Stereotypical Selection

Martina Zanella*

November 18, 2021

Latest version here

Abstract

Stereotypes can represent societal expectations based on an individual's observable identity. The cost of making choices that go against stereotypes is difficult to assess, as those who do so typically end up in a numerical minority, a condition which might matter on its own. In this paper I disentangle these two effects by combining a choice with well-defined stereotypes (university major) with variation in peer identity across small, exogenously formed, classes within the same course. Evidence from the performance of 14,000 students in an elite university indicates that those who go against stereotypes, e.g. women in maths, do not suffer from being in a numerical minority, but they impose negative externalities on those who select on stereotypes. This might explain why the majority upholds stereotypes and why policies to foster minority inclusion should target the majority.

JEL codes: D91, I24, J15, J16, J24

*Department of Economics, London School of Economics; email: M.Zanella1@lse.ac.uk. I acknowledge the collaboration with the London School of Economics, that I thank for the data and the possibility to administer the survey. I am grateful for the advice and support from Nava Ashraf, Oriana Bandiera, and Robin Burgess throughout the project. I also thank advice from Gharad Bryan, Jeremiah Dittmar, Alan Manning, Rachael Meager, Guy Michaels, Barbara Petrongolo, Steve Pischke, Daniel Reck, Mark Schankerman, Daniel Sturm. I thank Andrea Alati, Luca Citino, Amanda Dahlstrand, Alexia Delfino, Gaia Dossi, Sacha Dray, Nicola Fontana, Martina Fazio, Virginia Minni, Kilian Russ, Vincenzo Scrutinio, Celine Zipfel and seminar participants at LSE for the helpful suggestions. I thank Viola Salvestrini for the constructive feedback and the multiple rounds of revisions. A special acknowledgment goes to Judith Shapiro for priceless guidance in navigating the LSE system, feedback, and support. The use of the data and the survey were approved by the LSE Ethics Committee in October 2017 and April 2021.

1 Introduction

In recent years, a variety of policies targeting minority groups have been implemented to address the lack of diversity in learning environments and in the workplace.[1] Will these policies be successful in leveling the playing field? Does targeting minorities represent the most effective use of our resources? Minority status is not only related to under-representation, but also to stereotypical expectations. By influencing payoffs from economic choices, stereotypes shape the distribution of groups across fields (Akerlof and Kranton 2000). As a consequence, those individuals that we observe in a numerical minority in a field are often individuals who decided to bear the cost of making a choice against stereotypes ("stereotypical minority"). As such, they might react very differently to the composition of the environment compared to individuals who made choices in line with stereotypes.[2] Assessing whether this is the case is crucial to design effective policies as this makes findings from experiments, where selection is shut down by design, not necessarily generalizable to real-world environments. However, it is hard outside experimental settings unless we manage to find a setting with some independent variation in the two dimensions, numerical minority and stereotypical minority.

In this paper, I overcome this challenge by studying a real-world setting that combines a choice with well-defined stereotypes with exogenous variation in peer identity, which allows me to observe the stereotypical minority group in the field (for example women in Mathematics) in a numerical majority and vice-versa. By studying 14,313 students across 10 academic years and 16 departments at an elite UK university, I assess if selection into fields, and in particular whether individuals made a choice of major in line or against stereotypes regarding gender skills and roles, interacts with the effect of class gender composition on performance for students, once they are enrolled in their first year of bachelor.

I define a measure of stereotypical selection leveraging the variety of programs offered by the university. Lab and field experiments document the existence of stereotypically-female and stereotypically-male disciplines in the academic setting: women are believed to be worse than men in Mathematics and Science while being better at reading (Carlana 2019; Reuben et al. 2014; Ellemers 2018; Lane 2012). This translates into men and women making very different educational choices (Bertrand 2020; Bertrand 2011), which is what I observe in my setting. While 49% of the population of students enrolled in undergraduate programs at the university are women, they represent the minority of students enrolled in departments such as Mathematics, Economics and Finance, and the majority of students enrolled in programs related to disciplines such as Anthropology, Sociology, International relations.[3] In my analysis I will then indi-

[1]Within the Economic discipline alone, examples of such initiatives are the launch of the Committee on the Status of Minority Groups and the Committee on the Status of Women in the Economics Profession by the American Economics Association, or the Minorities in Economics Committee launched by the European Economics Association, or the multitude of programs implemented by universities in support of minority groups, such as experimental study groups promoted by MIT (Russell 2017), special training programs for women enrolled in STEM at Harvard Business School, the Undergraduate Women in Economics Challenge at Harvard University (Avilova and Goldin 2018), workshops to mentor young female assistant professors promoted by the American Economic Association (Blau et al. 2010), or provision of role models in mandatory first-year courses (Porter and Serra 2020).

