universities that changed their admission policies in 2012 and 2013 if removal of student quotas in fact increases the number of students with better grades in these universities.

In order to understand whether this reform biases the results of my analysis, I run the same difference-in-difference specification in Equation 1. My dependent variable, this time, is a dummy variable for AAB or better A Level grades (or equivalent) and ABB or better A Level grades (or equivalent). If the results show a negative (positive) and significant coefficient for *Contextual* dummy, then my results would be overestimated (underestimated). Appendix Table A2.11 shows that the removal of student quotas for AAB and ABB or above students does not bias the results of my analysis. Most of the universities that change their admissions policy in 2012 and 2013 to include contextualized admissions are selective universities and they mostly have had AAB or above students before the removal of the caps. Due to other constraints such as availability of classrooms and teaching staff, these universities might not have had a chance to increase their student numbers.

2.8 Conclusion

Due to the increase in the Widening Participation programs in the UK and government targeting to double the number of students coming from disadvantaged backgrounds, universities started applying contextualized admissions, an admission policy similar to affirmative action but based on socio-economic factors. In this paper, using linked administrative and survey data, I study the effect of the introduction of the contextualized admissions on the applications that the universities receive and students' academic and labor market outcomes.

I find that the introduction of the policy reduces the academic outcomes while has weak and negative effects on the labor market outcomes. Since this policy is likely to have heterogeneous effects, I look at the heterogeneity by several disadvantage factors. Heterogeneity results show that students coming from disadvantaged backgrounds are now coming with much lower grades than the students coming from non-disadvantaged backgrounds. When it comes to academic and labor market outcomes, I find that, on average, both the target group and other students are affected by this policy. However, the effect sizes are lower for the target group. The results also indicate that peer effects hypothesis are more pronounced than the mismatch hypothesis in the context of contextualized admissions.

The analysis shows that the policy leads to reduced outcomes. One way to eliminate these negative effects is to improve the student support at universities. Several papers show that remedial programs improve academic outcomes of the students who get into university with lower academic outcomes (such as Angrist *et al.* (2009); van der Steeg *et al.* (2015); Oreopoulos & Petronijevic (2018); Gordanier *et al.* (2019); Weiss *et al.* (2019)). Universities can implement this type of remedial programs to improve their students' outcomes to reduce the negative effects of this policy. Although the policy does not affect the employment in general, it negatively effects the characteristics of the jobs that the students hold. In order to eliminate this negative effect, the universities can use interventions that are aimed at increasing the knowledge about employability skills. A recent intervention that focuses on improving knowledge about the skills that are important in the labor market proved successful in terms of educating the students about what the labor market values in the potential candidates (Delavande *et al.*, 2020b). This type of interventions can be helpful in mitigating the negative effects of contextualized admission on the graduates' labor market outcomes.

The labor market outcomes that are studied here are short-term labor market outcomes that are measured only 6 months after the graduation. It is important to look at the long term effects of this policy. It is possible for disadvantaged students that are admitted to the universities due to contextualized admissions to signal their skills while on the job and if the students did not gain the skills needed to succeed in the job while at university, they might have worse long-term labor market outcomes. The negative effects found for non-disadvantaged students, in a similar way, might diminish over time once the graduates signal their skills through their tasks at work. It is also possible that the graduates who gained employment in non-graduate level jobs as a result of this policy might have long lasting negative effects as this is similar to the case of entering the labor market in a recession (Genda *et al.*, 2010; Kahn, 2010; Oreopoulos *et al.*, 2012). Thus, we need to study the effect of this policy on graduates' long-term labor market outcomes.

Another important next step is to understand how the universities respond to disadvantaged students with lower entry qualifications being accepted to the university due to the contextualized admission. Whether universities switch their resources to help disadvantaged students with lower entry qualifications to succeed is an important policy question as the student numbers do not significantly vary over time in English universities. Whether they increase their tuition fee income by recruiting more students, or more international students who pay much more than British students, to have more resources to help the disadvantaged students with lower entry qualifications is another important question to answer as the changes in other student characteristics may also affect students' outcomes.

Figures

Figure 2.1: Universities that use Contextualized Admissions

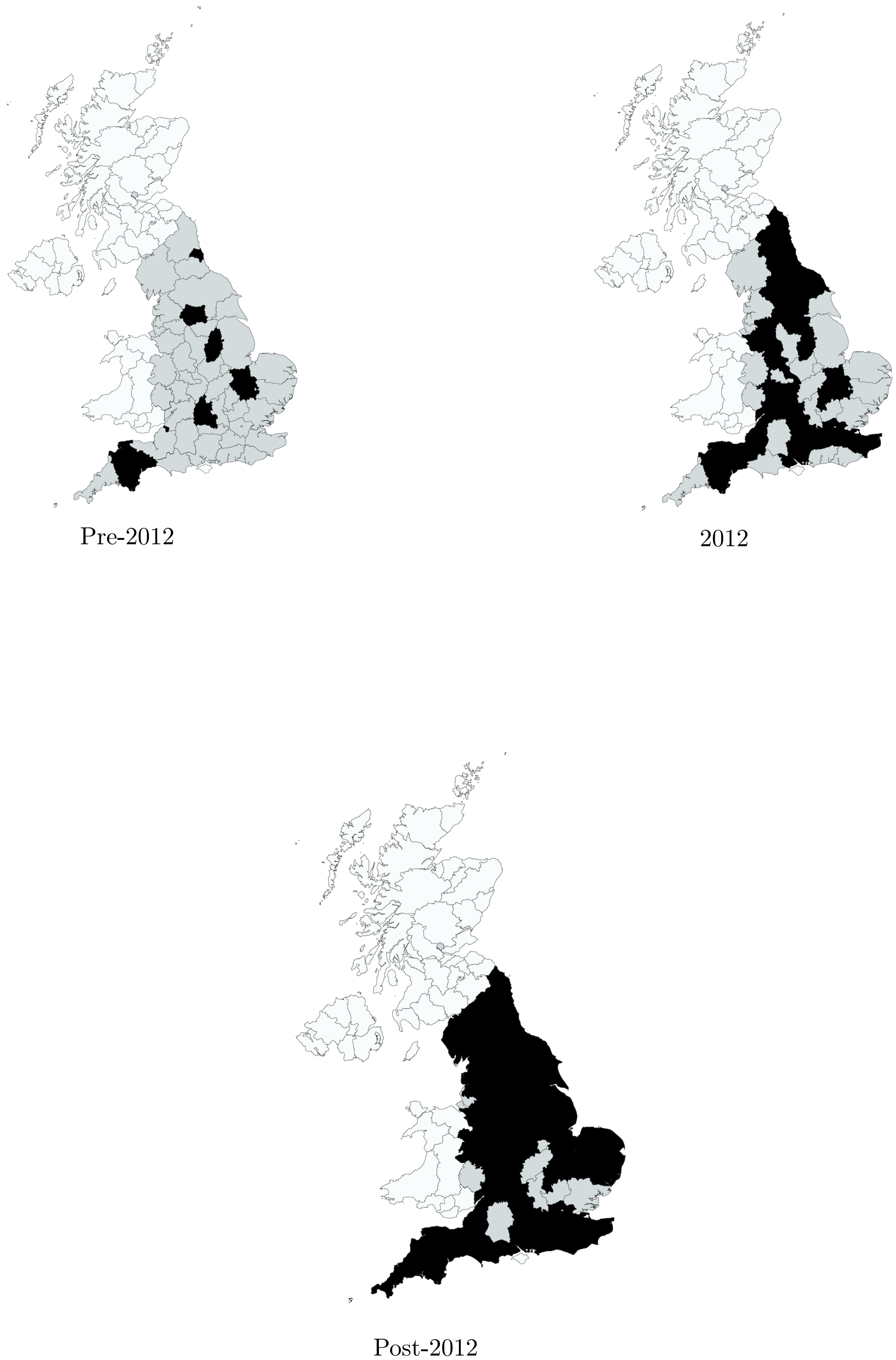


Figure 2.2: Average Tariff

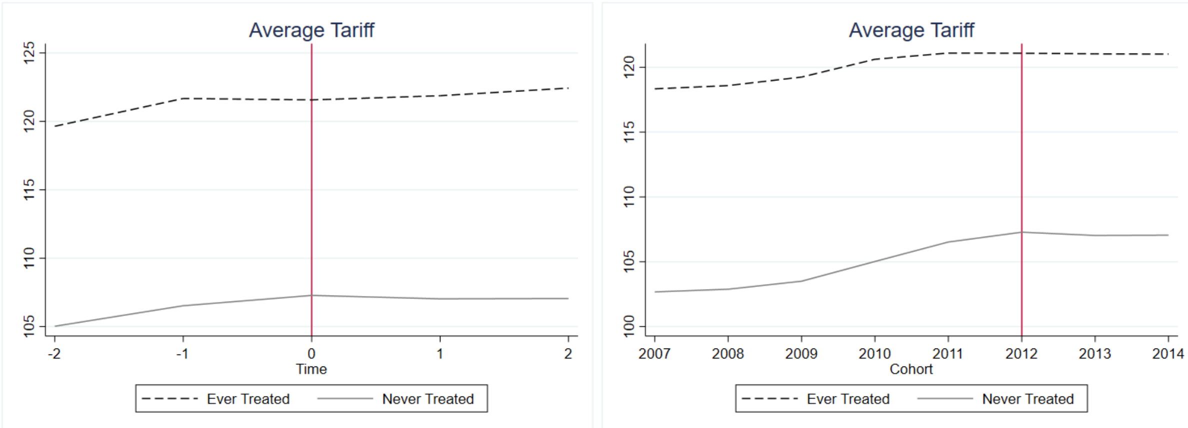
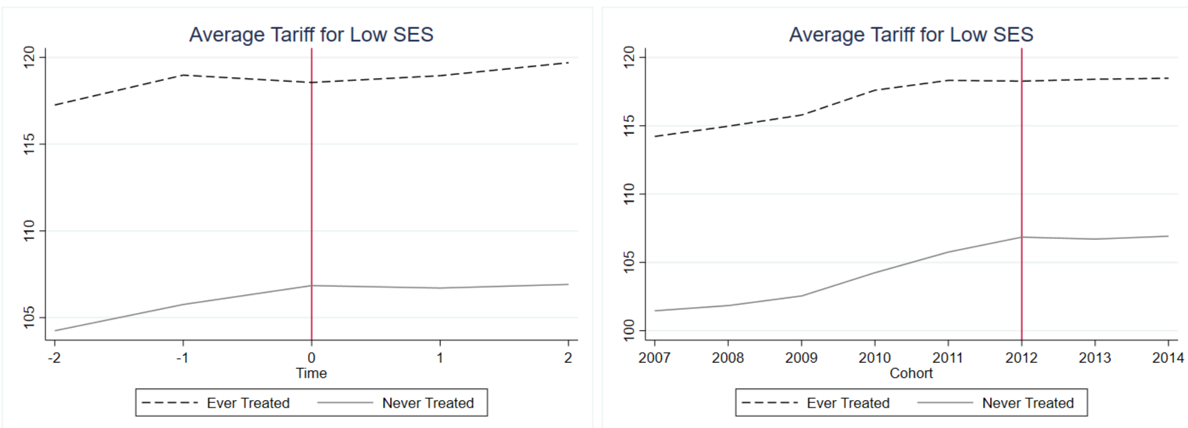


Figure 2.3: Average Tariff for Low SES Students



Tables

Table 2.1: Descriptive Statistics

Time	-2	-1	0	1	2
Characteristics					
Female	0.54	0.55	0.55	0.55	0.55
High SES	0.58	0.58	0.57	0.57	0.57
First in the Family	0.47	0.46	0.47	0.48	0.48
POLAR Q1 & 2	0.25	0.25	0.26	0.26	0.27
State School	0.89	0.88	0.88	0.89	0.89
Tariff	114.98	116.13	116.69	116.98	117.25
Tariff for High SES	116.75	118.04	118.70	118.95	119.16
Tariff for Low SES	112.36	113.29	113.84	114.15	114.51
Academic Outcomes					
First	0.20	0.22	0.23	0.26	0.27
Good	0.76	0.78	0.77	0.80	0.82
Graduated on Time	0.90	0.90	0.89	0.90	0.91
Dropout	0.09	0.09	0.09	0.10	0.10
Employment					
Full-time Work	0.67	0.69	0.69	0.70	0.68
Employed	0.85	0.85	0.86	0.86	0.85
Unemployed	0.08	0.07	0.07	0.06	0.07
Study	0.20	0.20	0.22	0.24	0.27
Job Characteristics					
Ln(Salary)	9.83	9.84	9.87	9.89	9.89
Permanent	0.63	0.64	0.65	0.64	0.64
Importance of Subject	0.22	0.22	0.22	0.23	0.25
Importance of Level	0.18	0.18	0.18	0.18	0.19
Qualifications Required	0.61	0.61	0.62	0.62	0.63
High SOC	0.71	0.71	0.74	0.75	0.75

Notes: First, good and graduated on time are conditional on graduation; full-time work, employed and unemployed are conditional on not being in further study; and all of the job characteristics are conditional on being in full-time employment. For salary, the top and bottom 2% are trimmed. School type and SES are available 2002/3 academic year onward and parental education is available 2008/9 onward.

Table 2.2: Applicant and Student Characteristics

Panel A: All Applications

	(1) State School	(2) Low SES	(3) POLAR Q1&2
Post	-0.017**	-0.002	-0.004
	(0.006)	(0.004)	(0.003)
Contextual	0.011**	0.001	0.003
	(0.005)	(0.004)	(0.003)
Observations	10,432,450	10,434,879	12,630,880

Panel B: Applications with Positive Response

	(1) State School	(2) Low SES	(3) POLAR Q1&2
Post	-0.016**	-0.003	-0.004
	(0.007)	(0.004)	(0.003)
Contextual	0.011**	0.002	0.003
	(0.005)	(0.004)	(0.003)
Observations	8,110,219	7,907,140	9,511,701

Panel C: Placed

	(1) State School	(2) Low SES	(3) POLAR Q1&2
Post	-0.020**	-0.003	-0.006*
	(0.008)	(0.004)	(0.0034)
Contextual	0.012*	0.003	0.003
	(0.006)	(0.005)	(0.004)
Observations	1,620,629	1,642,355	1,972,797

Panel D: Enrolled

	(1) State School	(2) Low SES	(3) POLAR Q1 & 2
Post	-0.017***	0.001	-0.008**
	(0.005)	(0.008)	(0.004)
Contextual	0.017***	-0.001	0.008**
	(0.004)	(0.008)	(0.004)
Observations	2,727,410	2,372,807	2,833,204
Available from	2002/3	2002/3	2001/2

Notes: All regressions control for gender, entry qualifications (both the type and the grades) and for university, subject and cohort fixed effects. Panel A shows the results for applications. Panel B shows the results for students who were accepted. Panel C shows the results for enrolled students. Panel A-C present results from UCAS applications dataset while Panel D presents the results from HESA Student Records. * denotes significance at 10% level, ** denotes significance at 5% level and *** denotes significance at 1% level. Standard errors are clustered at university level. Standard errors are in parenthesis.

Table 2.3: Applicants' Predicted and Achieved Tariff Scores

Panel A: All Applications (Predicted Tariff)

	(1)	(2)	(3)	(4)
Contextual	-1.365***	-0.960*	-1.502***	-1.412***
	(0.421)	(0.520)	(0.448)	(0.4201)
Contextual × State School		-0.464		
		(0.397)		
Contextual × Low SES			0.390**	
			(0.188)	
Contextual × POLAR Q1 & 2				0.364*
				(0.186)
Observations	9,021,993	7,386,949	7,445,762	9,004,209

Panel B: Applications with Positive Response (Predicted Tariff)

	(1)	(2)	(3)	(4)
Contextual	-1.678***	-1.117*	-1.776***	-1.706***
	(0.4614)	(0.582)	(0.485)	(0.461)
Contextual × State School		-0.592		
		(0.461)		
Contextual × Low SES			0.334*	
			(0.198)	
Contextual × POLAR Q1 &2				0.285
				(0.200)
Observations	6,877,476	5,820,844	5,706,332	6,864,505

Panel C: Placed (Predicted Tariff)

	(1)	(2)	(3)	(4)
Contextual	-1.741***	-0.990*	-1.858***	-1.778***
	(0.533)	(0.571)	(0.530)	(0.512)
Contextual × State School		-0.891*		
		(0.510)		
Contextual × Low SES			0.387	
			(0.247)	
Contextual × POLAR Q1 &2				0.314
				(0.299)
Observations	1,427,763	1,158,920	1,185,613	1,425,001

Panel D: Enrolled (Actual Tariff)

	(1)	(2)	(3)	(4)
Contextual	-1.688**	0.156	-1.234*	-1.405**
	(0.651)	(0.726)	(0.684)	(0.643)
Contextual × State School		-1.800***		
		(0.593)		
Contextual × Low SES			-0.429	
			(0.347)	
Contextual × POLAR Q1 & 2				-0.648*
				(0.392)
Observations	1,660,804	1,632,152	1,416,089	1,657,573

Notes: Tariff is calculated using top 3 A Level grades or equivalent grades from alternative qualifications. The grades are capped at A. Tariff is on a scale of 0-144. All regressions control for university, subject and cohort fixed effects. Panel A shows the results for applications. Panel B shows the results for students who were accepted. Panel C shows the results for enrolled students. Panel A-C are for students' *predicted* tariff scores from UCAS applications dataset while Panel D is for students' achieved tariff scores from HESA Student Records. * denotes significance at 10% level, ** denotes significance at 5% level and *** denotes significance at 1% level. Standard errors are clustered at university level. Standard errors are in parenthesis.

Table 2.4: Academic Outcomes

	First		Good		Graduated on Time		Dropout	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	0.019**	0.033***	0.026**	0.039***	0.016**	0.017**	-0.010	-0.015*
	(0.008)	(0.011)	(0.010)	(0.014)	(0.007)	(0.007)	(0.009)	(0.008)
Contextual	-0.022***	-0.067***	-0.044***	-0.078***	-0.023***	-0.025***	0.002	0.013**
	(0.008)	(0.012)	(0.011)	(0.015)	(0.008)	(0.008)	(0.005)	(0.005)
Observations	1,847,498	1,847,498	1,847,498	1,847,498	1,844,854	1,844,854	2,430,934	2,430,934
Mean	0.19	0.19	0.72	0.72	0.88	0.88	0.11	0.11
Tariff	No	Yes	No	Yes	No	Yes	No	Yes

Notes: All regressions control for gender, socio-economic status, coming from an area where Higher Education attainment is low (POLAR bottom two quintiles) in addition to university, subject and cohort fixed effects. Those achieving a final mark of 70 or above receive first class honors degree, while those with a final mark between 60 and 69 receive an upper second class honors degree. The dependent variable in Columns 3 and 4 is a dummy variable for receiving either a first class honors degree or an upper second class honors degree. First 6 columns are conditional on graduation. * denotes significance at 10% level, ** denotes significance at 5% level and *** denotes significance at 1% level. Standard errors are clustered at university level. Standard errors are in parenthesis.

Table 2.5: Employment

	Full-time Work		Employed		Unemployed		Study	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Post	0.008	0.006	-0.002	-0.003	0.000	0.001	0.023^{**}	0.020^{**}
	(0.007)	(0.007)	(0.005)	(0.005)	(0.005)	(0.004)	(0.009)	(0.009)
Contextual	-0.008	-0.006	-0.000	0.000	0.004	0.002	-0.029^{***}	-0.025^{***}
	(0.007)	(0.008)	(0.005)	(0.005)	(0.005)	(0.004)	(0.009)	(0.009)
Observations	1,035,766	1,012,109	1,035,766	1,012,109	1,035,766	1,012,109	1,349,721	1,316,785
Mean	0.67	0.67	0.83	0.83	0.09	0.09	0.23	0.23
Degree C. FE	No	Yes	No	Yes	No	Yes	No	Yes

Notes: All regressions control for the gender, socio-economic status of the students at the start of their undergraduate degree, coming from an area where Higher Education attainment is low (POLAR bottom two quintiles) in addition to university, subject and cohort fixed effects. The first 6 columns are conditioned on not being in further study. * denotes significance at 10% level, ** denotes significance at 5% level and *** denotes significance at 1% level. Standard errors are clustered at university level. Standard errors are in parenthesis.

Table 2.6: Job Characteristics

	Ln(Salary)		Permanent		Subject is Imp		Level is Imp		Quals Req		High SOC	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Post	0.010*	0.009	-0.015	-0.012	0.016	0.013	-0.006	-0.008	-0.006	-0.010	0.012	0.009
	(0.006)	(0.005)	(0.011)	(0.011)	(0.014)	(0.014)	(0.011)	(0.011)	(0.028)	(0.028)	(0.012)	(0.012)
Contextual	0.002	0.004	0.019**	0.016	-0.025*	-0.021	-0.007	-0.004	0.027	0.033	0.009	0.013
	(0.006)	(0.006)	(0.009)	(0.010)	(0.014)	(0.014)	(0.011)	(0.011)	(0.028)	(0.028)	(0.013)	(0.013)
Observations	420,405	413,157	655,892	642,483	655,892	642,483	655,892	642,483	655,892	642,483	655,892	642,483
Mean	9.81	9.81	0.64	0.64	0.20	0.20	0.18	0.18	0.61	0.61	0.69	0.69
Degree C. FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: All regressions control for the gender, socio-economic status of the students at the start of their undergraduate degree, coming from an area where Higher Education attainment is low (POLAR bottom two quintiles) in addition to university, subject and cohort fixed effects. All of the regressions in this table are conditional on being in full-time employment. For salary, the top and bottom 2% are trimmed. * denotes significance at 10% level, ** denotes significance at 5% level and *** denotes significance at 1% level. Standard errors are clustered at university level. Standard errors are in parenthesis.