[2]Recent literature on selection into occupations and majors provides evidence that stereotypes regarding group-specific skills, the composition of the environment, and identity considerations affect beliefs about expected returns, driving individuals out of counter-stereotypical occupations (Akerlof and Kranton 2000; Oxoby 2014; Kugler et al. 2021; Del Carpio and Guadalupe 2018). Furthermore, individuals incorporate their preferences towards the fraction of women and men in the occupation when making choices regarding the type of field to specialize in (Pan 2015; Card et al. 2008).

[3]This is in line with the distribution of men and women in academic fields across countries. While women have on average a higher probability to complete a bachelor's degree or equivalent in Education, Humanities, and Social Sciences (except

cate as "stereotypical" the choice of students who select in departments characterized by a high share of students of their own gender, while a "counter-stereotypical" choice is that of a student who selects in a department where they are the stereotypical minority, i.e. there is a low share of students of the same gender.[4]

I then assess how the choice of major impacts the effect of the gender composition of the environment on students' performance, by exploiting the exogenous allocation of students to classes conditional on scheduling constraints. Once students enroll in a program of study, they attend on average four courses in their first academic year. For each course, they attend classes (seminars), where they are divided into small groups of maximum 15-20 people solely based on their course selection and scheduling constraints. Thus, I can identify the causal effect of class gender composition by comparing the performance of the *same student* across the courses that they attend during their first year, exploiting the within-student exogenous variation in the share of same-gender classmates that they are exposed to after controlling for course and student fixed effects.[5]

Since students attend several courses outside their department of enrollment and first-year courses are large courses, students who are enrolled in the same program of study are not necessarily allocated to the same classes in all the courses they attend. So, men and women who are enrolled in the same program of study will not be exposed to the same within student variation in class composition. Thus, I can estimate the effect of class gender composition on performance for students who made stereotypical and counter-stereotypical choices independently. Furthermore, this allows me to observe a variation in class composition for each student that goes beyond the variation within the program of enrollment. Hence, I can exploit substantial common support in the variation of the share of same-gender classmates between students who made stereotypical choices and students who made counter-stereotypical choices of major.

I present four sets of results. First, I find that the students whose performance is negatively affected when their gender is outnumbered are students who chose to enroll in programs in line with stereotypes regarding gender skills, such as women in Humanities and men in Math and Science-intensive fields. On the other hand, students who selected against stereotypes do not appear to need to be surrounded by students of their own gender to perform well, but if anything perform better when outnumbered. Interestingly, the performance of students who are enrolled in departments with a balanced gender ratio is not affected by class composition. Consistently with findings that individuals internalize identity considerations and the composition of the environment when making occupational and educational choices (e.g. Goldin 2014; Oxoby 2014; Pan 2015; Del Carpio and Guadalupe 2018; Kugler et al. 2021), these results suggest that these factors impact students who made different choices to a different extent once they are in the

Economics), they still have a significantly lower probability to enrol and graduate in math-intensive and science fields in most countries (Beede et al. 2011; McNally 2020; OECD 2020).

[4]As a proxy of stereotypical selection, I use the average share of men and women enrolled in undergraduate programs in each department over the period 2008-2017. The relationship between stereotypes and gender segregation of the workforce has been documented in psychology (e.g. Garg et al. 2018), and the share of females as an indicator of friendliness/stereotypes of the sector/field has been widely used in the literature (e.g. Bostwick and Weinberg 2021; Kugler et al. 2021; Hebert 2020). The results are robust to other proxies of stereotypical selection. See Section 5.2

[5]Evidence on the validity of the assumptions, I perform three checks. (i) I provide evidence that class allocation does not predict students' individual characteristics. (ii) I provide evidence that the variation in the share of females in the class is not related to the variation in a number of predetermined student characteristics. (iii) I compare the observed allocation to a simulated unconstrained random allocation to provide evidence in support of the assumption that students of different gender do not select systematically different courses among the first-year optional courses. More details can be found in Section 4.

environment. In terms of the magnitude of the effect, the paper estimates that for students who are enrolled in stereotypical departments, a 10% increase in the share of same-gender classmates *increases* course grades by 0.325 points (2.0% of a standard deviation). On the other hand, for students enrolled in departments stereotypically associated with their gender, a 10% increase in the share of same-gender classmates *decreases* final course grades by 0.288 points (1.76% of a standard deviation). Consistently with stereotypes playing a role, I find that the students who are enrolled in stereotypical fields that benefit the most from being surrounded by same-gender classmates are those that come from countries with low Gender Gap Index, i.e. countries with more unequal gender norms. However, at the same time, students coming from these countries are also those that display the strongest negative effect on performance when surrounded by same-gender classmates if they are enrolled in counter-stereotypical majors.[6] This highlights the importance of considering selection into fields when formulating policy recommendations with the aim of equalizing opportunities and performance. Nudging and targeting under-represented groups might indeed not be effective in solving imbalances since they do not suffer from being in a minority.

The second result concerns gender differences in the effect of stereotypical selection. While the effect is present for both men and women, it appears to be stronger for men. Indeed, while men who make stereotypical choices are affected by the composition of the environment regardless of the measure of stereotypical selection used, women display nonlinearities in the effect. To capture nonlinearities I define stereotypical and counter-stereotypical selection using a definition that becomes gradually more extreme.[7] Women whose performance suffers when in a numerical minority, are those who selected in the departments with the highest share of females among undergraduate students, while the effect disappears when I consider less extreme choices.

The third set of results speaks to the margins through which selection into fields intervene to moderate the effect of being in a numerical minority. I rely on a theoretical framework to rationalize the channels traditionally used to explain how being in a numerical minority affects performance. I micro-found the model by exploiting evidence from a novel survey and rich administrative data. I assume that students invest in effort to maximize their performance in exams and their social image (Bursztyn et al. 2019; Bursztyn and Jensen 2017; Bursztyn et al. 2017; Austen-Smith and Fryer 2005; Akerlof and Kranton 2000), with different weights depending on the extent to which effort is visible to their peers. In this setting, numerical minority affects performance via two channels. First, studies in psychology and sociology show that we prefer to affiliate with those who share our attitudes and beliefs or demographic traits (Inzlicht and Good 2006). This is rationalized in the theoretical framework assuming that being in a numerical minority increases the marginal cost of effort for students by preventing them from benefiting from academic and emotional support.[8] Second, experiments in psychology and sociology show that being in a minority primes stereotyped aspects of individuals' identity in the mind of the outnumbered (Steele

[6] The effect is stronger for men, in line with the gender differences in magnitude and mechanisms.

[7] I start by considering students who are enrolled in the top five departments with the highest average share of same-gender students as students making stereotypical choices, while students who are enrolled in the five departments with the lowest share of same-gender students are considered to be students who made a choice not in line with stereotypes regarding gender roles and skills. I then replicate the same analysis by defining stereotypical and counter-stereotypical choices by considering the top and bottom three and two departments in terms of share of same-gender students among undergraduates.

[8] According to the education literature, social interaction and mutual assistance are factors directly related to persistence in college (Tinto 1975).

and Aronson 1995; Spencer et al. 2016). I follow Bordalo et al. (2019) and I assume that students do not have perfect information regarding their ability and the ability of their peers. Their beliefs are affected by stereotypical distortions, which are stronger the more group identity is top of mind. By increasing the salience of group identity, numerical minority increases the strength of stereotypical distortions, boosting (positive stereotypes) or depressing (negative stereotypes) beliefs on ability and, as a consequence, affecting expected returns to effort.

The model predicts that the relevance of these two channels is lower if stereotypical associations are weaker and the cost of interacting with the opposite gender is lower. This might be the case for students who made counter-stereotypical choices, since recent studies find that stereotypes and the composition of the environments are internalized in educational and occupational choices (e.g. Goldin 2014; Oxoby 2014; Pan 2015; Del Carpio and Guadalupe 2018; Kugler et al. 2021) and these students self-selected in a field dominated by the opposite gender in spite of the negative stereotypes regarding their group.

I test this by exploiting teaching assistants' evaluations of students' participation in class during the term. In line with the findings of lab and field experiments that relaxing minority status increases participation and willingness to contribute to discussions for individuals in counter-stereotypical domains (Coffman and Shurchkov 2021; Born et al. 2020; Chen and Houser 2019; Bordalo et al. 2019; Coffman 2014), the model predicts that, in absence of stereotypical selection, relaxing minority status induces students enrolled in counter-stereotypical fields to participate more in class.[9] However, consistently with selection playing a role, I find no evidence of an effect of class composition on participation for students who are enrolled in counter-stereotypical departments.

In particular, students who are enrolled in counter-stereotypical departments seem to be less affected by gender stereotypes. I find evidence that the performance of students who are enrolled in counter-stereotypical departments is not affected by the gender of the class teacher, contrary to the performance of students who made a stereotypical choice of major. Since the literature provides evidence that class teachers act as role models, helping breaking stereotypes (e.g. Breda et al. 2021; Porter and Serra 2020; Olsson and Martiny 2018), this result supports the theory that students who are part of the stereotypical minority group are indeed less subject to the effect of stereotypes. Furthermore, the results of an implicit association test (Greenwald et al. 1998) to elicit students' associations female-Humanistic and male-Scientific confirm that students who self-selected into a counter-stereotypical field in spite of the negative stereotype regarding their group indeed hold weaker implicit stereotypical associations.