Table 2.7: Academic Outcomes by Disadvantage Factors

	First		Good		Graduated on Time		Dropout	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Contextual	-0.052***	-0.024***	-0.095***	-0.046***	-0.032***	-0.026***	0.031***	0.002
	(0.010)	(0.008)	(0.017)	(0.011)	(0.009)	(0.009)	(0.007)	(0.005)
Contextual × State School	0.032***		0.054***		0.011		-0.030***	
	(0.007)		(0.015)		(0.007)		(0.005)	
Contextual × POLAR Q1 & 2		0.003		0.010		0.013***		0.000
		(0.006)		(0.008)		(0.004)		(0.004)
Observations	1,783,654	1,847,498	1,783,654	1,847,498	1,781,274	1,844,854	2,322,635	2,430,934
Mean	0.19	0.19	0.72	0.72	0.88	0.88	0.11	0.11
Contextual +	-0.020	-0.021	-0.041	-0.037	-0.022	-0.013	0.001	0.002
Contextual × Het.	(0.008)	(0.009)	(0.011)	(0.012)	(0.008)	(0.007)	(0.005)	(0.006)

Notes: All regressions control for gender, socio-economic status, coming from an area where Higher Education attainment is low (POLAR bottom two quintiles) in addition to university, subject and cohort fixed effects. Column 2 is a dummy variable for receiving either a first class honors degree or an upper second class honors degree. First 6 columns are conditional on graduation. * denotes significance at 10% level, ** denotes significance at 5% level and *** denotes significance at 1% level. Standard errors are clustered at university level. Standard errors are in parenthesis.

Table 2.8: Employment by Disadvantage Factors

	Full-time Work		Employed		Unemployed		Study	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Contextual	-0.006	-0.004	0.004	0.001	-0.006	0.003	-0.037***	-0.027***
	(0.012)	(0.008)	(0.012)	(0.005)	(0.010)	(0.005)	(0.011)	(0.009)
Contextual × State School	-0.005		-0.006		0.012		0.012	
	(0.012)		(0.012)		(0.010)		(0.009)	
Contextual × PQ1 & 2		-0.017**		-0.007		0.003		-0.002
		(0.007)		(0.005)		(0.004)		(0.007)
Observations	995,818	1,035,766	995,818	1,035,766	995,818	1,035,766	1,298,624	1,349,721
Mean	0.67	0.67	0.83	0.83	0.09	0.09	0.23	0.23
Contextual +	-0.011	-0.021	-0.002	-0.006	0.005	0.006	-0.025***	-0.029***
Contextual × Het.	(0.008)	(0.008)	(0.005)	(0.007)	(0.005)	(0.006)	(0.009)	(0.011)

Notes: All regressions control for the gender, socio-economic status of the students at the start of their undergraduate degree, coming from an area where Higher Education attainment is low (POLAR bottom two quintiles) in addition to university, subject and cohort fixed effects. The first 3 columns are conditioned on not being in further study. * denotes significance at 10% level, ** denotes significance at 5% level and *** denotes significance at 1% level. Standard errors are clustered at university level. Standard errors are in parenthesis.

Table 2.9: Job Characteristics by Disadvantage Factors

	Ln(Salary)		Permanent		Subject is Imp		Level is Imp		Quals Req		High SOC	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Contextual	-0.010	0.004	0.007	0.017*	-0.024	-0.029**	0.007	-0.005	0.027	0.025	0.012	0.014
	(0.013)	(0.006)	(0.017)	(0.009)	(0.018)	(0.014)	(0.022)	(0.011)	(0.033)	(0.027)	(0.013)	(0.013)
Contextual × State School	0.012		0.014		0.001		-0.017		0.000		-0.005	
	(0.012)		(0.017)		(0.012)		(0.017)		(0.017)		(0.012)	
Contextual × PQ1 & 2		-0.009*		0.008		0.014*		-0.010		0.002		-0.023***
		(0.005)		(0.009)		(0.008)		(0.006)		(0.009)		(0.008)
Observations	405,906	420,405	631,665	655,892	631,665	655,892	631,665	655,892	631,665	655,892	631,665	655,892
Mean	9.81	9.81	0.64	0.64	0.20	0.20	0.18	0.18	0.61	0.61	0.69	0.69
Contextual +	0.002	-0.005	0.021***	0.024***	-0.023*	-0.014	-0.010	-0.015	0.027	0.027	0.007	-0.009
Contextual × Het.	(0.006)	(0.008)	(0.010)	(0.012)	(0.014)	(0.016)	(0.010)	(0.011)	(0.029)	(0.032)	(0.013)	(0.014)

Notes: All regressions control for the gender, socio-economic status of the students at the start of their undergraduate degree, coming from an area where Higher Education attainment is low (POLAR bottom two quintiles)in addition to university, subject and cohort fixed effects. Panel A also controls for the degree class while Panel B does not. All of the regressions in this table are conditional on being in full-time employment. For salary, the top and bottom 2% are trimmed. * denotes significance at 10% level, ** denotes significance at 5% level and *** denotes significance at 1% level. Standard errors are clustered at university level. Standard errors are in parenthesis.

Chapter 3

Racial Representation and Students' Academic and Labor Market Outcomes

3.1 Introduction

It has been consistently shown that education is important for many outcomes. Of these, possibly the most widely studied are employment outcomes. Card (1999), for example, shows that reforms that increase compulsory education result in higher wages. Similar effects have been shown for the UK (Harmon & Walker, 1995) through increased human capital accumulation (Chevalier *et al.*, 2004) with repercussions onto the next generation's schooling (Chevalier *et al.*, 2013). Similarly, Maurin & McNally (2008) show that holding a university degree improves graduates labor market outcomes while these returns to university education vary by university selectivity (Walker & Zhu, 2018) and by subject (Walker & Zhu, 2011).

While education has these important effects on graduates' outcomes, recent statistics show that there are racial differences in graduates' employment (HESA, 2021). These differences also show little improvement over time. For example, official statistics show that 62% of the White graduates who graduated from an undergraduate degree in 2019/20 academic year work full time 6-months after graduation while only 53% and 55% of Black and Asian graduates do. The situation is not different when it comes to academic outcomes. While 82% of White university students in the UK graduate with a first class or an upper second class honors degree, only 64% of the Black students and 72% of Asian students do so.

There is a strand of literature that studies how we can explain these racial differences. The literature finds that high school attended and high school rank matter (Fletcher & Tienda, 2010) in addition to previous attainment (Arcidiacono & Koedel, 2014) and the type of qualification that the students come to the university with (Del Bono & Holford, 2018). On the labor market side, Zwysen & Longhi (2018) find that parental background, local area characteristics, and university choice can explain most of the racial differences in labor market outcomes of graduates. One important question is to understand how universities and governments can implement policies to mitigate these differences. Previous literature shows that racial representation in the classroom has positive effects on students' academic outcomes (Fairlie *et al.*, 2014). While this can provide evidence that representation in classroom is important, there is also a need to understand whether these positive effects persist into the labor market.

In this paper, using linked administrative and survey data, I study how representation among HE academics affects students' academic and labor market outcomes as well as their perception of HE and their likelihood of studying for a further degree. I use administrative data from the Higher Education Statistics Agency (HESA)'s Staff Records to calculate department level proportions of racial minority academics as well as academics from each racial group[1]. I then link this information to HESA's Student Records according to students'

[1] I calculate proportions for White, Black, South Asian and Other racial group. I include Chinese ethnic group along with other ethnic groups because the UK policy agenda mainly focuses on the disparities between White students and Black and South Asian students as they are the ones that are consistently found to achieve lower outcomes than White students.

department identifiers to study how representation among academic staff affects students' academic outcomes. Finally, I link student records to a representative graduate survey, HESA's Destinations of Leavers from Higher Education survey to study how representation in academia affects graduates short-term labor market outcomes as well as their perceptions about the usefulness of Higher Education and their course of study.

In order to study the effects of exposure to minority academics, I use data from seven graduating cohorts from all the universities in the UK. I control for cohort, university and subject of study as well as university group fixed effects interacted with subject group fixed effects. I, then, estimate how exposure to minority academics affects students' academic and labor market outcomes, as well as their perception of the usefulness of higher education and their likelihood of studying for a master or PhD degree within these subject groups and university clusters by controlling for subject, university and cohort fixed effects.

I first provide evidence on the heterogeneity in exposure to minority academics. I find that students' personal characteristics such as gender, socio-economic status, being a first generation university student, or coming from an area where Higher Education attainment is low do not predict students' exposure to minority academics. However, students' entry test scores negatively predict their exposure to minority instructors, implying that more successful students are less likely to be exposed to higher degrees of minority academics. I run another set of regressions following Fairlie *et al.* (2014) to see if proportion of minority academics in a given department predicts the White-minority gaps in personal characteristics that are correlated with academic and labor market outcomes (such as tariff, type of entry qualification, gender, etc). I find that White-minority gaps in personal characteristics and entry test scores cannot be predicted by the proportion of minority academics in university departments and this provides further evidence that the results are not biased due to selection on observables.

The results show that exposure to minority instructors improves White students' likelihood of graduating with a first class or a good degree[2] while having no effect on minority students. In terms of labor market outcomes, I find that exposure to minority academics increases White's graduates' propensity to be in full-time employment but reduces minority students' propensity to be in full-time employment and employment in general. Exposure to minority academics also increases White graduates' likelihood of holding a graduate level job while reducing minority graduates' likelihood of holding a professional job. On the other hand, exposure to minority academics increases minority graduates' likelihood of studying for a masters degree. This provides evidence that while minority academics provide better outcomes for all students, the context of these positive outcomes vary by students' race.

Further analysis shows that South Asian students are more likely to achieve a first class honors degree when they are exposed to academics from their own race. The results also show that racial minority academics positively affect Black students' likelihood of studying for a masters degree and for a further degree in general while negatively affecting their employment outcomes. These results provide evidence that racial minority students see their instructors as academic role models and even though the results only provide evidence on improved outcomes for White and South Asian students, the positive effects on Black students' likelihood of studying for a further degree shows that these graduates might go on to get better jobs after their masters degree. If the effect continues into studying for a PhD, exposure to minority academics might also improve the racial diversity in academia

[2] A good degree is defined as obtaining a first or an upper second class honors degree. A first or an upper second class honors degree is generally required to apply for graduate level jobs (Naylor *et al.*, 2016)

and improve innovation and the quality of academic studies.[3]

There is a large literature on the effect of representation in primary school classrooms and its short- and long-term effects. Dee (2004b, 2005) and Winters *et al.* (2013) find that when students are taught by teachers from their own gender and racial group, they achieve higher grades. The results on the students, in fact, go beyond their academic achievements. Holt & Gershenson (2019) find that when students are taught by teachers from their own demographic group, they are less likely to be suspended and be absent from the school while Lindsay & Hart (2017) find that students are less likely to be excluded. Ehrenberg *et al.* (1995) and Gershenson *et al.* (2016) find that representation also matters in the context of teacher expectations. They find that teachers evaluate their students more positively when they are matched in terms of gender and race. Similarly, Egalite & Kisida (2018) find that teacher demographic match (such as having a teacher from the same gender or same race) with students positively affect students' academic perceptions and attitudes. In this paper, I extend the literature by focusing on how representation in one setting (university) affects the following setting (i.e. labor market and further study outcomes).

Previous evidence mostly focuses on pre-university outcomes, with the exceptions of Fairlie *et al.* (2014) and Lusher *et al.* (2018). Fairlie *et al.* (2014) find that being taught a course by an academic from the students' own racial group increases the students' academic outcomes leading to higher GPA. Lusher *et al.* (2018) find that when the students are taught by foreign teaching assistants, the students get higher grades from the courses and the effects are higher when the exams are not multiple choice. They also find that the positive effects last longer and the students get better grades from the subsequent courses. I extend this literature by showing that not only the in-class interactions are important for the students but also being

[3] Parrotta *et al.* (2014) show that racial diversity increases firms' innovation.

represented among academics in general improves students' outcomes. I also show that this exposure to minority academics is not only important for the racial minority students but for White students as well.

The third extension is the unit of analysis. Previous papers, whether they are at the university or pre-university level, focus on either one institution or a group of institutions. I use administrative data and the universe of staff and students at UK universities and I extend the unit of analysis to all the university students in the UK. It is likely that students studying at different universities or subjects or those studying at different years may have different effects when they are exposed to minority academics. This is especially true for labor market outcomes where graduates from more selective universities might have better labor market outcomes no matter the degree of exposure to minority academics. Similarly, some degree subjects might have better labor market prospects than others and the effect of exposure to minority academics might have different effect sizes for these students than others that are studying for degree subjects that do not have very good labor market prospects. By using data from the universe of staff and students in the UK, the analysis also accounts for these possible differences between universities, subjects and cohorts. While the identification strategy I use in this paper is different than the ones used in other papers, it is also important to highlight the possible differences that may arise between subjects and universities.

The last contribution relates to the context and the duration of the effects. Previous literature mostly focuses on the effects of representation on courses after on semester or the behavioral outcomes during school hours. While Gershenson *et al.* (2016) study the longer term effects of representation in the classroom, their paper studies the effect of representation among teachers on students' aspirations for university, in other words, another academic settings. The rich administrative and survey data allows me to extend this literature by studying how being exposed to minority instructors at the university affects graduates' labor market outcomes 6 months after graduation as well as their perception of the usefulness of the university and their likelihood of further study.

The rest of the paper is organized as follows: Section 2 describes the institutional framework, Section 3 presents data and shows the descriptive statistics, Section 4 explains empirical strategy, Section 5 shows and discusses results, Section 6 presents the robustness check and Section 7 concludes.

3.2 Institutional Framework

Compulsory formal education in the UK ends when the students are aged 16. After 16, students either need to continue their formal education in school or they need to get a job as an apprentice where they learn a trade. Those who aspire to go to university generally continue to study for further 2 years but there are alternative routes to gain admission to university. Students who decide to continue their formal education study for end of year exams called AS Level and A Level which are taken in year 12 and 13, respectively but there are also other exams students can take as part of their post-16 education which can be used for university admissions such as BTECs.

As opposed to US where students apply to universities and then declare their majors later on, in the UK, students apply to study a specific program. In some cases, students need to decide the major that they would like to study well in advance because some programs require specific A Level subject grades and the subjects that the students would like to study as part of their A Level examinations are decided when the students are aged 16.

Another difference between the US and the UK is the duration of study. While undergraduate programs take 4 years to complete in the US, in the UK, this duration varies even within the country. In England, Wales and Northern Ireland, undergraduate programs take 3 years to complete while in Scotland, the duration of undergraduate study is 4 years. This is because Scottish undergraduate programs are combined with master programs and students graduate with MA/MSc degrees rather than BA/BSc degrees which students in England, Wales and Northern Ireland are awarded.

Double major, minor or track programs do not exist. Students, on the other hand, can apply to a program with components from two different courses. For example, a BSc in Economics and Politics is similar to double majoring in Economics and Politics but rather than taking all the required courses in two subjects, students take a subset of courses from both subjects. Similarly, students can choose to study for a degree program that has a component from a different subject. BSc in Economics with Mathematics would be similar to majoring in Economics and minoring in Mathematics. Another difference in the UK higher education is that students do not have a chance to study for a double major or a minor from any department that they would like. These programs are pre-determined by the university and universities generally allow students to study for two programs in this way only if the subjects are related to each other.[4] Similarly, switching majors is rare and students cannot do this without losing the credits accumulated for their current course (there are some exceptions to this such as dropping the extra component from the program of study, or minor, or switching from a BSc to a BA).[5]

In the UK system, students generally take "Lectures" which are generally 2 hours a week

[4]This ensures that once at the university, students who might be actively seeking minority academics cannot combine another program where there are higher proportion of minority academics with their program.

[5]Similarly, this ensures that students cannot switch programs to study at a department where there are higher proportion of ethnic minority academics.

and are taught by the main instructor (module director). Additionally, they take "Classes" which are 1 hour per week and are taught by either instructors or by teaching assistants. These classes can take many forms such as problem sessions, discussion sessions, labs or seminars depending on the content of the course. Students may also have additional support classes which are generally voluntary and targeted at students who are falling behind or who have less prior knowledge in the subject studied. Classes are more interactive than lectures due to the fact that classes have fewer students than the lectures. Delavande *et al.* (2021) show that the average weekly attendance for a student is around 10 hours. Additionally, academics hold office hours where students can interact with their instructors. These features of the UK Higher Education system ensures that there are high levels of interactions between the students and the academics.

3.3 Data and Descriptive Statistics

3.3.1 Data

For this paper, I use data from three sources. The first one is the Higher Education Statistics Agency (HESA)'s Student Records. HESA is the regulatory body in the UK that collects student data from all the degree-awarding HEIs. HESA Student Records include information about all the students regardless of their domicile, nationality or the program of study. The records provide an extensive set of information about students such as their family background, their qualifications prior to university, and their graduation outcomes. I use student characteristics and degree outcomes from this source.

The second source is the HESA's Destinations of Leavers from Higher Education (DLHE) survey. This survey is sent to all graduates from UK HEIs and it collects data about graduates' labor market outcomes. It is sent 6 months after graduation, so it measures only short-term labor market outcomes. It includes information about the type of employment that the graduates are in, whether they are studying for a further qualification, and if so, the type of qualification. It also includes information about the characteristics of the jobs that they hold such as contract type, the importance of level of qualification, and the socio-economic classification of the job. From this source, I use graduates' employment, job characteristics, perceptions of the usefulness of HE and type of further qualification they are studying for in the analysis.

The third source is the HESA's Staff Records. Similar to Student Records, HESA collects data from all the HE Institutions in the UK about their staff. This dataset includes information about the staff's background, qualifications, employment, salary and years of service in their current role. Using this dataset, I calculate department $\times$ university $\times$ academic year level averages for racial composition of the staff as well as other department level characteristics such as proportion of female academics, proportion of academics at the level of Reader and above, proportion of academics earning a high salary, etc. While calculating department level characteristics, rather than using JACS codes which are the detailed subject codes, I use information about the' "cost center". This is because some of the subjects that are taught as part of the program would belong to different subjects if I use subject codes while the usage of cost center information allows me to derive department level information. For example, there are several JACS codes for Law subjects but students studying for LLB in Law are exposed to most of these academics as they take courses in different Law subjects throughout their undergraduate study.

The current structure of these sources allows me to link them all together. I first link individual level Student Records to data from the DLHE survey. This allows me to follow students from the start of their undergraduate study until 6 months after they graduate. I, then, link these two datasets to the departmental level data that I created using HESA Staff Records. I link departmental level data to HESA Student Records and DLHE Survey using information about the subjects that the students studied for using cost center codes rather than JACS codes. Once I do the necessary linkages, I have a dataset that includes detailed information about student characteristics, their academic and labor market outcomes, and the exposure that they get from academics with different characteristics and race.

The data that I derive after these linkages includes 114 universities and 45 subjects (see Appendix Table A3.17). I drop two of the universities (Oxford and Cambridge) as their method of teaching is based on small groups (or tutorials) and students might be affected differently when they receive more attention from their instructors due to class sizes being lower. I also exclude students studying for a degree in Medicine and Dentistry. This is because student numbers in these programs are controlled by the Office for Students to ensure that these programs are not overcrowded. As these programs have limited number of students that they can admit, they are more likely to be highly selective. Students studying these subjects also have different career paths once they graduate from these programs.

3.3.2 Descriptive Statistics

Figure 3.1 and Figure 3.2 show the proportion of racial minorities, Black, South Asian and Other racial minorities first unweighted and then weighted by the student numbers. The figures show that, regardless of weighting, there are departments where there is a high proportion of minority staff. While the mean proportion of minority academics is around 20%, there are some departments that have over 80% of its staff belonging to a racial minority group. Additionally, there are also departments that have no minority academics. The figures also show that there are differences in minority academics' shares by race. For example, the mean proportions of South Asian and Other academics are nearly twice that of Black academics, which shows that students' exposure to academics from different racial groups also varies. In Figure 3.3, I present how minority shares change over time. While there are small increases over time in the proportion of overall racial minority shares, the change in proportion of Black academics is close to 0. When we look at the changes in racial minority instructor shares over time, Figure 3.4 and Figure 3.5 show that changes occur for each of the three university clusters and of the four university tariff groups.

In Table 3.1, I present the control variables and variables of interest, first for all students and then by students' race. The table shows that while 55% of White students are female, a characteristic that is correlated with the outcomes, 50% of South Asian students are female. Similarly, while 70% of White students come from high socio-economic backgrounds, only 48% of South Asian students do so. The table also shows that while 10% of White students come from private schools, only 3% of Black students do so while this proportion is 7% for South Asian students. As well as personal characteristics of the students, I also look at how students from different racial groups differ in their entry test scores. For this, I calculate students' tariff scores using their top 3 A Level (or equivalent qualification) grades and cap the grades at A so that the maximum tariff score would be 144. The table shows that Black and South Asian students arrive to universities with lower entry scores than their White peers. While the average tariff scores is 117.75 for White students, it is only 107.60 for Black students. On the other hand, minority students are more likely to come with vocational qualifications (BTECs): while 10% of White students come with vocational qualifications, 27% of Black students do so. Del Bono & Holford (2018) show that those arrive to universities with BTEC diplomas do worse than those arriving with academic qualifications (A Level) even if their test scores are similar in terms of continuous tariff score measure.

The table also shows racial differences in academic outcomes. While nearly one in four White students graduate with a first class honors degree, only one in ten Black students and one in six South Asian students do so. Similarly, 78% of White students graduate with a good degree outcome (defined as graduating with a first or an upper second class honors degree), only 57% of Black students do so. While the White-South Asian gap is reduced when it comes to achieving a good degree outcome, the differences still exist: Compared to 78% of White students, 66% of South Asian students graduate with a good degree outcome. Another important element of this table is dropout. While only 10% of White students dropout from their undergraduate programs, the proportion is 16% for Black students. This, coupled with the racial gaps in academic achievement, shows that there is a very wide racial gap in academic outcomes: Minority students are less likely to graduate and even for those graduating, they graduate with worse academic outcomes.

The situation is similar when it comes to employment outcomes. When I look at the proportion of graduates in full-time employment 6 months after graduation, I see that while 64% of White graduates are in full-time employment, this is 49% for Black and South Asian graduates. This shows that racial differences I see in academic achievement also translate into differences in employment outcomes. While there is no racial difference in studying for a further degree, I find that 40% of the White graduates who are working full time are in graduate level jobs and only 35% of the Black graduates do so. This shows that the gaps found in entry scores and academic outcomes also translate into employment outcomes as well as job characteristics.

3.4 Empirical Strategy

In order to study how exposure to minority academics affects students' academic and labor market outcomes I estimate the following model:

$$Y_{ijt} = \beta_1 \mathbf{X}_i + \beta_2 \Gamma_i + \beta_3 PrpnMin_{cjt} + \beta_4 \Gamma_i \times PrpnMin_{cjt} + \beta_5 \mathbf{D}_{cjt} + \beta_6 \lambda_{sg} \times \psi_{cl} + \beta_7 \tau_t + \beta_8 \delta_c + \beta_9 \theta_j + \epsilon_{ijt} \tag{3.1}$$

where $\mathbf{X}$ is a vector of student characteristics that includes gender, socio-economic status, mature student status, a dummy for coming from an area with low HE attainment , Γ is student race dummy. This is either i) White and Minority or ii) White, Black, South Asian and Other, *PrpnMin* is the proportion of minority academics that do not only hold an administrative role (ie. excludes admin only role, head of department, dean, etc.). This varies across departments and universities, and over time. In the in-depth analysis, I also divide this into proportion of Black academics, proportion of South Asian academics and proportion of Other racial academics, $\mathbf{D}$ is a vector of department level characteristics: Proportion of female academics, proportion of academics that are Reader of above, proportion of academics tenured, proportion of student facing academics, academics' average years of service in a given university, and proportion of academics earning a high salary (defined as earning over £60k per year), δ is subject fixed effects and θ is university fixed effects, τ is cohort fixed effects. The subscript i stands for individual, j for university studied, c for cohort and s for subject studied at the university, sg for subject group and cl for university cluster group. While my model controls for all these fixed effects, there might still be some unobservable student characteristics that might be correlated with the outcomes that I study in this paper. One approach to deal with these unobservable factors is including university $\times$ subject fixed effects. However, including these fixed effects absorbs too much of the variation and leaves little variation to study the effect of representation on student outcomes. In order to deal with these unobserved factors, I include subject group fixed effects, λ, interacted with university group (clusters) fixed effects, ψ.

I estimate the above model using Ordinary Least Squares method. Even though all the dependent variables are binary variables, the proportions are well interior of the margins and use of population level data ensures that the use of OLS is appropriate. In order to estimate the effect of exposure to minority instructors on students' outcomes, I make two assumptions:

1. Students will have a limited set of programs to choose from.

2. Students will have a limited set of universities to choose from.

The main reasoning behind these assumptions is related to the Higher Education system in the UK. As previously mentioned, students study 3 to 4 subjects in years 12 and 13, prior to coming to university. Some degree programs require students to take exams in specific subjects to be eligible for admission. This limits students' degree program choice as students can only take a limited number of A Level subjects in year 12 and 13. The second assumption, similarly, is needed to differentiate the universities that the students apply. This assumption is based on the fact that university applications in the UK are mostly based on test scores achieved by the students[6]. As test scores are the most important element of the university admissions, they are also the element that limit the students most. For example, a student who received average grades from their exams cannot apply to the most selective universities.

[6]Even though contextualized admissions offers students coming from disadvantaged backgrounds lower entry requirements (Sen, 2021), this would not violate the above assumption because the use of university clusters ensures that the assumption allows students to have a relatively high number of universities to choose from.

Similarly, students who scored well on the exams would not think about applying to less selective universities. Due to these two factors, I assume that students will have a choice set of university clusters and subject groups that they will choose their degree program and university from.

In order to define students' choice set, I use students' realized outcomes: subject of the degree program and the university attended. While one might think that use of ex-post choices does not give consistent information about the students' ex-ante choice set, the features of the UK university admission system (based on test scores, limited subject availability, etc) ensure that ex-post choices give enough information about students' ex-ante choice set. For students' subject group choice set, I create 5 subject groups: Allied to Health, STEM, Social Sciences (including Business), Humanities and Others. For students' university choice set, I use university clusters defined in Boliver (2015). This paper defines 4 different university clusters and uses several factors such as their selectivity, research output, teaching performance etc. to group universities. As it is using several measures of productivity, it is a better measure to use to define students' choice set, than self-selected university mission groups. For the analysis, I exclude those who study medicine and dentistry as these subjects have different labor market paths. I also exclude Oxford and Cambridge because these universities offer a different method of teaching (tutoring) and their method of teaching might result in academics having different influence on the students than other universities. This leaves me with 3 university clusters and 5 subject groups, resulting in 15 choice sets. Additionally, I also restrict the sample to non-disabled students as they are less represented among South Asians than White students which might bias the results.

I, then, assume that students' exposure to minority academics is random conditional on their university cluster - subject group set. The current availability of data does not allow me to measure the fully casual effect of exposure to minority academics on students' academic and labor market outcomes so this additional assumption is needed to understand the effect of exposure to minority academics on students' outcomes.

One typical worry is whether there is enough variation in proportion of minority academics between cohorts, subjects and the universities. As I also control for several department level characteristics as well as university cluster-subject group fixed effects, I might be controlling for most of the variation leaving little variation to exploit. In order to check whether this is the case, I follow Blanden *et al.* (2016) and first check the raw variation and how much variation is left when I control for cohort, department, and university fixed effects as well as department controls and university cluster - subject group fixed effects. Table 3.2 shows when weighted by student numbers, the mean share of racial minority academics in UK universities is 13.66% with a standard deviation of 0.1029. When I control for cohort, university, subject, university cluster-subject group fixed effects as well as department level characteristics, I can only explain 40% of the variation in the minority academic share. This shows that even after controlling for several factors, one can estimate the effect of exposure to minority instructors on students. Similarly, when I look at the shares of Black, South Asian and Other racial minority academics, I find that I can explain less than one-third of the variation when I control for department level characteristics as well as different levels of fixed effects. This reassures that there is still enough variation to exploit.

3.5 Results

3.5.1 Selection

When working with observational data, one typical worry is endogeneity. A group of students might have strong preferences for some group of universities while others might have strong preferences for some subjects. Some students might also have strong preferences for university *and* subjects. First, in order to understand whether students' exposure to minority academics can be predicted by their observable characteristics, in Table 3.3, I regress exposure to minority academics (measured at university-subject-year level) against several student characteristics. The table shows that students' tariff negatively predicts their exposure to minority academics. However, when I look at whether the joint significance of these personal characteristics and tests scores affect exposure to minority instructors, I find that they are not jointly significant. While these results show that exposure to the minority instructors is close to random, there is still a possibility that the students might have strong preferences for some university - degree programs which might result in them being more exposed to minority academics. For example, students might have strong preferences for minority academics and they might actively seek out for programs within university cluster and subject groups where they will have exposure to these minority academics. This effort might also affect students' academic and labor market outcomes. If they also exert more effort once at the university, they might have better academic as well as labor market outcomes due to this high level of effort. This would result in underestimation of the possible positive effects of minority academics.

In addition to presenting evidence on selection on observables, I also present evidence on whether White-minority gaps in departments can be explained by the proportion of minority academics in given departments. I follow Fairlie *et al.* (2014) and look at several demographic characteristics as well as students' entry tariff scores. Here, the important point is to find variables that are highly correlated with the outcome variables. The main idea is that if I find that minority students are significantly different than White students in courses where there are higher proportion of minority academics, then the results that I find would be biased. If I find positive selection, the effect of minority academics on minority students would be underestimated while for the opposite scenario, the results would be overestimated. I create minority-specific level averages for each of the explanatory variables for each year, university, and subject.

In Table 3.4, I present the results on whether the share of minority instructors predict the differences in student characteristics. In order to create this table, first I calculate minority specific student characteristics (i.e. calculating proportions of White and minority students that have these characteristics in subjects) and then regress them against the share of minority instructors in these departments interacted with students' minority status dummy. Then, I do this separately by students' racial group. I first look at entry test scores and type of qualification that the students arrive to university with. As the table suggest, minority students do not differ in terms of their entry test scores and type of qualification that they come with as the share of minority instructors increase.

I then look at the differences by personal characteristics. Namely, I look at whether the students are studying full time, their gender, whether they are traditional students (aged 20 or younger at the time of starting their undergraduate degree) and whether they come from a neighborhood where HE participation belongs to the bottom half. The results show that when it comes to White-minority differences, share of minority academics does not predict these differences. When it comes to differences in White - Black, White - South Asian and White - Other racial groups, again, there is no difference except in one case. When we look at gender, we see that Black and Other racial minority students are less likely to be male than their White peers in the departments that have higher share of minority instructors. This shows that any possible positive results would be underestimated. As this shows some evidence on the likely selection bias, I include student gender alongside the list of controls when I estimate how exposure to minority instructors predicts students' academic and labor market outcomes.

3.5.2 Effects of Minority Academics

In this section, I present how exposure to minority instructors predicts students' academic and labor market outcomes. When looking at the results, one expects that exposure to minority academics will have differential effects by students' race. This might be due to students' seeing their academics as role models or the perceived effectiveness of the advice they get from academics.

In Table 3.5, I present the results on academic outcomes. In columns (1), (5) and (9), I present the basic model, in (2), (6) and (10), I include interactions of proportion of minority academics with minority status of the students and in columns (3), (7) and (11), I also control for department level characteristics such as proportion of female academics, proportion of academics who are Reader or higher, etc. In columns (4), (8) and (12), I also control for university cluster - subject groups. These last columns of each set of regressions are the closest I can get to causality. If the assumption that a students' exposure to minority academics is random conditional on the subject group of their degree program and the university group that they are studying at holds, then these last columns show the causal effect of this exposure on students' academic outcomes.

The results show that when students are exposed to higher proportion of minority academics, White students benefit from this exposure. 10% increase in students' exposure to minority academics which is a similar magnitude of 1 standard deviation increase in the exposure (see Table 3.2) increases White students' likelihood of achieving a first class honors degree by 0.5 percentage point. While White students achieve better outcomes when they are exposed to minority academics, the results show that minority students do not see any improvements form this exposure. Interaction term of minority student and proportion of minority academics is negative, significant, and very close to the magnitude of the positive effect of minority academics. This is an interesting finding because previous literature shows that students see their teachers and instructors as role models and having a teacher or an instructor from one's own racial group increases their academic outcomes. However, when I use the proportion of minority academics at department level, I find that this is not the case. These null effects on the minority students can be attributed to the fact that my measure of exposure to minority academics is different than the ones used in previous studies. While previous studies examine the effects of direct exposure, mine is a measure that also combines out-of-classroom interactions. As one cannot be sure how much the students interact with the academics outside of classroom, the lack of out-of-class interaction might be the reason of null effects on academic outcomes of minority students. While exposure to minority academics positively affects White students' likelihood of obtaining a first class honors degree, the results show that there is no effect on their likelihood of achieving a good degree or dropping out.

Table 3.6 presents the results on employment outcomes. Similar to the effect on academic outcomes, White students who are exposed to more minority academics have better labor market outcomes: They are more likely to be in full-time employment. While there is no effect on their likelihood of being in further study, the results show that conditional on being in full-time employment, exposure increases White students' likelihood of holding a graduate level job[7]. The results show a completely opposite picture for minority students. Minority students who are exposed to more minority academics are less likely to be in full-time employment and employment in general and the effect sizes are quite large. 10% increase in proportion of minority academics in a department decreases graduates' likelihood of being in full-time employment and employment in general by 1.6 and 1.3 percentage points. Additionally, the last two columns show that conditional on being in full-time employment, minority students are less likely to hold professional jobs[8]. The effect size, again, is quite large. 10% increase in the proportion of minority academics decreases minority students' likelihood of holding a professional job by 1.7 percentage points. These results suggest that while exposure to minority academics results in positive outcomes for White students, minority students have worse outcomes when they are exposed to minority academics.

While these results are important, it is also important to see whether exposure to minority academics affects graduates' other outcomes. Students might be more likely to find HE useful when they are exposed to minority academics if minority academics provide advice on student success, employment or other things that we cannot measure. In Table 3.7, I study the perceptions of the usefulness of HE for work and for further study, as well as students' further study outcomes. While the results show that exposure to minority instructors does not predict White or minority students' perception of HE, some important results emerge in

[7] I define graduate level job as a job where subject or level of study at the university is important for the job that the graduates hold or that requires university qualification

[8] Professional job is defined as a job that belongs to the highest 3 levels of 9 level socio-economic classification.

terms of students' further study behavior. The table shows that when students are exposed to more minority instructors, White students shy away from studying for a master degree (PG Taught). On the other hand, minority students are more likely to study for a masters degree when they are exposed to more minority instructors. 10% increase in proportion of minority academics they are exposed to increases their likelihood of studying for a masters degree by 0.5 percentage point. Considering only 10% of the students study for a masters degree, this is not a small effect.

These results show that exposure to minority academics provides better outcomes both for White and minority students but in different contexts. White students who are exposed to more minority academics have better academic and employment outcomes while having no effect on their further study behavior. On the other hand, minority students are more likely to be studying for a masters degree while having negative impact on their employment outcomes. While the negative results on employment outcomes of minority students may sound like bad news, we need to understand why this is happening. One possible explanation for these negative effects would be the shift from employment to study. Minority students might see minority academics in their departments as their *role models* and as a result, exposure to minority academics might encourage students to study for a masters degree rather than gaining employment. In the UK, a masters degree is generally required to gain admission for PhD study. If the positive effects of exposure on the likelihood of studying for a masters degree also increase students' likelihood of continuing to study for a PhD degree, then this might result in increasing diversity in academia. Current research shows that academia is not as diverse as the population of the UK (Advani *et al.*, 2020). Exposure to minority academics might be one of the possible ways to increase diversity in academia. The negative effects on the employment of minority graduates can also be explained by this shift. If successful minority students who are exposed to more minority academics shift from gaining employment to studying for a further degree while less successful minority students still look for jobs as they cannot gain admission for a masters degree, it is expected for these students to have worse employment outcomes. Additionally, evidence shows that UK labor market rewards a postgraduate degree (Lindley & Machin, 2016). If these minority students who gain admission to study for a masters degree do not continue studying for a PhD degree but end up entering labor market, they might have better employment outcomes as they would gain more skills as part of their masters degree.[9]

3.5.3 Effects of Academics from One's Own Race and Other Minorities

The effects of minority academics on students might vary by the students' and academics' own race. If students only see academics from their own race as role models, they might not benefit from having academics from other racial minority backgrounds. At the same time, students from different racial groups might have different stereotypes. For example, a Black student might not see a South Asian academic as a role model because they might believe that South Asian academics are more represented in their field (for example in STEM fields). Previous literature shows that students are generally affected from stereotype threat, being at the risk of conforming a negative stereotype relating to one's own identity (Steele & Aronson, 1995) and this threat affects their academic outcomes (Good *et al.*, 2003; Dee, 2014). In order to understand these mechanisms, I run additional set of regressions to understand how exposure to minority academics from one's own racial group and from other minority racial groups affect students' academic, employment, and study outcomes as well as their

[9] The data does not allow me to follow the graduates into their postgraduate years. As there is no longitudinal data, I cannot analyze what the graduates do after they finish their postgraduate study.

perceptions of the usefulness of HE.

I first study the academic outcomes. The results in Table 3.8 show that while Black students do not benefit from exposure to Black academics, they are less likely to achieve a first class honors degree when they are exposed to minority academics from other racial groups. On the other hand, South Asian students are more likely to achieve a first class honors degree when they are exposed to academics from their own race group. On average, an increase of 10% in South Asian students' exposure to South Asian academics results in 1.16 percentage points increase in their likelihood of achieving a first class honors degree. Considering other results on the effect of exposure to minority academics on students' academic outcomes, this is the largest effect found in this paper. When it comes to achieving a good degree, I find that South Asian students are more likely to achieve a good degree outcome when they are exposed to more academics from other racial minority groups, an increase of 10% in the proportion of minority academics increases their likelihood of achieving a good degree by 1.45 percentage points. These results show that for South Asian students, exposure to academics from their own group or from other racial minority groups always increases their academic outcomes, while there is evidence on the negative effects of exposure to other racial minority for Black students. The literature on stereotype threat finds that when students are confronted about the stereotypes, their achievement is negatively affected. If seeing academics from other racial groups triggers Black students' stereotype threat, the negative effects on their academic outcomes are expected. Additionally, Black academics are under-represented in academia compared to their shares in UK population while some South Asian groups (namely Indian) and Chinese ethnic groups are over-represented. The lack of Black academics coupled with the results in Table 3.1 which shows that Black students are the group of students that graduate with worst outcomes provides evidence of stereotype threat for Black students.

While the results on academic outcomes suggest that Black students graduate with worse outcomes when they are exposed to minority instructors from other race groups, there might be different effects on the labor market outcomes because while the students might not increase their effort in the university as a result of having role models, they might have better employment outcomes. Academics from one's own racial group might be useful in giving advice to students to be successful in the labor market or they might encourage students to pursue a masters degree. The results in Table 3.9 show that the negative results shown in Table 3.6 on the employment outcomes come mostly from Black students. Black students who are exposed to more Black academics are less likely to be in full-time employment and employment in general. In addition to this, they are also negatively affected by academics from other racial groups. As well as negative effects on full-time employment and employment in general, Black students who are exposed to more other racial minority instructors are less likely to hold a professional job. These negative effects on the likelihood of holding a professional job also exist for South Asian students. On the other hand, Black students who are more exposed to other racial minority academics are more likely to pursue a further degree.

When I study the effect of minority academics on the perceptions of the usefulness of HE and the type of qualification that the graduates are studying for in Table 3.10, I find that Black students who are exposed to other racial minority academics are more likely to find HE useful for study but there is no other effect of exposure on their perceptions. On the other hand, some important results emerge on the likelihood of studying for a masters and PhD degree. The results in Table 3.10 show that Black students who are exposed to more Black academics are more likely to study for a PhD degree. Although as opposed to US, in the UK, students generally need to study for a masters degree before being admitted to PhD programs, there are certain exceptions to this (mainly in STEM subjects). Similarly, Black students who are exposed to other racial minority academics are more likely to study for a masters degree. These two findings show some important results. Advani *et al.* (2020) show that Black graduates are less likely to go into PhD study and there is an even lower proportion of Black academics in the UK universities. As Black academics are under-represented in academia and Black graduates have worse labor market outcomes than others, this increase in the likelihood of studying for a masters degree might improve these graduates' labor market outcomes as well as their likelihood of studying for a PhD.

3.4 Robustness Checks

I run several robustness checks to see if the results hold for different levels of clustering, a different measure of representation, and then for different sub-samples. For this part of the analysis, rather than looking at the effect of minority instructors on minority students in general, I study the effects separately by students' race. I first check the results by clustering the standard errors at different levels. The standard errors in the main specification are clustered at subject level. In Appendix Table A3.5, Appendix Table A3.6 and Appendix Table A3.7, I cluster the standard errors at university, cohort and cohort-department level. Each of these tables give the same conclusion with the main tables.