Finally, the paper closes with a replication of the analysis along ethnic lines. The diversity of the environment (47% of students are Asian, while 37% are White) and the variety of programs offered by the institution allow me to study the effect of classmates' ethnic composition on students' course performance and define a measure of stereotypical selection along ethnic lines. The results confirm the finding for gender, indicating that the estimated patterns are not group-specific, but are related to stereotypical selection moderating the effect of being under-represented more in general.

These results have important policy implications. First, they point towards the stereotypical majority group in the field being the perpetrator of stereotypes. Second, my findings indicate that policies that aim to foster minority inclusion should target the majority, as minority groups are often composed of

[9] According to the model, relaxing minority status reduces the strength of the stereotypical distortions that were inducing students to underestimate their absolute and relative ability. Furthermore, it reduces the marginal cost of effort by increasing the sense of comfort, belonging, and emotional reciprocity.

individuals who decided to work or study in fields stereotypically associated with a different group, and as such are less affected by the composition of the environment and by identity considerations.

My work contributes to the literature that aims at assessing the effect of stereotypes on performance in stereotypically congruent and in-congruent domains and their interaction with the composition of the group (e.g. Coffman and Shurchkov 2021; Karpowitz and Stoddard 2020; Born et al. 2020; Bordalo et al. 2019; Chen and Houser 2019; Bordalo et al. 2016; Coffman 2014). This paper is the first to provide evidence that results in a natural field setting might differ from experimental evidence due to the fact that individuals who self-select into counter-stereotypical fields are less affected by the composition of the environment and stereotypes. Furthermore, by being able to replicate the analysis along ethnic lines within the same setting, the paper can also speak to the extent to which the results found are due to gender-specific dynamics, rather than under-representation more in general.

My paper relates also to fields experiments and observational studies that estimate the effect of the gender composition of the environment on performance in higher education (Shan 2020; Zölitz and Feld 2018; Griffith and Main 2019; Booth et al. 2018; Huntington-Klein and Rose 2018; Hill 2017; Oosterbeek and van Ewijk 2014; Giorgi et al. 2012). To the best of my knowledge, the evidence to date does not provide a conclusive picture, probably due to the different settings and fields studied, and the different sources of variation exploited. Both the methodology and the analysis of my paper build on this work. However, by studying the effect of the composition of the environment on performance across multiple fields within the same setting and exploiting the same source of variation, my paper can shed light on the importance of the field and the selectivity of the environment in explaining differences in results. Moreover, thanks to the rich administrative data and the survey, I can speak to the mechanisms underlying the results in an unusually rich way.

The remainder of the paper is organized as follows. The next section explains the institutional setting. Section 3 describes the data and descriptive statistics. Section 4 presents the empirical strategy and the tests in support of the identifying assumptions. Section 5 illustrates the main results, and Section 6 presents the theoretical framework and the evidence in support of the different mechanisms underlying the results. In Section 7, the analysis is replicated for ethnicity. Finally, Section 8 concludes.

2 Institutional Setting

The paper is based on administrative data on individual students from The London School of Economics and Political Science (LSE), a top UK university, for the academic years 2008/2009 to 2017/18.

2.1 Institutional Environment

LSE is characterized by a very diverse and multicultural environment: 49% of undergraduate students are women, and roughly 45% are Asian (Chinese, Indian, and other ethnic minorities).

During the academic years considered, the university offered a very diverse portfolio of courses with 16 academic departments and 44 undergraduate degree programmes, that spanned across different fields from Math-intensive disciplines degree programs in Mathematics, Economics, Finance, and Statistics, to programs in Humanities such as Anthropology, Sociology, International Relations or International History. The variation in gender composition is significant as we can observe majority-male departments men represent 65-69% of the students enrolled in undergraduate programs, alongside majority-female departments, which are characterized by 75-78% of women (Figure 1).

The academic system is homogeneous across programs belonging to different fields as students take on average 4 courses during each academic year, that are worth either one or half a credit. Each degree program has its own list of core courses – that are either compulsory or offering a very constrained choice – as well as a list of elective courses. During the first year, which is the focus of this paper, the most of the courses are compulsory and students have a very limited possibility for choices of electives[10]. Depending on the program of enrolment, students might be required (or allowed) to attend courses outside their department or program of enrolment. This is especially true during the first year, when students will attend several courses outside their own department of enrollment[11].