I then calculate a different measure of exposure to minority academics. I restrict the sample to those academics who are student facing (instructors from this point on). The results in Appendix Table A3.8 show that the results on White students hold. Additionally, I find that Black students who are exposed to more minority instructors are less likely to obtain a first class honors degree but there is no other effect on their academic outcomes. On the other hand, South Asian students are more likely to achieve a first class honors degree and a good degree outcome when they are exposed to more minority instructors. Similar to the results on academic outcomes, the results on employment outcomes are in line with the main results.

I then restrict my sample to students who are studying full-time as part-time students might have different unobservable characteristics than those whose main activity is university. Appendix Table A3.9 shows that main results hold. In addition to the main results on academic outcomes, I find that South Asian and Other minority students are less likely to dropout of their study when they are exposed to more minority academics.

Lastly, I run the main analysis separately for subject groups. I separate the subjects into 5 groups: i) Allied to Health Sciences, ii) STEM, iii) Social Sciences and Business, iv) Humanities and v) Arts, Education and Others. In Appendix Table A3.10 through Appendix Table A3.14, I present the results separately for each subject group and for each race. I summarize the findings for students studying for a STEM degree as these courses are the ones that are generally more diverse. Appendix Table A3.11 shows that when White students are exposed to higher proportion of minority academics, their likelihood of achieving a first class honors degree increases but there is no effect on their likelihood of achieving a good degree or dropout. When I look at Black students, I find no effect of exposure on their academic outcomes. South Asian students, on the other hand, have better academic outcomes when they are exposed to more minority academics. Exposure increases both their likelihood of achieving a first class honors degree and a good degree outcome. Similar to the main results, I do not find any effect on the dropout behavior.

On employment outcomes, I find that exposure to minority academics increases White students' likelihood of being in full-time employment but this is significant only at 10% significance level. Exposure also increases their likelihood of holding a graduate level job and a professional job. On the other hand, Black students who are exposed to more minority instructors are less likely to be in full-time employment or employment in general but more likely to be in further study. Of those who are working full time, they are less likely to hold a professional job. If high achieving Black students are encouraged by the exposure to minority academics to study for a further degree rather than entering labor force after their undergraduate study, this is expected. When I study the type of qualification they are studying for, I find that the positive effects are driven by those studying for a PhD. When I look at the effects on South Asian graduates, I find similar results. They are less likely to be in full-time employment and employment in general but more likely to be in further study and specifically in PhD study. Additionally, the negative effects found on Black graduates' likelihood of holding a professional job do exist for South Asian students. While there are negative effects on graduates' employment outcomes, the positive effects found on further study are important. Students studying for a research degree might go on to work for in academia or in R&D sector. Previous studies show that diversity improve innovation and quality. This, in return, might have other effects in the economy as a whole (Parrotta *et al.*, 2014).

3.5 Conclusion

It is now a well-known fact that racial minority students have worse academic and labor market outcomes than White students in the UK. Previous research shows that representation in classroom improves students' academic and behavioral outcomes both at pre-university and at university level. In this paper, I provide evidence on the effect of representation among academics on the students' academic and labor market outcomes.

I use an alternative measure of exposure to minority instructors, proportion of academics who are racial minority in a given department and study how this exposure affects students' academic and short-term labor market outcomes. On labor market outcomes, I focus on graduates' employment outcomes, job characteristics of those who are in full-time employment, perceptions about usefulness of Higher Education, and the type of qualification that the graduates are studying towards.

I find that representation among academics does affect students' academic outcomes. Exposure to minority academics increases South Asian students' likelihood of achieving a first class honors degree and a good degree outcome. I also find that this exposure improves White students' academic outcomes. On the other hand, I do not find any effect of representation on students' dropout or Black students' academic outcomes as a whole.

On labor market outcomes, I find that exposure to minority instructors decreases minority graduates' likelihood of being in full-time employment but I find that this decrease is mainly due to an increase in minority graduates' likelihood of studying for a further degree. On the other hand, this exposure reduces White graduates' likelihood of studying for a further degree but increases their likelihood of being in full-time employment. In terms of job characteristics, when I restrict the sample to those working full time, I see an improvement on White graduates' job prospects while I see a reduction for those of minority graduates. I argue that this might be because more able minority graduates changing their post-graduation paths from working full time towards studying for a further degree while it might be the opposite for White graduates.

The results suggest that minority students may in fact see academics as their role models. If governments and the universities would like to increase the diversity of PhD students and researchers in academia, increasing representation among academics might be a possible policy. Literature shows that diversity also improves innovation of the firms. If the students who went on to study for a further degree end up in R&D departments of the firms (Parrotta *et al.*, 2014), representation among academics might also affect innovation and development in non-academic settings.

Figures

Figure 3.1: Proportion of Minority Academics - Unweighted

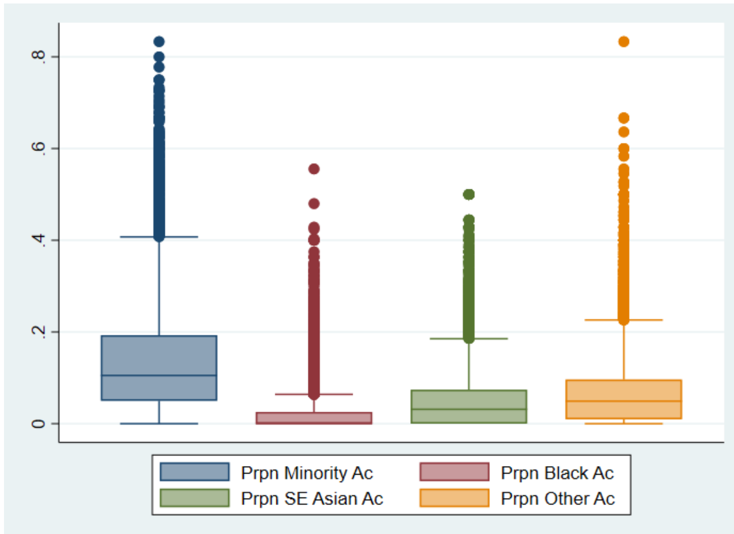


Figure 3.2: Proportion of Minority Academics - Weighted by Student Numbers

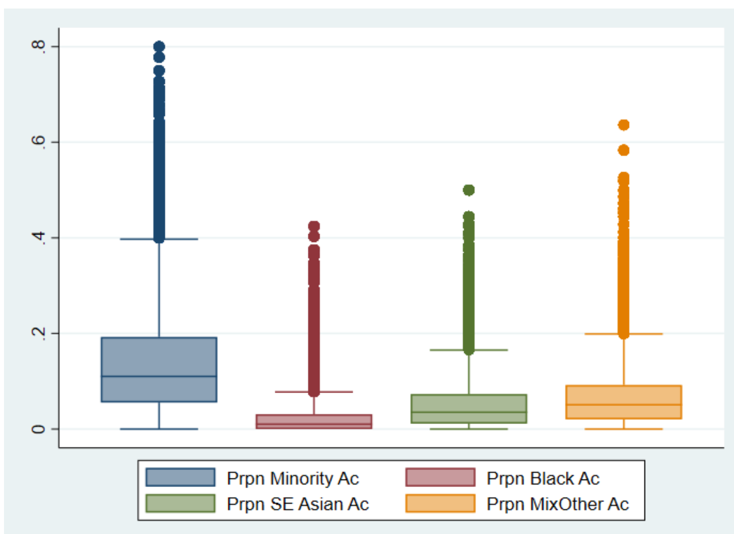


Figure 3.3: Proportion of Minority Academics - Unweighted

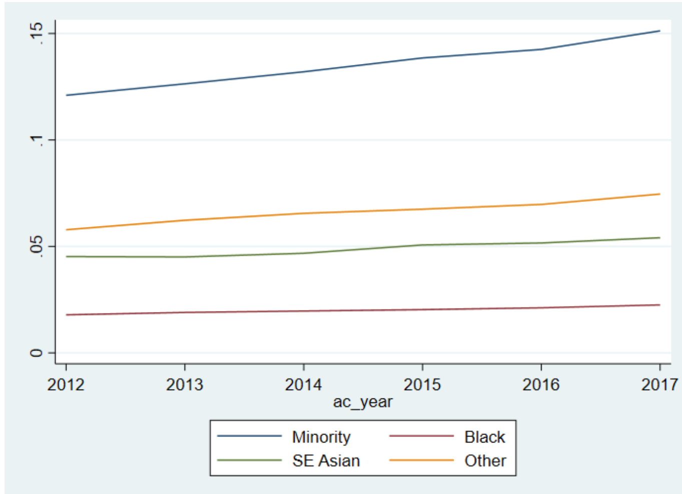


Figure 3.4: Proportion of Minority Academics by University Cluster - Unweighted

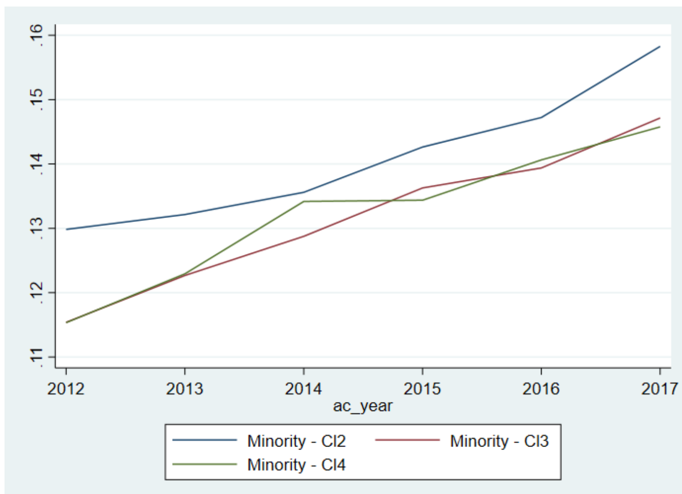
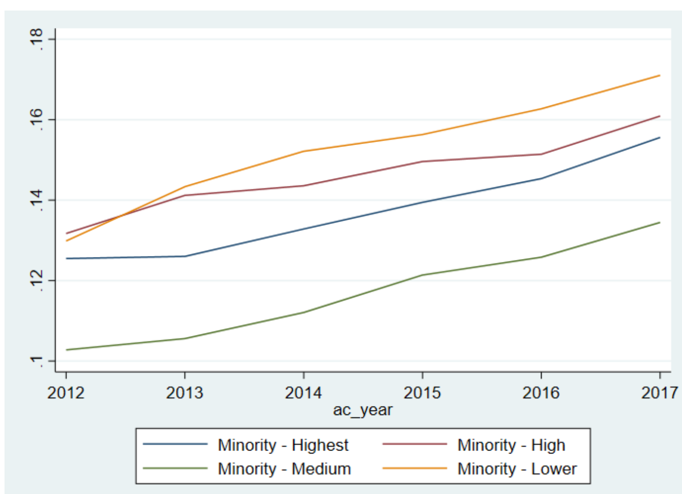


Figure 3.5: Proportion of Minority Academics by University Tariff Groups - Unweighted



Tables

Table 3.1: Descriptive Statistics

	All	White	Black	SE Asian	Other
Personal Characteristics					
Female	0.54	0.55	0.56	0.50	0.54
High SES	0.67	0.70	0.62	0.48	0.62
State School	0.91	0.90	0.97	0.93	0.90
Mature	0.20	0.20	0.27	0.17	0.19
FT Student	0.87	0.87	0.85	0.84	0.87
Previous Outcomes					
Tariff	116.84	117.75	107.61	113.09	116.70
BTEC	0.11	0.10	0.27	0.16	0.13
Academic Outcomes					
First	0.22	0.23	0.10	0.17	0.20
Good	0.76	0.78	0.57	0.66	0.73
Dropout	0.10	0.10	0.16	0.12	0.12
Employment Outcomes					
FT Work	0.54	0.56	0.49	0.49	0.49
Employed	0.67	0.68	0.67	0.63	0.63
Study	0.22	0.22	0.21	0.23	0.23
Graduate Job	0.39	0.40	0.35	0.38	0.35
High SOC	0.65	0.65	0.60	0.66	0.65
Perceptions of HE					
HE Useful for Study	0.89	0.90	0.85	0.86	0.87
HE Useful for Work	0.79	0.80	0.74	0.76	0.74
PG Study					
Research	0.02	0.02	0.01	0.01	0.02
Taught	0.11	0.10	0.12	0.11	0.13

Notes: First and Good are conditional on not dropping out and Graduate Job and High SOC are conditional on being in full-time employment.

Table 3.2: Variation - Weighted by Student Numbers

Panel A: Minority Shares

	Mean	SD	Min	Max	N
Weighted Proportion	0.1301	0.1029	0.0000	0.8000	1,017,328
Net of Year FE	0.0000	0.1027			
Net of University FE	-0.0000	0.0899			
Net of Department FE	0.0000	0.0627			
Net of Department Char.	0.0000	0.0616			
Net of Cluster x Subject FE	0.0000	0.0615			

Panel B: Black Shares

	Mean	SD	Min	Max	N
Weighted Proportion	0.0203	0.0332	0.0000	0.5556	1,017,328
Net of Year FE	0.0000	0.0331			
Net of University FE	-0.0000	0.0288			
Net of Department FE	-0.0000	0.0263			
Net of Department Char.	0.0000	0.0261			
Net of Cluster x Subject FE	0.0000	0.0260			

Panel C: South Asian Shares

	Mean	SD	Min	Max	N
Weighted Proportion	0.0471	0.0492	0.0000	0.5000	1,017,328
Net of Year FE	0.0000	0.0492			
Net of University FE	-0.0000	0.0447			
Net of Department FE	0.0000	0.0345			
Net of Department Char.	0.0000	0.0343			
Net of Cluster x Subject FE	-0.0000	0.0342			

Panel D: Other Group Shares

	Mean	SD	Min	Max	N
Weighted Proportion	0.0627	0.0578	0.0000	0.6364	1,017,328
Net of Year FE	-0.0000	0.0577			
Net of University FE	-0.0000	0.0514			
Net of Department FE	-0.0000	0.0416			
Net of Department Char.	-0.0000	0.0412			
Net of Cluster x Subject FE	0.0000	0.0410			

Notes: Department characteristics refers to department level controls such as proportion of female academics, proportion of academics that are on teaching or teaching and research contracts, proportion of academics that are reader or above, proportion of full-time academics, and proportion of academics on permanent contract.

Table 3.3: Selection

	(1) Proportion Minority
Continuous Tariff	-0.007*
	(0.004)
Has IB	-0.052
	(0.174)
Has BTec	-0.043
	(0.148)
Foundation	0.242
	(0.771)
Female	0.005
	(0.038)
High SES (2-group)	-0.037*
	(0.022)
First Generation Student	-0.028
	(0.018)
Low HE Participation Area	-0.002
	(0.023)
p-value for joint sig	0.120
Observations	530,078

Notes: Controls include department level controls and university, cohort, subject as well as cluster $\times$ subject group fixed effects. Standard errors are clustered at subject level. Standard errors are in parentheses. * p <0.1, ** p <0.05, *** p <0.01

Table 3.4: Are Minority Students Different than White Students?

	Tariff	BTEC	FT Stu	Male	Trad Stu	LPA
Ethnic Minority						
b	-0.9180	0.0386	0.0341	-0.0786	0.0020	0.0212
se	3.7957	0.0324	0.0204	0.0506	0.0271	0.0388
p-value	0.8102	0.2407	0.1023	0.1291	0.9410	0.5883
Seperately						
Black						
b	-2.5072	-0.0120	0.0200	-0.1229	-0.0030	0.0926
se	4.7105	0.0591	0.0332	0.0671	0.0317	0.0561
p-value	0.5976	0.8402	0.5508	0.0748	0.9259	0.1072
SE Asian						
b	5.0939	0.0322	0.0367	-0.0458	-0.0099	-0.0224
se	5.5356	0.0341	0.0257	0.0619	0.0414	0.0496
p-value	0.3633	0.3509	0.1611	0.4642	0.8122	0.6537
Other						
b	-9.2157	0.0039	0.0405	-0.1027	-0.0191	0.0432
se	4.5449	0.0289	0.0224	0.0488	0.0273	0.0399
p-value	0.0496	0.8941	0.0781	0.0421	0.4890	0.2859

Notes: Controls include department level controls and university, cohort, subject as well as cluster × subject group fixed effects. Standard errors are clustered at subject level. Standard errors are in parentheses. * p <0.1, ** p <0.05, *** p <0.01

Table 3.5: Academic Outcomes

	First				Good				Dropout			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Prpn Minority Academics	0.027	0.050**	0.048*	0.049**	0.053*	0.048	0.047	0.041	-0.021	-0.022	-0.018	-0.016
	(0.023)	(0.024)	(0.025)	(0.023)	(0.030)	(0.029)	(0.028)	(0.026)	(0.013)	(0.015)	(0.014)	(0.014)
Minority Student		-0.084***	-0.084***	-0.084***		-0.106***	-0.106***	-0.105***		0.002	0.002	0.003
		(0.005)	(0.005)	(0.005)		(0.007)	(0.007)	(0.007)		(0.005)	(0.005)	(0.005)
Prpn Min Ac × Min Stu		-0.079***	-0.077***	-0.083***		0.017	0.014	0.011		0.003	0.002	-0.001
		(0.022)	(0.022)	(0.021)		(0.030)	(0.030)	(0.030)		(0.021)	(0.021)	(0.021)
TE on Minorities		-0.028	-0.030	-0.034		0.065	0.061	0.052		-0.019	-0.015	-0.017
		(0.029)	(0.028)	(0.026)		(0.040)	(0.038)	(0.036)		(0.020)	(0.019)	(0.018)
Observations	794,691	794,691	794,691	794,691	794,691	794,691	794,691	794,691	953,642	953,642	953,642	953,642
Dept Cont	No	No	Yes	Yes	No	No	Yes	Yes	No	No	Yes	Yes
Clu x Sub FE	No	No	No	Yes	No	No	No	Yes	No	No	No	Yes

Notes: Controls include gender, tariff, type of qualification, socio-economic status, POLAR Q1, 2 & 3, being a first generation university student, and university, cohort, subject as well as cluster × subject group fixed effects. First and Good are conditional on graduating. Standard errors are clustered at subject level. Standard errors are in parentheses. * p <0.1, ** p <0.05, *** p <0.01

Table 3.6: Employment

	FT Work		Employed		Study		Grad Job		High SOC	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Prpn Minority Academics	0.066**	0.064**	0.023	0.022	-0.025	-0.024	0.096***	0.091***	0.068*	0.057*
	(0.031)	(0.029)	(0.027)	(0.026)	(0.026)	(0.025)	(0.033)	(0.031)	(0.035)	(0.033)
Minority Student	-0.059***	-0.060***	-0.036***	-0.036***	0.008	0.009	-0.006	-0.007	-0.004	-0.005
	(0.010)	(0.010)	(0.012)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
Prpn Min Ac $\times$ Min Stu	-0.225***	-0.223***	-0.154***	-0.152***	0.086**	0.085**	-0.171***	-0.164***	-0.234***	-0.228***
	(0.060)	(0.059)	(0.046)	(0.045)	(0.038)	(0.037)	(0.049)	(0.047)	(0.060)	(0.059)
TE on Minorities	-0.159***	-0.158***	-0.131***	-0.129***	0.061*	0.061*	-0.075	-0.073	-0.165***	-0.171***
	(0.054)	(0.052)	(0.043)	(0.041)	(0.036)	(0.035)	(0.053)	(0.052)	(0.061)	(0.060)
Observations	526,263	526,263	526,263	526,263	526,263	526,263	352,650	352,650	352,156	352,156
Clu x Sub FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Controls include gender, socio-economic status, POLAR Q1, 2 & 3, being a first generation university student, and university, cohort, subject as well as cluster $\times$ subject group fixed effects. Standard errors are clustered at subject level. Standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3.7: Perceptions of HE and Type of Further Study

	HE for Study		HE for Work		PhD		Master	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Prpn Minority Academics	-0.022	-0.022	-0.017	-0.019	0.001	0.006	-0.034**	-0.031**
	(0.014)	(0.014)	(0.018)	(0.017)	(0.007)	(0.005)	(0.014)	(0.012)
Minority Student	-0.027***	-0.027***	-0.039***	-0.040***	-0.005*	-0.006*	0.014**	0.014**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)
Prpn Min Ac × Min Stu	0.035**	0.035***	-0.006	-0.003	-0.011	-0.008	0.100***	0.094***
	(0.013)	(0.013)	(0.016)	(0.017)	(0.011)	(0.010)	(0.024)	(0.023)
TE on Minorities	0.012	0.013	-0.023	-0.022	-0.009	-0.003	0.065***	0.063***
	(0.013)	(0.013)	(0.023)	(0.023)	(0.008)	(0.007)	(0.024)	(0.022)
Observations	372,174	372,174	395,635	395,635	526,263	526,263	526,263	526,263
Clu x Sub FE	No	Yes	No	Yes	No	Yes	No	Yes

Notes: Controls include gender, socio-economic status, POLAR Q1, 2 & 3, being a first generation university student, and university, cohort, subject as well as cluster × subject group fixed effects. Standard errors are clustered at subject level. Standard errors are in parentheses. * p <0.1, ** p <0.05, *** p <0.01

Table 3.8: Academic Outcomes

	First		Good		Dropout	
	(1)	(2)	(3)	(4)	(5)	(6)
Prpn Black Academics	0.044	0.057	0.095*	0.153**	-0.078**	-0.085**
	(0.080)	(0.095)	(0.048)	(0.060)	(0.034)	(0.040)
Prpn South Asian Academics	0.057**	0.121***	0.027	0.040	0.002	0.002
	(0.025)	(0.032)	(0.044)	(0.046)	(0.022)	(0.024)
Prpn Other Minority Academics	0.003	0.038	-0.006	-0.008	-0.009	-0.007
	(0.029)	(0.033)	(0.033)	(0.028)	(0.016)	(0.017)
Black Student		-0.115***		-0.173***		0.015*
		(0.006)		(0.009)		(0.008)
S Asian Student		-0.100***		-0.118***		-0.005
		(0.007)		(0.008)		(0.007)
Prpn Black Ac × Black Stu		-0.031		-0.171		-0.030
		(0.075)		(0.112)		(0.094)
Prpn S Asian Ac × S Asian Stu		-0.005		0.105		0.022
		(0.065)		(0.069)		(0.058)
TE on Blacks from Black Ac		0.026		-0.018		-0.116
		(0.079)		(0.101)		(0.089)
TE on S Asians from S Asian Ac		0.116 **		0.145**		0.024
		(0.047)		(0.073)		(0.053)
TE on Blacks from other ME Ac		-0.229***		0.183		0.110
		(0.081)		(0.141)		(0.088)
TE on S Asians from other ME Ac		0.145*		0.228***		-0.171**
		(0.093)		(0.086)		(0.075)
Observations	797,993	794,691	797,993	794,691	570,240	567,887

Notes: Controls include gender, tariff, type of qualification, socio-economic status, POLAR Q1, 2 & 3, being a first generation university student, and university, cohort, subject as well as cluster × subject group fixed effects. First and Good are conditional on graduating. Standard errors are clustered at subject level. Standard errors are in parentheses. * p <0.1, ** p <0.05, *** p <0.01

Table 3.9: Employment

	(1) FT Work	(2) Employed	(3) Study	(4) Grad Job	(5) High SOC
Prpn Black Academics	0.166**	0.041	-0.055	0.178***	0.192**
	(0.076)	(0.067)	(0.056)	(0.063)	(0.081)
Prpn South Asian Academics	0.011	-0.014	-0.011	0.112**	0.072
	(0.052)	(0.046)	(0.041)	(0.042)	(0.049)
Prpn Other Minority Academics	0.090**	0.055*	-0.034	0.073	0.047
	(0.037)	(0.033)	(0.031)	(0.044)	(0.038)
Black Student	-0.049***	0.000	-0.014	-0.016	-0.013
	(0.017)	(0.017)	(0.013)	(0.017)	(0.017)
S Asian Student	-0.090***	-0.065***	0.028**	-0.003	-0.013
	(0.011)	(0.011)	(0.012)	(0.011)	(0.015)
Prpn Black Ac × Black Stu	-0.482***	-0.313***	0.139*	-0.335**	-0.190
	(0.171)	(0.085)	(0.077)	(0.160)	(0.146)
Prpn S Asian Ac × S Asian Stu	-0.089	-0.119	0.067	-0.185**	-0.252**
	(0.119)	(0.093)	(0.067)	(0.071)	(0.094)
TE on Blacks from Black Ac	-0.316**	-0.272***	0.084	-0.157	0.002
	(0.151)	(0.083)	(0.069)	(0.161)	(0.122)
TE on S Asians from S Asian Ac	-0.078	-0.133	0.056	-0.073	-0.180**
	(0.122)	(0.099)	(0.074)	(0.073)	(0.089)
TE on Blacks from other ME Ac	-0.384***	-0.358***	0.236**	-0.163	-0.471***
	(0.104)	(0.100)	(0.100)	(0.144)	(0.164)
TE on S Asians from other ME Ac	-0.235**	-0.103	-0.012	-0.113	-0.292**
	(0.111)	(0.097)	(0.082)	(0.100)	(0.129)
Observations	526,263	526,263	526,263	352,650	352,156

Notes: Controls include gender, socio-economic status, POLAR Q1, 2 & 3, being a first generation university student, and university, cohort, subject as well as cluster × subject group fixed effects. Standard errors are clustered at subject level. Standard errors are in parentheses. * p <0.1, ** p <0.05, *** p <0.01

Table 3.10: Perceptions of HE and Type of Further Study

	(1) HE for Study	(2) HE for Work	(3) PhD	(4) Master
Prpn Black Academics	-0.021	0.035	-0.025**	-0.031
	(0.036)	(0.046)	(0.012)	(0.038)
Prpn South Asian Academics	-0.041**	-0.060**	0.008	0.002
	(0.018)	(0.028)	(0.009)	(0.028)
Prpn Other Minority Academics	-0.018	-0.006	0.017*	-0.062***
	(0.016)	(0.024)	(0.009)	(0.017)
Black Student	-0.035***	-0.050***	-0.006*	0.011
	(0.005)	(0.008)	(0.003)	(0.010)
S Asian Student	-0.032***	-0.035***	-0.009**	0.017***
	(0.006)	(0.006)	(0.004)	(0.006)
Prpn Black Ac × Black Stu	0.016	-0.026	0.064***	0.102*
	(0.080)	(0.083)	(0.023)	(0.059)
Prpn S Asian Ac × S Asian Stu	0.100**	0.059	-0.017	0.088*
	(0.040)	(0.052)	(0.020)	(0.048)
TE on Blacks from Black Ac	-0.005	0.009	0.039	0.071
	(0.095)	(0.075)	(0.018)	(0.055)
TE on S Asians from S Asian Ac	0.059	-0.002	-0.009	0.090
	(0.030)	(0.045)	(0.018)	(0.050)
TE on Blacks from other ME Ac	0.135**	-0.109	-0.028	0.233***
	(0.054)	(0.092)	(0.016)	(0.084)
TE on S Asians from other ME Ac	-0.002	-0.075	0.070	0.013
	(0.071)	(0.094)	(0.038)	(0.063)
Observations	372,174	395,635	526,263	526,263

Notes: Controls include gender, socio-economic status, POLAR Q1, 2 & 3, being a first generation university student. and university, cohort, subject as well as cluster × subject group fixed effects. Standard errors are clustered at subject level. Standard errors are in parentheses. * p <0.1, ** p <0.05, *** p <0.01

Conclusion

This thesis studies three different ways to mitigate gender, socio-economic and ethnic inequalities in Higher Education by focusing on UK university students. First, we provide new evidence on the effectiveness of an randomized controlled trial that is focused on shaping students' beliefs about the determinants of success. We document positive results of our intervention on students' beliefs, study habits and methods as well as short- and long-term academic outcomes. We also provide evidence on its effectiveness on mitigating the gender differences in academic outcomes.

In the second chapter, I focus on an affirmative action policy on university admissions that has been widely discussed by the politicians and policy-makers. I provide the first evidence on the effects of this policy on the applications that the universities received, student population and students' academic and labor market outcomes. I find negative effects on the academic outcomes with little to no effect on the labor market outcomes. This implies that while the policy might have negative effects in one setting, there is little to no effect in the other setting, labor market. I also provide evidence from the literature on how universities can implement new support programs to reduce the negative effects of this admission policy on students' academic outcomes. While these are important results, we also need to understand the mechanisms about how these effects are arising. Further data work is needed to understand these channels but the current structure of data sources available in the country does not allow researchers to study these. We need further data linkages on pre-university student data (National Pupil Database) and university applications data (UCAS) to see whether this policy increases students' likelihood of applying to university (external margin of the effect), and between university applications data and university students data to understand whether this policy improves students' likelihood of placing into a better university (internal margin of the effect). These linkages are important to understand the possible channels of the negative effects found in the second chapter. We also need to study the long-term effects of this policy. Availablity of Longitudinal Education Outcomes dataset which links students' pre-university records, university records and tax records is crucial to study the effect of this policy on graduates long-term labor market outcomes as the policy might have different effect on the long-term outcomes of the graduates

Lastly, I provide evidence on the effect of role models (defined as academics from one's own racial group) on the students' academic and labor market outcomes. I extend the literature by looking at not only the direct interaction of academics with students in the classroom but also the out-of-classroom interactions that the students might have with the academics. I show that minority academics provide better academic outcomes for White students and for students from some racial minority groups while not negatively affecting the others. I also provide evidence on the positive effects of minority academics on graduates labor market outcomes, albeit in different contexts. I find that minority academics improve White students' employment outcomes while they improve minority students' likelihood of studying for a further degree. I finalize this chapter by stating that minority academics generally improve students' academic as well as labor market outcomes so the governments should try to encourage minority students' enrollment into PhD programs. Similar to the results of the second chapter, this chapter also carries some shortcomings. For example, one cannot be sure about the causality of the results found in this chapter. Further data linkages on the university applications data and administrative data on university students would allow researchers to understand the fully causal effect of the share of minority instructors on students' outcomes following the methodology proposed in Kirkeboen *et al.* (2016).

Overall, this thesis proposes three different ways to reduce the inequalities in academic and labor market outcomes of university students. The results of this thesis can be applied by the government and policy makers to improve students' academic and labor market outcomes as well as reducing the inequalities with a view of closing the gaps in later life outcomes.

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Appendix

Appendix for Chapter 1: Skills Accumulation and Expectations about the Education Production Function: Evidence from a Randomized Information Intervention

Figure A1.1: Expected Grade Conditional on Effort and Ability

Now, it's your turn!

We would like now to ask you to think what your **average final mark** (between 0 and 100) might be depending on:

- How many **hours you study per week** during term time (outside of lectures and classes)
- The **proportion of lectures and classes you attend** this year
- Your **rank when answering a problem-solving task** involving patterns similar to the one you just did.

When answering this question, assume that you will study and attend lectures and classes during your 2nd and 3rd year as you have answered before.

Recall that you previously answered that you currently study hours a week, attend % of your lectures, % of your classes and ranked yourself at /1000.

On a scale from 0 to 100, **what do you expect your average final mark** to be if you ... ?

	Rank 200 out of 1000	Rank 500 out of 1000	Rank 800 out of 1000
Study 5 hours per week and attend 60% of lectures and classes			
Study 5 hours per week and attend 95% of lectures and classes			
Study 15 hours per week and attend 60% of lectures and classes			
Study 15 hours per week and attend 95% of lectures and classes			

Figure A1.2: Expected Rank Conditional on Effort

Remember we asked you to think about your rank in this task, assuming that 1000 first-year students drawn from all UK universities were given 50 questions from a similar problem-solving task in the January of their first year. You thought that your rank would be , where 1 is the highest rank and 1000 the lowest.

Now, suppose that you and these 1000 students from all UK universities were doing a similar problem-solving task with 50 questions again next year. We would like now to ask you to think what your **next year rank** on this problem-solving task might be depending on:

- How many hours you study per week
- The proportion of lectures and classes you attend during your current year at university.

When answering this question, assume that you will study and attend lectures and classes during 2nd and 3rd year as you have answered before.

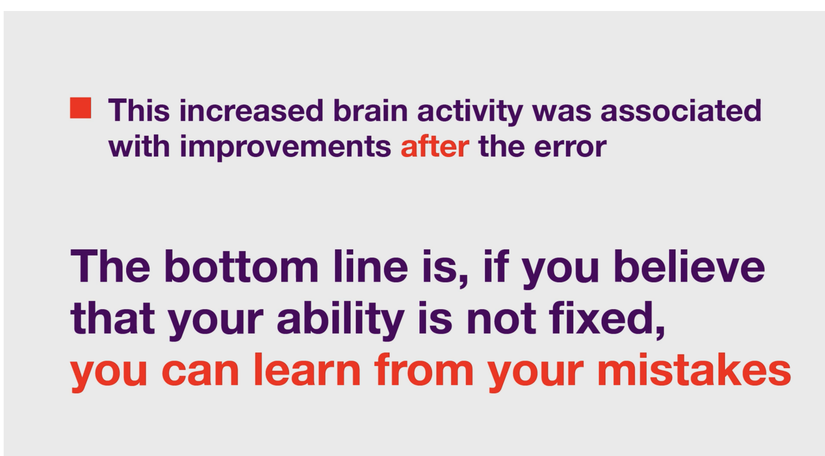
Recall that you previously answered that you currently study hours a week, attend % of your lectures, % of your classes and ranked yourself at /1000.

Please complete your expected rank (from 1, highest rank to 1000, lowest rank) for each combination of study time and lecture and class attendance during your current year.

	Expected next year's rank (out of 1000)
study 5 hours per week and attend 60% of lectures and classes	
study 5 hours per week and attend 95% of lectures and classes	
study 15 hours per week and attend 60% of lectures and classes	
study 15 hours per week and attend 95% of lectures and classes	

Note: Participants were first asked their unconditional rank expectations. Based on their rank expectations, they received two possible rank scenarios. If their answer for their expected rank to be less than 500, they were shown the rank scenarios of 500 and 800 and if their answer for their expected rank was more than 500, then they were shown the scenarios of 200 and 500.

Figure A1.3: Screenshots from Treatment Video



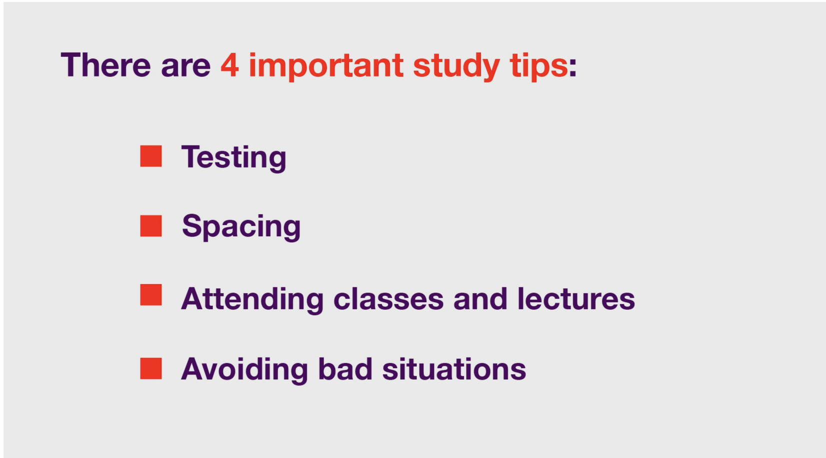


Figure A1.4: Screenshots from Control Video

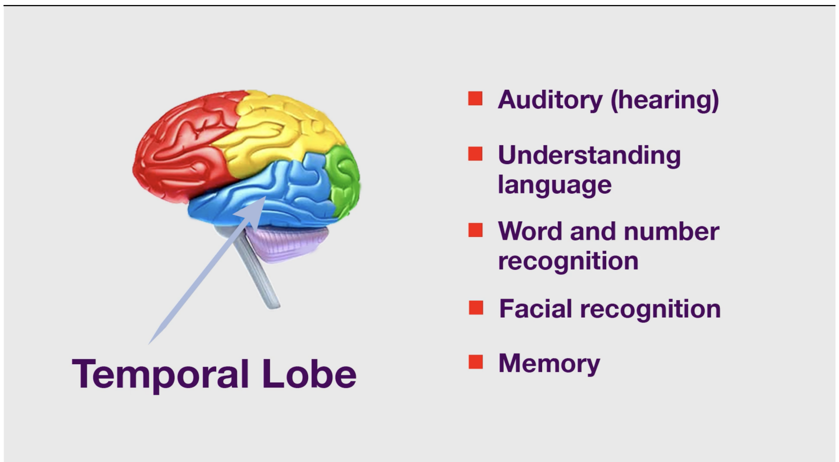


Table A1.1: Expectations about Grades and Ability at Baseline

	(1) Expected Mark	(2) Expected Ability
LnAttendance	0.303***	0.126***
	(0.021)	(0.006)
LnStudy	0.189***	0.076***
	(0.009)	(0.002)
LnAbility	0.725***	
	(0.076)	
Observations	5,374	2,708
Individuals	684	686

Notes: Estimation sample is those who attended wave 2. The coefficients shown are from individual fixed-effect regressions of expected grade and expected ability ranking onto the values of attendance, study hours, and ability as specified in the hypothetical scenarios. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A1.2: Correlation between Different Measures of Beliefs

	Grade Expectations			Ability Expectations	
	α_{att}	α_s	α_{ab}	β_{att}	β_s
Growth Mindset	0.02	0.05	-0.02	0.05	0.08
	[0.69]	[0.21]	[0.71]	[0.26]	[0.06]
α_{att}		0.74	-0.14	0.06	0.03
		[0.00]	[0.00]	[0.10]	[0.38]
α_s			-0.12	0.04	0.05
			[0.00]	[0.31]	[0.16]
α_{ab}				-0.05	-0.08
				[0.19]	[0.05]
β_{att}					0.76
					[0.00]

Notes: The first row shows the Pearson's correlation coefficient and the second row (in square brackets) the associated p-value. Expectations are measured at wave 2, while the growth mindset score is measured at wave 1.

Table A1.3: Correlations of Inputs and Beliefs at Baseline

	Attendance (%)	Attendance (Hours)	Study (Hours)	Study Quality Index
Growth Mindset Score	-0.00	0.01	0.06*	0.01*
	(0.00)	(0.00)	(0.03)	(0.00)
Grade expectations				
α_{att}	0.03**	0.45	2.17***	-0.08
	(0.02)	(0.29)	(0.74)	(0.09)
α_s	-0.01	-0.18	2.49***	0.02
	(0.02)	(0.40)	(1.07)	(0.16)
α_{ab}	-0.00	-0.00	-0.12	0.01
	(0.05)	(0.05)	(0.12)	(0.01)
Ability expectations				
β_{att}	0.03	0.53	0.58	0.23*
	(0.02)	(0.48)	(1.51)	(0.13)
β_s	0.07	0.083	5.98*	0.64*
	(0.04)	(0.81)	(3.23)	(0.35)
Beliefs Index	0.00	-0.05	1.02***	0.06
	(0.01)	(0.14)	(0.39)	(0.05)

Notes: Results shown represent coefficients from separate regressions of inputs on different measures of beliefs. All regressions also control for gender, socio-economic status, mature student status, tariff quintiles, and department fixed effects. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A1.4: Other Inputs at Baseline

	All	Female	Male	High SES	Low SES	High Tariff	Low Tariff
Time Diary							
Sleeping (Hours)	7.90	8.22	7.52***	7.84	8.00	8.15	7.69**
	[2.75]	[2.63]	[2.84]	[2.68]	[2.88]	[2.88]	[2.71]
Exercising (Hours)	0.45	0.26	0.67***	0.51	0.34***	0.48	0.43
	[0.90]	[0.62]	[1.10]	[0.94]	[0.74]	[0.92]	[0.90]
Non-cognitive Skills							
Grit	3.18	3.20	3.14*	3.17	3.18	3.14	3.18
	[0.51]	[0.54]	[0.49]	[0.52]	[0.49]	[0.51]	[0.51]
Learning Orientation	4.09	4.01	4.18**	4.08	4.06	4.08	4.01
	[1.11]	[1.06]	[1.15]	[1.10]	[1.13]	[1.11]	[1.09]

Notes: Means and standard deviations (in square brackets) of variables observed at baseline. Differences are tested using a two-way t-test. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A1.5: Balancing on Baseline Measures

	Assignment			Treatment		
	Control	Assignment	p-value	Control	Treatment	p-value
Beliefs						
Growth Mindset	36.77	36.63	0.82	37.40	37.18	0.78
Grade Expectations						
α_att	0.31	0.30	0.79	0.32	0.29	0.49
α_s	0.21	0.19	0.38	0.21	0.19	0.28
α_ab	0.72	0.67	0.72	0.72	0.67	0.76
Ability Expectations						
α_att	0.15	0.15	0.98	0.15	0.16	0.77
α_s	0.09	0.09	0.81	0.09	0.09	0.84
Beliefs Index	-0.03	0.01	0.63	-0.02	0.00	0.84
Quantity						
Attendance (%)	0.65	0.65	0.80	0.68	0.69	0.71
Attendance (Hours)	10.20	9.95	0.32	11.04	10.64	0.25
Study (Hours)	11.70	12.25	0.34	11.97	12.48	0.48
Study Quantity Index	0.03	0.06	0.57	0.13	0.14	0.89
Study Methods						
Compulsory	0.46	0.44	0.23	0.46	0.44	0.24
Reading	0.22	0.23	0.69	0.22	0.23	0.54
Note Taking	0.18	0.19	0.14	0.18	0.20	0.12
Testing	0.09	0.09	0.49	0.09	0.08	0.43
Other	0.05	0.05	0.59	0.05	0.05	0.98
Study Methods Index	0.02	-0.01	0.55	0.01	0.00	0.93
Study Next						
Overdue	0.85	0.86	0.66	0.85	0.86	0.87
Longest	0.32	0.36	0.21	0.31	0.36	0.21
Interest	0.42	0.49	0.06	0.40	0.46	0.10
Doing Worst	0.57	0.56	0.72	0.56	0.54	0.66
Scheduled	0.23	0.26	0.30	0.25	0.24	0.94
Study Next Index	-0.07	0.01	0.26	-0.08	-0.04	0.60
Study Quality Index	-0.00	-0.01	0.92	-0.02	-0.01	0.92
Time Diary						
Sleeping	7.76	8.04	0.13	7.90	8.12	0.33
Exercising	0.48	0.42	0.28	0.49	0.40	0.23
Non-Cognitive Skills						
Grit	3.18	3.18	0.98	3.18	3.17	0.95
Learning Orientation	4.09	4.08	0.94	4.09	4.06	0.77
N	442	437		278	303	

Notes: Mean of the variables by treatment status at baseline. The p-value of the difference is shown in columns 3 and 6. The measures of growth mindset beliefs and of all inputs are from wave 1, while the subjective expectation measures are from wave 2.

Table A1.6: Treatment Effect on Other Variables

Panel A: TE on All Students

	Sleeping	Exercise	Grit	Orientation
Treatment	0.289	-0.034	-0.014	0.042
	(0.229)	(0.086)	(0.031)	(0.083)
Baseline	0.218***	0.218***	0.679***	0.508***
	(0.059)	(0.080)	(0.032)	(0.042)
Observations	520	520	520	464

Panel B: TE by Gender

	Sleeping	Exercise	Grit	Orientation
TE on Females	0.472*	-0.172*	-0.011	0.025
	(0.272)	(0.097)	(0.042)	(0.107)
TE on Males	-0.050	0.140	-0.028	0.050
	(0.413)	(0.152)	(0.050)	(0.122)
p-value difference	0.29	0.08	0.80	0.88

Notes: All regressions control for gender, socio-economic status, mature student status, tariff quintiles, and department fixed effects. Standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table A1.7: OLS and Attrition Corrected Estimates

Panel A: TE on All Students

	OLS [b]	OLS [SD]	IPW [b]	IPW [SD]
Beliefs				
Growth M (Y2)	0.963	0.631	0.897	0.642
Growth M (Y3)	0.693	0.833	0.739	0.829
Beliefs Index (Y2)	-0.028	0.088	-0.028	0.088
Inputs				
Study: Quantity (Y2)	0.000	0.002	0.000	0.002
Study: Quantity (Y3)	0.019	0.064	0.039	0.066
Study: Methods (Y2)	0.101	0.069	0.105	0.070
Study: Methods (Y3))	-0.051	0.103	-0.036	0.100
N (Year 2)		595		
N (Year 3)		433		

Panel B: TE By Gender

	Female		Male		
	OLS [b]	OLS [SD]	OLS [b]	OLS [SD]	p-value
Beliefs					
Growth M (Y2)	0.623	0.793	1.213	1.050	0.654
Growth M (Y3)	0.523	1.006	1.496	1.357	0.565
Beliefs Index (Y2)	0.009	0.123	-0.092	0.119	0.554
Inputs					
Study: Quantity (Y2)	0.001	0.002	0.001	0.002	0.982
Study: Quantity (Y3)	-0.100	0.079	0.213	0.106	0.018
Study: Methods (Y2)	0.142	0.087	0.043	0.123	0.509
Study: Methods (Y3))	-0.054	0.148	-0.010	0.136	0.825

Notes: All regressions control for gender, socio-economic status, mature student status, tariff quintiles, and department fixed effects. The Beliefs Index includes the growth mindset score, grade and ability expectations; the Study Quantity Index includes hourly attendance, percentage of the events attended, and weekly study hours; the Study Methods Index includes the variables relating to the division of study time. Regressions in Panel A are obtained through OLS and Inverse Probability Weighting (IPW) to control for attrition.

Table A1.8: Replication Study Participant Characteristics

Characteristics	Target	Participants	Control	Treatment	p-value
Female	0.61	0.72	0.72	0.73	0.73
High SES	0.66	0.61	0.61	0.61	0.83
Low SES	0.20	0.25	0.25	0.25	1.00
SES Missing	0.14	0.14	0.15	0.14	0.77
Tariff (Std)	0.29	0.02	0.02	0.02	0.99
Tariff Quintiles					
Lowest	0.20	0.18	0.20	0.15	0.04
Second	0.21	0.18	0.17	0.20	0.23
Third	0.20	0.19	0.19	0.19	0.87
Forth	0.20	0.16	0.15	0.18	0.29
Fifth	0.19	0.19	0.20	0.18	0.62
N	5,585	907	606	301	

Notes: Column 1 shows the characteristics of the target population of students enrolled at the university here the replication study took place. Column 2 shows the sample of study participants. Columns 3 and 4 show the sample of control and treated students, respectively. Column 5 reports the p-value of a two-tailed test of the difference between these two groups.

Table A1.9: ITT on Outcomes

	All	Female	Male	p-value
Beliefs				
Growth Mindset	2.250	2.173	2.333	0.90
	0.604	0.785	0.966	
Strong GM	0.075	0.362	0.353	0.96
	0.019	0.117	0.138	
N		842		
Year 1 Outcomes				
GPA	1.195	0.766	1.700	0.45
	0.616	0.764	0.971	
Exam	1.233	0.167	2.319	0.08
	0.615	0.775	0.949	
First	0.034	0.014	0.060	0.25
	0.020	0.028	0.029	
Good	0.037	0.016	0.058	0.42
	0.026	0.036	0.037	
Pass	0.011	0.007	0.015	0.75
	0.012	0.013	0.021	
Attainment Index	0.071	-0.000	0.151	0.16
	0.054	0.068	0.083	
Fail to Progress	-0.015	-0.015	-0.015	1.00
	0.019	0.025	0.029	
N		1300		
Indexes				
Study - Quantity	0.083	-0.089	0.280	0.00
	0.052	0.074	0.075	
Study - Methods	0.077	0.007	0.201	0.22
	0.077	0.090	0.130	
Study - Next	0.083	0.058	0.129	0.62
	0.071	0.098	0.105	
N		667		

Notes: The results are obtained from OLS regressions. All regressions control for gender, socio-economic status, mature student status, tariff quintiles and include department fixed effects. The first rows show the coefficient while the second rows show the standard errors for assignment dummy. The last column shows the p-value for differences between Female and Male students.

Table A1.9: ITT on Outcomes (Cont'd)

	All	Female	Male	p-value
Graduation Outcomes				
Grad on Time	0.003	-0.022	0.027	0.31
	0.024	0.032	0.035	
Conditional on Graduation				
GPA	0.197	-0.284	0.826	0.27
	0.499	0.625	0.775	
First	0.007	-0.013	0.029	0.40
	0.025	0.034	0.037	
Good	0.002	-0.027	0.035	0.22
	0.025	0.033	0.038	
Attainment Index	0.036	-0.034	0.103	0.23
	0.056	0.072	0.086	
N		1130		

Notes: The results are obtained from OLS regressions. All regressions control for gender, socio-economic status, mature student status, tariff quintiles and include department fixed effects. The first rows show the coefficient while the second rows show the standard errors for assignment dummy. The last column shows the p-value for differences between Female and Male students.

Table A1.10: Treatment Effects on Outcomes for Home, EU and Overseas Students

	All	Female	Male	p-value
Beliefs				
Growth Mindset	2.712	3.109	2.048	0.35
	0.547	0.687	0.890	
Strong GM	0.071	0.386	0.281	0.52
	0.016	0.103	0.127	
Attendance on Mark	0.045	0.049	0.039	0.87
	0.029	0.038	0.045	
Study on Mark	0.032	0.027	0.042	0.66
	0.018	0.024	0.026	
Ability on Mark	-0.001	0.091	-0.151	0.49
	0.168	0.214	0.280	
Attendance on Ability	-0.002	-0.004	0.005	0.63
	0.010	0.014	0.014	
Study on Ability	0.001	-0.002	0.008	0.40
	0.007	0.009	0.009	
Belief Index	0.205	0.224	0.211	0.93
	0.074	0.099	0.114	
N		771		
Year 1 Outcomes				
GPA	1.071	0.488	2.006	0.29
	0.688	0.866	1.146	
Exam	1.407	0.932	2.028	0.48
	0.729	0.890	1.254	
First	0.061	0.023	0.120	0.06
	0.025	0.032	0.039	
Good	0.021	-0.013	0.073	0.16
	0.029	0.037	0.048	
Pass	0.012	0.007	0.019	0.64
	0.012	0.014	0.021	
Attainment Index	0.133	0.037	0.270	0.06
	0.059	0.071	0.102	
Fail to Progress	-0.001	0.002	-0.005	0.87
	0.017	0.022	0.029	
N		1019		
Indexes				
Study - Quantity	0.028	-0.094	0.208	0.00
	0.044	0.057	0.069	
Study - Methods	0.023	-0.001	0.077	0.60
	0.071	0.086	0.119	
Study - Next	0.126	0.135	0.096	0.76
	0.064	0.086	0.095	
N		705		

Notes: The results are obtained from OLS regressions. All regressions control for gender, socio-economic status, mature student status, tariff quintiles, and department fixed effects. The first rows show the coefficient while the second rows show the standard errors for treatment dummy The last column shows the p-value for differences between Female and Male students.

Table A1.10: Treatment Effects on Outcomes for Home, EU and Overseas Students (Cont'd)

	All	Female	Male	p-value
Graduation Outcomes				
Grad on Time	0.011	-0.006	0.040	0.37
	0.024	0.031	0.040	
Conditional on Graduation				
GPA	1.809	1.003	2.862	0.12
	0.552	0.649	0.998	
First	0.053	0.032	0.077	0.46
	0.030	0.038	0.049	
Good	0.055	0.013	0.117	0.06
	0.027	0.034	0.044	
Attainment Index	0.136	0.060	0.245	0.14
	0.061	0.074	0.101	
N		914		

Notes: The results are obtained from OLS regressions. All regressions control for gender, socio-economic status, mature student status, tariff quintiles, and department fixed effects. The first rows show the coefficient while the second rows show the standard errors for treatment dummy. The last column shows the p-value for differences between Female and Male students.

Table A1.11: Growth Mindset

	Strongly Disagree	Disagree	Somewhat Disagree	Neither	Somewhat Agree	Agree	Strongly Agree
You can learn new things, but you can't really change your basic intelligence	3	2	1.75	1.5	1.25	1	0
You have a certain amount of intelligence and you really can't do much to change it	3	2	1.75	1.5	1.25	1	0
No matter how much intelligence you have, you can always change it quite a bit	0	1	1.25	1.5	1.75	2	3
You can change even your basic intelligence level considerably	0	1	1.25	1.5	1.75	2	3

The Growth Mindset Score is 5 $\times$ the sum of the scores for each statement.

Table A1.12: Grit

	Not like me at all	Not much like me	Somewhat like me	Mostly like me	Very much like me
I have overcome setbacks to conquer an important challange	1	2	3	4	5
New ideas and projects sometimes distract me from previous ones	5	4	3	2	1
My interests change from year to year	5	4	3	2	1
Setbacks don't discourage me	1	2	3	4	5
I have been obsessed with a certain idea or project for a short time but later lost interest	5	4	3	2	1
I am a hard worker .	1	2	3	4	5
I often set a goal but later chose to pursue a different one.	5	4	3	2	1
I have difficulty maintaining my focus on projects that take more than a few months to complete.	5	4	3	2	1
I finish whatever I begin. I have achieved a goal that took years of work.	1	2	3	4	5
I become interested in new pursuits every few months.	5	4	3	2	1
I am diligent.	5	4	3	2	1

Grit Score = Average of the scores for each statement.

Source: Duckworth *et al.* (2007)

Table A1.13: Planning Efficacy

	Strongly Disagree	Disagree	Somewhat Disagree	Neither Agree nor Disagree	Somewhat Agree	Agree	Strongly Agree
I usually do my work assignment the day before it is due	7	6	5	4	3	2	1
I usually keep track of my work assignment on a schedule or planner	1	2	3	4	5	6	7
I don't need to plan ahead to get good marks	7	6	5	4	3	2	1
I often underestimate the time that will be required to finish a project	7	6	5	4	3	2	1

Planning Efficacy Score = Average of the scores for each statement.

Source: Revised version of Lynch *et al.* (2010)

Table A1.14: Learning Goals

	Strongly Disagree	Disagree	Somewhat Disagree	Neither	Somewhat Agree	Agree	Strongly Agree
Although I hate to admit it, what matters to me are the grades rather than what I learn in the course	7	6	5	4	3	2	1
If I knew I was not going to do well at a task, I probably wouldnt do it even though i might learn a lot from it	7	6	5	4	3	2	1
It is much more important for me to learn things in my classes than it is to get the best grades	1	2	3	4	5	6	7

Learning Goals Score = Average of the scores for each statement.

Source: Dweck (2013)

Appendix 1.2: Components of Indexes

- Attainment Index: GPA, Exam Mark, First, Good, Pass
- Graduation Index: GPA, First, Good, Graduated on time
- Study Quantity Index: Attendance (% of events attended), Attendance (% of hours attended), Study (hours)
- Study Methods Index: Compulsory, Reading, Note Taking, Testing
- Study Habits Index: Overdue, Longest Since, Interested, Doing Worst, Scheduled
- Beliefs Index: Growth Mindset Score, Strong Growth Mindset, Subjective Beliefs about Grades (α_{att}, α_s, α_{ab}), Subjective Beliefs about Ability (β_{att}, β_s)

Appendix for Chapter 2: SES-Based Affirmative Action and Academic and Labor Market Outcomes: Evidence from UK's Contextualized Admissions

Table A2.1: Timing of the Policy Change

	Started Using Contextualized Admissions								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Δ2_3 State	-0.673						-2.295		-3.220
	(1.679)						(3.004)		(3.866)
Δ2_3 Low SES		0.003					0.003		-0.015
		(0.024)					(0.024)		(0.030)
Δ2_3 PQ1&2			0.075				0.235		0.168
			(0.148)				(0.199)		(0.350)
Δ3_4 State				-0.233				-0.901	-1.316
				(0.359)				(2.491)	(3.156)
Δ3_4 Low SES					-0.189			-0.182	-0.191
					(0.225)			(0.227)	(0.239)
Δ3_4 PQ1&2						-0.591		-0.375	-0.323
						(0.553)		(0.553)	(0.703)
Constant	-1.692***	-1.683***	-1.711***	-1.644***	-1.625***	-1.658***	-1.687***	-1.619***	-1.616***
	(0.066)	(0.067)	(0.065)	(0.068)	(0.068)	(0.067)	(0.067)	(0.068)	(0.070)
Observations	1,082	1,059	1,143	979	957	1,039	1,057	955	950

Notes: Results are obtained from Tobit regressions where upper limit is set to 2021 and lower limit is set to 2005. * denotes significance at 10% level, ** denotes significance at 5% level and *** denotes significance at 1% level. Standard errors are in parenthesis.

Table A2.2: Effect of Contextualized Admissions on Student Composition

	(1) Female	(2) Disabled	(3) Minority	(4) BTEC
Post	0.009	0.002	-0.012	0.030
	(0.006)	(0.004)	(0.013)	(0.019)
Contextual	-0.012**	0.001	0.014	-0.038**
	(0.006)	(0.003)	(0.011)	(0.018)
Observations	2,844,202	2,844,381	2,844,381	1,660,804

Notes: All regressions control for entry qualifications (both the type and the grades) and for university, subject and cohort fixed effects. All columns except column 3 also control for the ethnicity. * denotes significance at 10% level, ** denotes significance at 5% level and *** denotes significance at 1% level. Standard errors are clustered at university level. Standard errors are in parenthesis.

Table A2.3: Heterogeneity by Personal Characteristics

	FiF b/se	p-value	Low SES b/se	p-value	Female b/se	p-value
Academic Outcomes						
First	0.004	0.489	0.013	0.008	-0.010	0.068
	0.005		0.005		0.006	
Good	0.012	0.023	0.030	0.000	-0.014	0.029
	0.005		0.006		0.006	
Graduated on Time	0.005	0.147	0.006	0.125	-0.017	0.039
	0.003		0.004		0.008	
Dropout	-0.004	0.193	-0.006	0.089	0.008	0.054
	0.003		0.004		0.004	
Employment						
Full-time Work	-0.004	0.528	-0.012	0.041	0.006	0.362
	0.007		0.006		0.006	
Employed	0.003	0.493	-0.006	0.179	0.008	0.042
	0.005		0.005		0.004	
Unemployed	0.001	0.855	0.002	0.563	-0.007	0.022
	0.004		0.004		0.003	
Study	0.007	0.201	0.006	0.292	0.004	0.352
	0.006		0.005		0.005	
Job Characteristics						
Ln(Salary)	0.002	0.713	-0.000	0.993	-0.000	0.997
	0.005		0.005		0.006	
Permanent	0.020	0.047	0.006	0.475	-0.016	0.019
	0.010		0.009		0.007	
Importance of Subject	0.001	0.923	0.007	0.412	0.005	0.541
	0.008		0.008		0.008	
Importance of Level	-0.008	0.204	-0.023	0.003	0.010	0.117
	0.007		0.008		0.006	
Qualifications Required	0.000	0.959	-0.009	0.344	-0.006	0.483
	0.007		0.009		0.009	
High SOC	0.001	0.880	-0.020	0.042	0.011	0.239
	0.010		0.010		0.009	

Notes: Results represent the coefficients, standard errors and p-values corresponding to $Contextual \times PersonalCharactetistics$ variable. All regressions control for student characteristics in addition to university, subject and cohort fixed effects. Standard errors are clustered at university level.

Table A2.4: Heterogeneity by Entry Scores

	10th pct b/se	p	10-25th pct b/se	p-value	25-50th pct b/se	p	50-75th pct b/se	p	75-90th pct b/se	p	90th pct b/se	p
Academic Outcomes												
First	-0.069	0.000	-0.007	0.487	-0.022	0.023	-0.031	0.002	-0.016	0.137	0.012	0.289
	0.016		0.010		0.010		0.010		0.011		0.011	
Good	-0.032	0.358	-0.016	0.378	-0.038	0.002	-0.035	0.002	-0.019	0.054	0.021	0.009
	0.034		0.018		0.012		0.011		0.010		0.008	
Graduated on Time	-0.012	0.418	-0.007	0.459	-0.009	0.251	-0.013	0.072	-0.008	0.284	-0.008	0.178
	0.015		0.010		0.008		0.007		0.008		0.006	
Dropout	-0.028	0.059	0.001	0.945	0.008	0.203	-0.003	0.678	-0.000	0.939	-0.009	0.059
	0.015		0.009		0.006		0.007		0.006		0.005	
Employment												
Full-time Work	0.067	0.044	-0.023	0.130	-0.023	0.018	-0.026	0.001	-0.014	0.118	-0.011	0.314
	0.033		0.015		0.009		0.008		0.009		0.011	
Employed	0.029	0.367	-0.003	0.720	-0.003	0.636	-0.005	0.463	-0.015	0.023	-0.003	0.685
	0.032		0.009		0.007		0.007		0.007		0.008	
Unemployed	-0.025	0.060	0.002	0.774	-0.002	0.708	0.006	0.253	0.008	0.165	-0.004	0.499
	0.013		0.007		0.005		0.005		0.006		0.006	
Study	0.080	0.002	0.042	0.150	0.048	0.072	0.053	0.054	0.066	0.010	0.040	0.082
	0.026		0.029		0.026		0.027		0.025		0.023	
Job Characteristics												
Ln(Salary)	0.039	0.074	-0.004	0.721	-0.010	0.215	-0.005	0.463	-0.015	0.113	-0.008	0.289
	0.021		0.013		0.008		0.007		0.009		0.007	
Permanent	-0.021	0.476	0.024	0.173	0.014	0.331	0.014	0.209	0.017	0.259	0.008	0.551
	0.029		0.017		0.014		0.011		0.015		0.013	
Importance of Subject	0.060	0.239	-0.023	0.303	-0.009	0.466	-0.011	0.379	-0.028	0.072	-0.018	0.237
	0.051		0.022		0.013		0.012		0.015		0.015	
Importance of Level	-0.005	0.880	0.012	0.467	-0.004	0.605	-0.020	0.029	-0.021	0.039	0.006	0.607
	0.030		0.017		0.008		0.009		0.010		0.011	
Qualifications Required	0.034	0.476	0.019	0.459	0.012	0.602	0.008	0.729	0.013	0.612	0.024	0.332
	0.047		0.026		0.022		0.024		0.025		0.025	
High SOC	0.000	0.995	-0.019	0.289	-0.014	0.303	-0.019	0.219	-0.013	0.331	0.010	0.479
	0.041		0.018		0.014		0.015		0.014		0.013	

Notes: Results represent the coefficients, standard errors and p-values corresponding to $Contextual + Contextual \times Tariff$ variable. All regressions control for student characteristics in addition to university, subject and cohort fixed effects. First, good and graduated on time regressions are conditional on graduation. All academic and employment variables and all but Ln(salary) variable for job characteristics are dummy variables. Full-time work, employed and unemployed are conditional on not being in further study. All job characteristics regressions are conditional on being in full-time employment. For Ln(Salary), the top and bottom 2% are trimmed. Standard errors are clustered at university level.

Table A2.5: Heterogeneity by Subject

	Health b/se	p-value	STEM b/se	p-value	Social b/se	p-value	Humanities b/se	p-values	Others b/se	p-value
Academic Outcomes										
First	-0.020	0.060	-0.007	0.578	-0.021	0.056	-0.035	0.001	-0.015	0.213
	0.010		0.013		0.011		0.010		0.012	
Good	-0.048	0.003	-0.009	0.439	-0.053	0.001	-0.081	0.000	-0.016	0.228
	0.016		0.012		0.015		0.015		0.014	
Graduated on Time	-0.034	0.002	0.008	0.583	-0.030	0.007	-0.034	0.000	-0.031	0.037
	0.011		0.015		0.011		0.009		0.015	
Dropout	0.006	0.325	-0.003	0.715	-0.002	0.819	0.012	0.162	0.006	0.321
	0.006		0.008		0.007		0.009		0.006	
Employment										
Full-time Work	-0.010	0.295	-0.012	0.235	-0.009	0.242	-0.021	0.145	0.003	0.844
	0.009		0.010		0.008		0.015		0.014	
Employed	-0.001	0.920	-0.003	0.684	0.003	0.614	-0.004	0.607	0.001	0.938
	0.006		0.009		0.006		0.009		0.008	
Unemployed	-0.001	0.809	0.004	0.598	0.005	0.319	0.005	0.457	0.008	0.177
	0.004		0.008		0.005		0.006		0.006	
Study	-0.014	0.282	-0.060	0.000	-0.029	0.012	-0.034	0.024	-0.020	0.090
	0.013		0.012		0.011		0.015		0.012	
Job Characteristics										
Ln(Salary)	0.008	0.338	0.005	0.532	-0.001	0.827	-0.010	0.411	-0.001	0.954
	0.008		0.007		0.007		0.012		0.012	
Permanent	0.013	0.319	0.021	0.127	0.023	0.064	0.032	0.010	0.034	0.033
	0.013		0.014		0.012		0.012		0.016	
Importance of Subject	-0.031	0.169	-0.039	0.020	-0.025	0.070	-0.025	0.049	0.006	0.772
	0.023		0.016		0.014		0.013		0.020	
Importance of Level	-0.012	0.208	-0.029	0.031	-0.002	0.901	-0.007	0.706	-0.009	0.522
	0.010		0.013		0.014		0.018		0.014	
Qualifications Required	0.017	0.594	0.032	0.323	0.030	0.310	-0.026	0.415	0.052	0.059
	0.031		0.032		0.029		0.032		0.027	
High SOC	-0.002	0.913	-0.004	0.728	0.012	0.439	0.001	0.959	0.021	0.272
	0.014		0.012		0.015		0.023		0.019	

Notes: Results represent the coefficients, standard errors and p-values corresponding to *Contextual* variable. All regressions control for student characteristics in addition to university, subject and cohort fixed effects. First, good and graduated on time regressions are conditional on graduation. All academic and employment variables and all but Ln(salary) variable for job characteristics are dummy variables. Full-time work, employed and unemployed are conditional on not being in further study. All job characteristics regressions are conditional on being in full-time employment. For Ln(Salary), the top and bottom 2% are trimmed. Standard errors are clustered at university level.

Table A2.6: Controlling for Unemployment Rate

	Annual b/se	p-value	Q2 b/se	p-value	Q3 b/se	p-value
Employment						
Full-time Work	-0.009	0.230	-0.009	0.226	-0.009	0.218
	0.007		0.007		0.007	
Employed	-0.001	0.903	-0.001	0.907	-0.001	0.885
	0.005		0.005		0.005	
Unemployed	0.004	0.377	0.004	0.377	0.004	0.368
	0.005		0.005		0.005	
Study	-0.029	0.002	-0.029	0.002	-0.029	0.002
	0.009		0.009		0.009	
Job Characteristics						
Ln(Salary)	0.002	0.733	0.002	0.750	0.002	0.756
	0.006		0.006		0.006	
Permanent	0.019	0.049	0.019	0.051	0.019	0.048
	0.009		0.009		0.009	
Importance of Subject	-0.025	0.084	-0.025	0.084	-0.025	0.083
	0.014		0.014		0.014	
Importance of Level	-0.007	0.501	-0.007	0.507	-0.007	0.502
	0.011		0.011		0.011	
Qualifications Required	0.027	0.347	0.026	0.351	0.027	0.347
	0.028		0.028		0.028	
High SOC	0.009	0.490	0.009	0.499	0.009	0.490
	0.013		0.013		0.013	

Notes: Results represent the coefficients, standard errors and p-values corresponding to *Contextual* variable. All regressions control for student characteristics in addition to university, subject and cohort fixed effects. Column 1 controls for annual unemployment rate in the graduation year, Column 2 controls for unemployment rate in the second quarter of the graduation year and Column 3 controls for unemployment rate in the third quarter of the graduation year. First, good and graduated on time regressions are conditional on graduation. All academic and employment variables and all but Ln(salary) variable for job characteristics are dummy variables. Full-time work, employed and unemployed are conditional on not being in further study. All job characteristics regressions are conditional on being in full-time employment. For Ln(Salary), the top and bottom 2% are trimmed. Standard errors are clustered at university level.

Table A2.7: Weighted and Unweighted DiD Results

Variable	Weighted DiD	Main Results
Academic Outcomes		
First	-0.022	-0.022
Good	-0.045	-0.044
Dropout	0.003	0.002
Graduated on Time	-0.024	-0.023
Employment Outcomes		
Full-time Work	0.002	-0.008
Employed	0.015	-0.000
Unemployed	-0.002	0.004
Study	-0.028	-0.029
Job Characteristics		
Ln Salary	0.003	0.002
Permanent	0.024	0.019
Importance of Subject	-0.018	-0.025
Importance of Level	-0.015	-0.008
Qualifications Required	0.026	0.027
High SOC	0.015	0.009

Notes: Weighted results are calculated as follows: Following Goodman-Bacon (2021), DiD estimates have been calculated for each year that there is at least one universities that changed their admission policy to include contextualized admissions. Then these results are weighted by the number of students treated in each of these years in a similar manner to Callaway & SantAnna (2020). First, good and graduated on time regressions are conditional on graduation. All academic and employment variables and all but Ln(salary) variable for job characteristics are dummy variables. Full-time work, employed and unemployed are conditional on not being in further study. All job characteristics regressions are conditional on being in full-time employment. For Ln(Salary), the top and bottom 2% are trimmed. Standard errors are clustered at university level.

Table A2.8: Effect of Contextualized Admissions on Academic Outcomes at Aggregate Level

University - Subject Level

	(1) First	(2) Good	(3) Dropout	(4) Graduated on Time
Post	0.019**	0.026**	0.002	0.042***
	(0.009)	(0.012)	(0.009)	(0.011)
Contextual	-0.020**	-0.042***	-0.005	-0.037***
	(0.009)	(0.012)	(0.006)	(0.011)
Observations	17,830	17,830	17,830	17,815

Notes: All regressions control for the proportion of females, proportion of students coming from high SES backgrounds and proportion of students coming from the lowest 2 quintiles of Higher Education attainment measure (POLAR) in addition to subject and cohort fixed effects. Standard errors are clustered at university level. Standard errors are in parenthesis.

Table A2.9: Effect of Contextualized Admissions on Employment at Aggregate Level

University - Subject Level

	(1) FT Work	(2) Employed	(3) Unemployed	(4) Study
Post	0.017	-0.006	-0.004	0.036***
	(0.011)	(0.009)	(0.008)	(0.013)
Contextual	-0.019*	0.002	0.006	-0.037***
	(0.010)	(0.009)	(0.008)	(0.012)
Observations	16,743	16,743	16,743	17,211

Notes: All regressions control for the proportion of females, proportion of students coming from high SES backgrounds and proportion of students coming from the lowest 2 quintiles of Higher Education attainment measure (POLAR) in addition to subject and cohort fixed effects. Standard errors are clustered at university level. Standard errors are in parenthesis.

Table A2.10: Effect of Contextualized Admissions on Job Characteristics at Aggregate Level

University - Subject Level

		Importance of				
	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(Salary)	Permanent	Subject	Level	Qualifications Required	High SOC Classification
Post	0.015**	-0.028**	0.015	0.009	0.006	0.004
	(0.007)	(0.013)	(0.014)	(0.013)	(0.020)	(0.017)
Contextual	-0.007	0.021	-0.039***	-0.034***	-0.007	-0.002
	(0.008)	(0.013)	(0.015)	(0.012)	(0.018)	(0.017)
Observations	15,622	16,249	16,249	16,249	16,249	16,249

Notes: All regressions control for the proportion of females, proportion of students coming from high SES backgrounds and proportion of students coming from the lowest 2 quintiles of Higher Education attainment measure (POLAR) in addition to subject and cohort fixed effects. Standard errors are clustered at university level. Standard errors are in parenthesis.

Table A2.11: Removal of Student Quotas for Students with ABB or Better

	(1) AAB or Better	(2) ABB or better
Post	0.019**	0.017
	(0.009)	(0.013)
Contextual	-0.007	-0.000
	(0.011)	(0.013)
Observations	1,688,489	1,688,489

Notes: Both regressions control for the gender, socio-economic status of the students at the start of their undergraduate degree, coming from an area where Higher Education attainment is low (POLAR bottom two quintiles) in addition to university, subject and cohort fixed effects. Standard errors are clustered at university level. Standard errors are in parenthesis.

Table A2.12: Effects on Subject and Duration of Course

	Course Subject Choice					Duration
	(1) Health	(2) STEM	(3) Social	(4) Humanities	(5) Other	(6) Additional Year
Post	-0.004	-0.008	0.006	0.004	0.002	0.056***
	(0.010)	(0.009)	(0.009)	(0.008)	(0.008)	(0.019)
Contextual	-0.004	0.008	0.008	-0.005	-0.007	-0.022
	(0.008)	(0.010)	(0.009)	(0.007)	(0.009)	(0.028)
Observations	2,844,381	2,844,381	2,844,381	2,844,381	2,844,381	2,940,608

Notes: All regressions control for the gender, socio-economic status of the students at the start of their undergraduate degree, coming from an area where Higher Education attainment is low (POLAR bottom two quintiles) in addition to university and cohort fixed effects. Last column also controls for subject fixed effects. The first column is for Allied to Health Sciences, third column is for Social Sciences and Business and last column is for Arts, Design and Education. Additional Year is a dummy variable for studying for a course that includes a component of study abroad or placement. Standard errors are clustered at university level. Standard errors are in parenthesis.

Table A2.13: Effects on How Job is Found and Working during Study

	Work during University		How Found Job			
	(1) Placement	(2) Other	(3) Prev Emp	(4) Careers Office	(5) Job Portal	(6) Network
Post	-0.033	-0.005	-0.008	0.006	0.006	0.002
	(0.023)	(0.018)	(0.005)	(0.005)	(0.008)	(0.007)
Contextual	0.036*	-0.011	0.007	0.001	-0.008	0.002
	(0.021)	(0.018)	(0.006)	(0.007)	(0.006)	(0.005)
Observations	316,659	316,659	365,788	365,788	365,788	365,788

Notes: All regressions control for the gender, socio-economic status of the students at the start of their undergraduate degree, coming from an area where Higher Education attainment is low (POLAR bottom two quintiles) in addition to university and cohort fixed effects. Last column also controls for subject fixed effects. The first column is for Allied to Health Sciences, third column is for Social Sciences and Business and last column is for Arts, Design and Education. Standard errors are clustered at university level. Standard errors are in parenthesis.

Table A2.14: Grouped and Detailed Subject Groups

Grouped	Detailed
Health Sciences	Medicine and Dentistry
	Allied to Medicine
	Biological Sciences
	Veterinary Sciences
STEM	Agriculture and Related
	Physical Sciences
	Mathematical Sciences
	Engineering and Technology
	Architecture
Social Sciences and Business	Social, Economic and Poli Sciences
	Law
	Business Studies
Humanities	Information Science
	Languages
	Humanities
Arts, Education and Others	Arts and Design
	Education
	Combined

Table A2.15: Detailed Subject Groups and Courses

Detailed	Courses
Medicine and Dentistry	Pre-clinical and Clinical Medicine, Pre-clinical and Clinical Dentistry
Allied to Medicine	Anatomy, Pharmacology, Nutrition, Nursing, Medical Technology
Biological Sciences	Biology, Zoology, Molecular Biology, Biochemistry
Veterinary Sciences	
Agriculture and Related	Agriculture, Food Science
Physical Sciences	Chemistry, Material Science, Physics, Astronomy
Mathematical Sciences	Mathematics, Statistics
Engineering and Technology	Engineering, Metallurgy, Biotechnology
Architectural	Architecture, Building, Planning
Social, Economic and Poli Sciences	Antropology, Economics, Social Policy, Sociology, Pyschology, Politics
Law	
Business Studies	Management, Accountancy, Finance, Operational Research
Information Science	Communications, Journalism, Librarianships, Media Studies
Languages	Linguistics, Comparative Literature, Language Studies
Humanities	Archeology, History, History of Art, Philoshopy, Theology
Arts and Design	Cinematics, Design Studies, Drama, Fine Art, Music
Education	
Combined	

Appendix for Chapter 3: Racial Diversity and Students' Academic and Labor Market Outcomes

Table A3.1: Descriptive Statistics - by University Tariff Classification

	All	Highest	High	Medium	Lower
Minority Academics					
Ethnic Minority	0.13	0.13	0.14	0.12	0.15
Black	0.02	0.01	0.02	0.02	0.04
SE Asian	0.05	0.05	0.05	0.04	0.05
Other	0.06	0.07	0.07	0.05	0.06
Students					
Ethnic Minority	0.21	0.16	0.20	0.20	0.34
Black	0.05	0.02	0.04	0.04	0.12
SE Asian	0.10	0.08	0.10	0.10	0.14
Other	0.00	0.00	0.00	0.00	0.00
Academic Outcomes					
First	0.22	0.26	0.23	0.20	0.19
Good	0.76	0.86	0.79	0.70	0.66
Dropout	0.10	0.05	0.08	0.13	0.15
Employment Outcomes					
FT Work	0.54	0.51	0.53	0.57	0.54
Employed	0.67	0.59	0.64	0.72	0.72
Study	0.22	0.28	0.26	0.18	0.17
Graduate Job	0.39	0.40	0.39	0.40	0.35
High SOC	0.65	0.75	0.68	0.63	0.56
Perceptions of HE					
HE Useful for Study	0.89	0.92	0.91	0.87	0.85
HE Useful for Work	0.79	0.79	0.80	0.80	0.76
PG Study					
Research	0.02	0.04	0.02	0.01	0.00
Taught	0.11	0.13	0.14	0.09	0.08

Table A3.2: Descriptive Statistics - by University Clusters

	All	Cluster2	Cluster3	Cluster4
Minority Academics				
Ethnic Minority	0.13	0.14	0.13	0.12
Black	0.02	0.01	0.03	0.03
SE Asian	0.05	0.05	0.05	0.04
Other	0.06	0.07	0.06	0.05
Students				
Ethnic Minority	0.21	0.18	0.23	0.24
Black	0.05	0.03	0.06	0.08
SE Asian	0.10	0.08	0.11	0.10
Other	0.00	0.00	0.00	0.00
Academic Outcomes				
First	0.22	0.25	0.20	0.18
Good	0.76	0.85	0.71	0.63
Dropout	0.10	0.06	0.12	0.16
Employment Outcomes				
FT Work	0.54	0.51	0.56	0.54
Employed	0.67	0.60	0.71	0.72
Study	0.22	0.28	0.19	0.17
Graduate Job	0.39	0.40	0.39	0.33
High SOC	0.65	0.72	0.63	0.55
Perceptions of HE				
HE Useful for Study	0.89	0.92	0.87	0.85
HE Useful for Work	0.79	0.79	0.79	0.78
PG Study				
Research	0.02	0.04	0.01	0.00
Taught	0.11	0.14	0.09	0.07

Table A3.3: Descriptive Statistics - by Cost Centers' Proportion of Minority Academics

	All	Below Median	Above Median
Students			
Ethnic Minority	0.21	0.13	0.30
Black	0.05	0.03	0.06
SE Asian	0.10	0.06	0.16
Other	0.00	0.00	0.00
Previous Outcomes			
Tariff	116.84	118.26	118.66
BTEC	0.11	0.11	0.10
Academic Outcomes			
First	0.22	0.22	0.27
Good	0.76	0.77	0.78
Dropout	0.10	0.04	0.04
Employment Outcomes			
FT Work	0.54	0.52	0.58
Employed	0.67	0.67	0.68
Study	0.22	0.23	0.20
Graduate Job	0.39	0.37	0.44
High SOC	0.65	0.62	0.72
Perceptions of HE			
HE Useful for Study	0.89	0.90	0.89
HE Useful for Work	0.79	0.79	0.80
PG Study			
Research	0.02	0.02	0.02
Taught	0.11	0.12	0.10

Table A3.4: Variation - Unweighted

Panel A: Minority Shares

	Mean	SD	Min	Max	N
Weighted Proportion	0.1334	0.1185	0.0000	0.8333	16,116
Net of Year FE	-0.0000	0.1181			
Net of University FE	0.0000	0.1054			
Net of Department FE	-0.0000	0.0799			
Net of Department Char.	-0.0000	0.0793			
Net of Cluster x Subject G FE	-0.0000	0.0792			

Panel B: Black Shares

	Mean	SD	Min	Max	N
Weighted Proportion	0.0200	0.0384	0.0000	0.5556	16,116
Net of Year FE	-0.0000	0.0384			
Net of University FE	-0.0000	0.0343			
Net of Department FE	-0.0000	0.0326			
Net of Department Char.	-0.0000	0.0324			
Net of Cluster x Subject G FE	0.0000	0.0324			

Panel C: South East Asian Shares

	Mean	SD	Min	Max	N
Weighted Proportion	0.0480	0.0592	0.0000	0.5000	16,116
Net of Year FE	-0.0000	0.0591			
Net of University FE	0.0000	0.0544			
Net of Department FE	-0.0000	0.0459			
Net of Department Char.	0.0000	0.0458			
Net of Cluster x Subject G FE	-0.0000	0.0456			

Panel D: Other Group Shares

	Mean	SD	Min	Max	N
Weighted Proportion	0.0653	0.0704	0.0000	0.8333	16,116
Net of Year FE	0.0000	0.0702			
Net of University FE	0.0000	0.0649			
Net of Department FE	0.0000	0.0544			
Net of Department Char.	0.0000	0.0541			
Net of Cluster x Subject G FE	-0.0000	0.0540			

Notes: Department characteristics refers to department level controls such as proportion of female academics, proportion of academics that are on teaching or teaching and research contracts, proportion of academics that are reader or above, proportion of full-time academics and proportion of academics on permanent contract.

Table A3.5: Results by Clustering at University Level

Variable	White	Black	S Asian	Other
Academic Outcomes				
First	0.070	-0.085	0.065	-0.038
se	0.026	0.031	0.032	0.026
Good	0.037	0.065	0.119	-0.024
se	0.020	0.044	0.046	0.025
Dropout	-0.018	0.018	-0.033	-0.026
se	0.016	0.031	0.023	0.022
Employment Outcomes				
FT Work	0.076	-0.216	-0.055	-0.210
se	0.029	0.056	0.039	0.042
Employed	0.029	-0.195	-0.040	-0.197
se	0.023	0.042	0.035	0.037
Study	-0.030	0.108	-0.007	0.109
se	0.021	0.032	0.035	0.035
Grad Job	0.106	-0.100	-0.054	-0.034
se	0.024	0.053	0.035	0.039
High SOC	0.083	-0.183	-0.130	-0.106
se	0.027	0.053	0.041	0.050
Perception of HE				
HE for Study	-0.027	0.052	0.017	-0.031
se	0.013	0.028	0.019	0.026
HE for Work	-0.017	-0.040	-0.017	-0.010
se	0.019	0.030	0.021	0.026
Type of Further Study				
PG Research	0.007	-0.002	0.007	-0.001
se	0.005	0.005	0.006	0.006
PG Taught	-0.035	0.104	0.031	0.068
se	0.014	0.023	0.021	0.027

Notes: Controls include gender, socio-economic status, POLAR Q1, 2 & 3, being a first generation university student and university, cohort, subject as well as cluster × subject group fixed effects.For academic outcomes, the regressions also control for tariff and type of qualification a student comes to university with. First and Good are conditional on graduating. Standard errors are in parentheses. * p <0.1, ** p <0.05, *** p <0.01

Table A3.6: Results by Clustering at Cohort Level

Variable	White	Black	S Asian	Other
Academic Outcomes				
First	0.070	-0.085	0.065	-0.038
se	0.014	0.019	0.025	0.022
Good	0.037	0.065	0.119	-0.024
se	0.008	0.017	0.022	0.016
Dropout	-0.018	0.018	-0.033	-0.026
se	0.003	0.003	0.021	0.022
Employment Outcomes				
FT Work	0.076	-0.216	-0.055	-0.210
se	0.021	0.026	0.020	0.029
Employed	0.029	-0.195	-0.040	-0.197
se	0.017	0.041	0.012	0.039
Study	-0.030	0.108	-0.007	0.109
se	0.017	0.024	0.010	0.038
Grad Job	0.106	-0.100	-0.054	-0.034
se	0.025	0.023	0.026	0.051
High SOC	0.083	-0.183	-0.130	-0.106
se	0.024	0.039	0.024	0.051
Perception of HE				
HE for Study	-0.027	0.052	0.017	-0.031
se	0.009	0.031	0.011	0.032
HE for Work	-0.017	-0.040	-0.017	-0.010
se	0.007	0.023	0.022	0.032
Type of Further Study				
PG Research	0.007	-0.002	0.007	-0.001
se	0.003	0.003	0.004	0.005
PG Taught	-0.035	0.104	0.031	0.068
se	0.011	0.016	0.010	0.020

Notes: Controls include gender, socio-economic status, POLAR Q1, 2 & 3, being a first generation university student and university, cohort, subject as well as cluster × subject group fixed effects. For academic outcomes, the regressions also control for tariff and type of qualification a student comes to university with. First and Good are conditional on graduating. Standard errors are in parentheses. * p <0.1, ** p <0.05, *** p <0.01

Table A3.7: Results by Clustering at Year x Department Level

Variable	White	Black	S Asian	Other
Academic Outcomes				
First	0.070	-0.085	0.065	-0.038
se	0.019	0.020	0.021	0.023
Good	0.037	0.065	0.119	-0.024
se	0.015	0.034	0.026	0.023
Dropout	-0.018	0.018	-0.033	-0.026
se	0.012	0.028	0.024	0.025
Employment Outcomes				
FT Work	0.076	-0.216	-0.055	-0.210
se	0.020	0.038	0.036	0.036
Employed	0.029	-0.195	-0.040	-0.197
se	0.018	0.035	0.030	0.034
Study	-0.030	0.108	-0.007	0.109
se	0.017	0.031	0.028	0.030
Grad Job	0.106	-0.100	-0.054	-0.034
se	0.023	0.047	0.032	0.039
High SOC	0.083	-0.183	-0.130	-0.106
se	0.023	0.052	0.033	0.041
Perception of HE				
HE for Study	-0.027	0.052	0.017	-0.031
se	0.011	0.025	0.020	0.021
HE for Work	-0.017	-0.040	-0.017	-0.010
se	0.013	0.034	0.024	0.032
Type of Further Study				
PG Research	0.007	-0.002	0.007	-0.001
se	0.004	0.006	0.007	0.007
PG Taught	-0.035	0.104	0.031	0.068
se	0.011	0.025	0.017	0.021

Notes: Controls include gender, socio-economic status, POLAR Q1, 2 & 3, being a first generation university student and university, cohort, subject as well as cluster × subject group fixed effects. For academic outcomes, the regressions also control for tariff and type of qualification a student comes to university with. First and Good are conditional on graduating. Standard errors are in parentheses. * p <0.1, ** p <0.05, *** p <0.01

Table A3.8: Results Using only Student Facing Instructors

Variable	White	Black	S Asian	Other
Academic Outcomes				
First	0.064	-0.079	0.068	-0.040
se	0.022	0.028	0.031	0.030
Good	0.044	0.062	0.107	-0.031
se	0.025	0.052	0.036	0.026
Dropout	-0.014	0.031	-0.029	-0.009
se	0.015	0.037	0.024	0.027
Employment Outcomes				
FT Work	0.075	-0.230	-0.071	-0.216
se	0.032	0.055	0.049	0.053
Employed	0.027	-0.204	-0.049	-0.201
se	0.028	0.045	0.039	0.049
Study	-0.031	0.114	-0.000	0.113
se	0.026	0.042	0.035	0.044
Grad Job	0.100	-0.104	-0.064	-0.043
se	0.030	0.070	0.045	0.058
High SOC	0.084	-0.188	-0.135	-0.107
se	0.036	0.082	0.054	0.064
Perception of HE				
HE for Study	-0.030	0.049	0.008	-0.036
se	0.014	0.025	0.019	0.021
HE for Work	-0.029	-0.038	-0.020	-0.017
se	0.017	0.044	0.023	0.032
Type of Further Study				
PG Research	0.000	0.001	0.015	-0.000
se	0.006	0.010	0.013	0.007
PG Taught	-0.029	0.105	0.029	0.074
se	0.012	0.035	0.025	0.027

Notes: Controls include gender, socio-economic status, POLAR Q1, 2 & 3, being a first generation university student and university, cohort, subject as well as cluster × subject group fixed effects.For academic outcomes, the regressions also control for tariff and type of qualification a student comes to university with. First and Good are conditional on graduating. Standard errors are clustered at subject level. Standard errors are in parentheses. * p <0.1, ** p <0.05, *** p <0.01

Table A3.9: Results Using only Full-time Students

Variable	White	Black	S Asian	Other
Academic Outcomes				
First	0.045	-0.110	0.061	-0.052
se	0.025	0.027	0.034	0.039
Good	0.032	0.040	0.117	-0.044
se	0.027	0.056	0.039	0.032
Dropout	-0.022	0.021	-0.046	-0.054
se	0.017	0.034	0.023	0.028
Employment Outcomes				
FT Work	0.080	-0.201	-0.068	-0.219
se	0.033	0.065	0.061	0.058
Employed	0.040	-0.175	-0.049	-0.205
se	0.031	0.048	0.047	0.049
Study	-0.033	0.090	-0.011	0.125
se	0.029	0.043	0.041	0.044
Grad Job	0.091	-0.104	-0.035	-0.007
se	0.030	0.072	0.052	0.059
High SOC	0.063	-0.214	-0.154	-0.097
se	0.034	0.095	0.059	0.065
Perception of HE				
HE for Study	-0.029	0.030	0.007	-0.032
se	0.017	0.036	0.021	0.027
HE for Work	-0.025	-0.060	-0.028	0.015
se	0.018	0.046	0.026	0.028
Type of Further Study				
PG Research	0.006	-0.009	0.001	-0.005
se	0.005	0.010	0.011	0.009
PG Taught	-0.036	0.089	0.031	0.073
se	0.014	0.033	0.026	0.027

Notes: Controls include gender, socio-economic status, POLAR Q1, 2 & 3, being a first generation university student and university, cohort, subject as well as cluster × subject group fixed effects. For academic outcomes, the regressions also control for tariff and type of qualification a student comes to university with. First and Good are conditional on graduating. Standard errors are clustered at subject level. Standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3.10: Results for Health Sciences

Variable	White	Black	S Asian	Other
Academic Outcomes				
First	0.095	-0.028	-0.052	-0.123
se	0.077	0.044	0.064	0.092
Good	0.013	0.312	0.054	-0.101
se	0.090	0.140	0.123	0.125
Dropout	-0.055	-0.241	-0.165	-0.129
se	0.080	0.052	0.036	0.078
Employment Outcomes				
FT Work	0.112	-0.156	0.489	0.062
se	0.063	0.088	0.161	0.207
Employed	0.097	-0.150	0.421	0.036
se	0.073	0.131	0.122	0.185
Study	-0.106	0.001	-0.362	-0.074
se	0.090	0.144	0.110	0.143
Grad Job	0.127	0.060	0.100	0.120
se	0.083	0.128	0.181	0.182
High SOC	0.011	-0.106	-0.032	-0.042
se	0.074	0.092	0.083	0.132
Perception of HE				
HE for Study	0.002	0.011	-0.005	-0.107
se	0.026	0.085	0.040	0.041
HE for Work	0.041	-0.035	0.066	0.125
se	0.030	0.071	0.099	0.031
Type of Further Study				
PG Research	0.023	-0.013	-0.055	-0.033
se	0.018	0.011	0.019	0.035
PG Taught	-0.059	0.053	-0.100	0.046
se	0.054	0.096	0.030	0.052

Notes: Controls include gender, socio-economic status, POLAR Q1, 2 & 3, being a first generation university student and university, cohort, subject as well as cluster × subject group fixed effects. For academic outcomes, the regressions also control for tariff and type of qualification a student comes to university with. First and Good are conditional on graduating. Standard errors are clustered at subject level. Standard errors are in parentheses. * p <0.1, ** p <0.05, *** p <0.01

Table A3.11: Results for STEM

Variable	White	Black	S Asian	Other
Academic Outcomes				
First	0.126	-0.024	0.115	0.068
se	0.039	0.037	0.053	0.053
Good	0.056	0.057	0.154	0.007
se	0.035	0.095	0.049	0.039
Dropout	0.013	0.082	-0.019	0.073
se	0.016	0.057	0.040	0.043
Employment Outcomes				
FT Work	0.045	-0.199	-0.188	-0.251
se	0.031	0.105	0.080	0.062
Employed	-0.008	-0.207	-0.175	-0.271
se	0.026	0.078	0.073	0.049
Study	0.014	0.162	0.140	0.158
se	0.015	0.070	0.057	0.073
Grad Job	0.187	-0.079	-0.047	-0.025
se	0.040	0.077	0.045	0.102
High SOC	0.128	-0.243	-0.112	-0.031
se	0.044	0.090	0.062	0.071
Perception of HE				
HE for Study	-0.008	-0.002	0.046	0.002
se	0.011	0.050	0.022	0.027
HE for Work	-0.014	0.018	0.012	0.018
se	0.022	0.090	0.033	0.060
Type of Further Study				
PG Research	0.001	0.048	0.068	0.018
se	0.009	0.031	0.026	0.028
PG Taught	-0.030	0.061	0.039	0.058
se	0.025	0.074	0.046	0.055

Notes: Controls include gender, socio-economic status, POLAR Q1, 2 & 3, being a first generation university student and university, cohort, subject as well as cluster × subject group fixed effects. For academic outcomes, the regressions also control for tariff and type of qualification a student comes to university with. First and Good are conditional on graduating. Standard errors are clustered at subject level. Standard errors are in parentheses. * p <0.1, ** p <0.05, *** p <0.01

Table A3.12: Results for Social Sciences and Business

Variable	White	Black	S Asian	Other
Academic Outcomes				
First	0.085	-0.059	0.047	-0.083
se	0.047	0.039	0.038	0.038
Good	0.011	0.038	0.122	-0.015
se	0.026	0.048	0.021	0.020
Dropout	-0.036	0.054	-0.041	-0.010
se	0.014	0.025	0.036	0.033
Employment Outcomes				
FT Work	0.077	-0.131	0.008	-0.138
se	0.038	0.047	0.038	0.033
Employed	0.038	-0.094	0.028	-0.091
se	0.043	0.053	0.032	0.053
Study	-0.009	0.034	-0.051	0.029
se	0.047	0.064	0.032	0.054
Grad Job	0.072	-0.110	0.001	-0.068
se	0.035	0.096	0.062	0.081
High SOC	0.138	-0.136	-0.029	-0.080
se	0.055	0.106	0.111	0.053
Perception of HE				
HE for Study	-0.055	0.047	-0.080	-0.073
se	0.028	0.059	0.027	0.049
HE for Work	-0.035	-0.009	-0.032	-0.079
se	0.034	0.078	0.049	0.037
Type of Further Study				
PG Research	-0.008	-0.004	0.001	-0.009
se	0.005	0.005	0.003	0.007
PG Taught	-0.023	0.012	-0.015	-0.012
se	0.012	0.045	0.035	0.052

Notes: Controls include gender, socio-economic status, POLAR Q1, 2 & 3, being a first generation university student and university, cohort, subject as well as cluster × subject group fixed effects. For academic outcomes, the regressions also control for tariff and type of qualification a student comes to university with. First and Good are conditional on graduating. Standard errors are clustered at subject level. Standard errors are in parentheses. * p <0.1, ** p <0.05, *** p <0.01

Table A3.13: Results for Humanities

Variable	White	Black	S Asian	Other
Academic Outcomes				
First	0.050	0.102	0.001	0.090
se	0.030	0.030	0.065	0.035
Good	0.009	0.040	0.038	-0.095
se	0.023	0.080	0.070	0.025
Dropout	0.035	-0.008	0.042	-0.083
se	0.011	0.062	0.021	0.056
Employment Outcomes				
FT Work	-0.086	-0.248	0.064	-0.194
se	0.056	0.094	0.073	0.044
Employed	-0.060	-0.502	0.080	-0.127
se	0.056	0.087	0.109	0.061
Study	0.006	0.249	-0.219	0.046
se	0.031	0.165	0.093	0.080
Grad Job	-0.003	-0.260	0.199	-0.004
se	0.044	0.121	0.094	0.153
High SOC	-0.006	-0.306	-0.010	0.071
se	0.043	0.215	0.178	0.110
Perception of HE				
HE for Study	0.019	0.189	-0.004	-0.058
se	0.016	0.095	0.073	0.065
HE for Work	-0.031	-0.173	-0.014	0.037
se	0.023	0.251	0.074	0.057
Type of Further Study				
PG Research	0.009	-0.017	0.002	0.009
se	0.005	0.019	0.015	0.021
PG Taught	-0.016	0.197	-0.097	-0.113
se	0.021	0.079	0.060	0.057

Notes: Controls include gender, socio-economic status, POLAR Q1, 2 & 3, being a first generation university student and university, cohort, subject as well as cluster × subject group fixed effects. For academic outcomes, the regressions also control for tariff and type of qualification a student comes to university with. First and Good are conditional on graduating. Standard errors are clustered at subject level. Standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3.14: Results for Arts, Education, Other

Variable	White	Black	S Asian	Other
Academic Outcomes				
First	-0.039	-0.196	-0.221	-0.110
se	0.062	0.035	0.126	0.066
Good	-0.025	-0.305	-0.211	-0.115
se	0.038	0.079	0.220	0.067
Dropout	0.021	0.102	0.052	0.030
se	0.043	0.087	0.123	0.106
Employment Outcomes				
FT Work	0.174	0.139	-0.129	0.013
se	0.114	0.130	0.179	0.124
Employed	0.103	0.099	0.162	0.165
se	0.058	0.050	0.086	0.046
Study	-0.136	-0.158	-0.013	-0.218
se	0.042	0.026	0.042	0.061
Grad Job	-0.129	0.060	-0.041	-0.314
se	0.102	0.182	0.045	0.095
High SOC	-0.002	0.046	-0.214	-0.176
se	0.013	0.314	0.302	0.236
Perception of HE				
HE for Study	-0.144	-0.017	-0.027	-0.221
se	0.083	0.164	0.376	0.107
HE for Work	-0.031	-0.288	0.032	-0.142
se	0.029	0.200	0.139	0.129
Type of Further Study				
PG Research	-0.009	-0.008	-0.004	0.003
se	0.004	0.013	0.008	0.011
PG Taught	-0.080	-0.034	-0.063	-0.126
se	0.014	0.032	0.041	0.050

Notes: Controls include gender, socio-economic status, POLAR Q1, 2 & 3, being a first generation university student and university, cohort, subject as well as cluster × subject group fixed effects. For academic outcomes, the regressions also control for tariff and type of qualification a student comes to university with. First and Good are conditional on graduating. Standard errors are clustered at subject level. Standard errors are in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A3.15: University Clusters

Group 1	Group 2		Group 3
University of Aberdeen	Abertay Dundee University	Keele University	Anglia Ruskin University
University of Bath	Aberystwyth University	Kingston University	Bishop Grosseteste University
University of Birmingham	Aston University	Leeds Beckett University	University College Birmingham
University of Bristol	Bangor University	University of Lincoln	University of Bolton
Cardiff University	Bath Spa University	Liverpool John Moores University	Buckinghamshire New University
University of Dundee	University of Bedfordshire	London South Bank University	University of Cumbria
Durham University	Birmingham City University	Manchester Metropolitan University	University of East London
University of East Anglia	Bournemouth University	Middlesex University	Edge Hill University
University of Edinburgh	University of Bradford	Newman University	Glyndwr University
University of Exeter	University of Brighton	University of Northampton	Leeds Trinity University
University of Glasgow	Brunel University London	Nottingham Trent University	Liverpool Hope University
Goldsmiths, University of London	Cantenbury Christ Church University	Northumbria University	London Metropolitan University
Heriot-Watt University	Cardiff Metropolitan University	Oxford Brookes University	University of Wales, Newport
Imperial College London	University of Central Lancashire	Plymouth University	University of St Mark and St John
University of Kent	University of Chester	University of Portsmouth	Solent University
King's College London	University of Chichester	Queen Margaret University	University Campus Suffolk
Lancaster University	City University of London	Robert Gordon University	University of Wales Trinity Saint David
University of Leeds	Coventry University	University of Roehampton	University of Wolverhampton
University of Leicester	De Montfort University	University of Salford	York St John University
University College London	University of Derby	Sheffield Hallam University	
LSE	Edinburgh Napier University	Staffordshire University	
Loughborough University	University of Essex	University of Stirling	
University of Manchester	Falmouth University	University of Sunderland	
Newcastle University	University of Glamorgan	Swansea University	
University of Nottingham	Glasgow Caledonian University	Teeeside University	
Queen Mary University of London	University of Gloucestershire	Ulster University	
Queen's University Belfast	University of Greenwich	University of West of England	
University of Reading	Harper Adams University	University of West London	
Royal Holloway, University of London	University of Hertfordshire	University of West of Scotland	
University of St Andrews	University of Highlands and Islands	University of Westminster	
SOAS, University of London	University of Huddersfield	University fof Winchester	
University of Sheffield	University of Hull	University of Worcester	
University of Southampton			
University of Strathclyde			
University of Surrey			
University of Sussex			
University of Warwick			
University of York			

Table A3.16: University Tariff Groups

Highest Tariff	High Tariff	Medium Tariff	Low Tariff
University of Bath	University of Aberdeen	University of Albertay Dundee	University of Bedfordshire
University of Birmingham	Aston University	Anglia Ruskin University	Bishop Grosseteste University
University of Bristol	Brunel University	Bournemouth University	University of Bolton
University of Cambridge	Cardiff University	University of Bradford	University of Buckingham
University College London	City University of London	University of Brighton	University of Cumbria
University of Durham	University of Dundee	Cantenbury Christ Church University	University of Derby
University of Edinburgh	University of East Anglia	Birmingham City University	University of East London
University of Glasgow	University of Essex	University of Central Lancashire	University of Greenwich
Imperial College London	University of Exeter	University of Chester	Kingston University
King's College London	Glasgow Caledonian University	University of Chicester	Leeds Trinity and All Saints University
University of Leeds	Goldsmiths, Universiy of London	Coventry University	Liverpool Hope University
London School of Economics	Heriot-Watt University	De Montfort University	London Metropolitan University
University of Manchester	University of Hull	Edge Hill University	London South Bank University
University of Newcastle	Keele University	University of Glamorgan	Middlesex University
University of Nottingham	University of Kent	University of Gloucestershire	University of Northampton
Oxford University	Lancaster University	University of Hetfordshire	Roehampton University
University of St Andrews	University of Leicester	University of Huddersfield	St Marys College, Twickenham
University of Sheffield	Loughborough University	Leeds Metropolitan University	Southampton Solent University
University of Southampton	Northumbria University	University of Lincoln	Swansea Metropolitan University
University of Strathclyde	Oxford Brookes University	Liverpool John Moores University	Thames Valley University
University of Warwick	Quen Margaret University College	Manchester Metropolitan University	University of Wales Institute Cardiff
University of York	Queen Mary, University of London	Napier University	University of Wales, Newport
	Queens's University Belfast	Nottingham Trent University	University of Wolverhampton
	University of Reading	University of Paisley	University of Worchester
	Robert Gordon University	University of Portsmouth	
	Royal Holloway, University of London	University of Plymouth	
	SOAS, University of London	University of Salford	
	University of Stirling	Sheffield Hallam University	
	University of Surrey	Staffordshire University	
	University of Sussex	University of Sunderland	
	University of Wales, Aberystwyth	University of Teesside	
	University of Wales, Swansea	University of Ulster	
		University of Wales, Bangor	
		University of Wales, Lampeter	
		University of Westmister	
		University of West of England	
		University of Winchester	
		York St John University	

Table A3.17: Subject Groups

Subject Group	Subject
Allied to Health	Nursing and Allied Health Professions Psychology & Behavioral Sciences Health & Community Studies Anatomy & Physiology Pharmacy & Pharmacology Sports Science & Leisure Studies Veterinary Science
STEM	Agriculture, Forestry & Food Science Earth, Marine & Environmental Sciences Biosciences Chemistry Physics General Engineering Chemical Engineering Mineral, Metallurgy & Materials Engineering Civil Engineering Electrical, Electronic & Computer Engineering Mechanical, Eero & Production Engineering IT, Systems Sciences & Computer Software Engineering Mathematics Architecture, Built Environment & Planning
Social Sciences	Geography & Environmental Studies Area Studies Archaeology Anthropology & Development Studies Politics & International Studies Economics & Econometrics Law Social Work & Social Policy Sociology Business & Management Studies Catering & Hospitality management
Humanities	Modern languages English Language & Literature History Classics Philosophy Theology & Religious Studies
Art, Education and Others	Art & design Music, Dance, Drama & Performing Arts Education Continuing Education