Each academic year is composed of three terms. Michaelmas term (September- December) and Lent term (January-April) are 10 weeks long and are teaching terms during which students attend lectures. The third term is called Summer term (May - June). During this term students primarily take exams.

For each course that students take, they attend lectures and classes. Lectures last generally for 3 hours and are attended by all the students enrolled in the course. Classes are usually 1 hour long, and are taught by teaching assistants in small groups of maximum 15-20 students. Students attend a total of 10 hours of classes each term, one per week. The empirical strategy of the paper exploits students assignment to classes and class composition.

2.2 Assignment of students to classes

Students are allocated to classes before the beginning of the academic year, when each student receives a schedule with the day of the week and time of the day of all his/her lectures and classes for the whole academic year.

According to the university's timetable office, there are only two criteria that are used to allocate students to a class. First of all, students cannot attend more than 4 consecutive hours of teaching. Secondly, the timetable office considers scheduling constraints, i.e. the potential clashes with other courses that students attend during the academic year. The measure of class composition for each student that is considered for the analysis is based on the characteristics of all the students (undergraduate, general course, intercollegiate, exchange, and postgraduate) that are officially allocated to the same class at the beginning of the academic year.

Once students are enrolled to a class, they can only changes under exceptional circumstances and via an official request, that has to be approved. Furthermore, the official allocation of students into classes reflects very closely actual attendance since classes are compulsory and teaching assistants are required to register students' attendance[12]. Thus, the students officially allocated to the same class, represent the peers each student will engage with during classes for the whole year.

[10]Students are generally allowed to choose at most one course

[11]See Table A3 in Appendix A for more detailed information

[12]Whenever students are absent without reason to two consecutive times, they receive an "ammunition" and their advisor is contacted. Failing to attend classes might result in the impossibility to take the exam at the end of the year. Unofficial changes are possible, but this type of switching is usually limited to one or two sessions. It is difficult to obtain reliable numbers on unofficial switching. From my own experience and consultation with teaching staff, these instances are very limited, given that students have to notify their teaching assistant to be recorded as present when attending a different class

3 Data and Descriptive Statistics

The paper combines four sources of data: the university administrative records, the university class register, Human Resources records, and additional information from an online survey.

The university's administrative records contain information on academic history and performance in each course for the universe of students enrolled in undergraduate courses at LSE during the academic years 2008/09 - 2017/18. I therefore observe the degree programs students are enrolled into and all the courses that they attend during each term of each academic year, with the students' performance.

The university's administrative records contains also some background individual characteristics for students, like gender, age at enrolment, country of origin, ethnicity, term time accommodation, and the previous schools attended.

Lastly, the university collects and stores students' application information. I have the complete list of all the qualifications that students submitted when filling their applications for all the students that enrolled in the university between 2011 and 2017. Lastly, for the academic years 2007/08 - 2019/2020, I have information on the total number of the students who applied, got accepted, or rejected to each program at the university, divided by gender, ethnicity and country of birth.

The class register contains information on lectures and classes allocation for each student, professor and teaching assistant. This allows me to identify all the students that attend classes in the same class group and construct measures related to the composition of the class group on the basis of students' demographic characteristics for each class students attend. Furthermore, I can match the students class group allocation with the teachers class group allocation, allowing me to identify which teaching assistant or professor is teaching the class, and construct a matched teacher-student database. The university requires teaching assistants to keep track of students' attendance during the classes and to evaluate their participation and overall class performance (problem set grades and overall class performance assessment). These information are collected through a software students, teaching assistants and professors have access to, and are stored to prove visa's requirements and to be used by academic mentors, professors and teaching assistants to write reference letters for students.

Human Resources provided some background information (gender and ethnicity) for the subsample of teachers that are employed by LSE with a contract over the years considered.

Lastly, information from administrative data are complemented with information gathered from an online survey that I administered to all the students enrolled in undergraduate programs at LSE during the academic year 2020/2021. 498 students completed the survey, representing 10% of the overall population. The survey includes questions on demographic characteristics, educational experience, social networks, explicit attitudes towards gender-specific skills, and an Implicit Association Test eliciting the association male-Scientific, female-Humanistic. More information on the survey can be found in Appendix.

3.1 Sample Selection

The full sample of students that enrolled in undergraduate programs at LSE between 2008 and 2018 consists of 14,389 students. I restrict the sample for the analysis to undergraduate students enrolled in their first year that are attending courses for the first time. The focus on first year courses is motivated by three factors. First of all, the choices of students are strongly restricted in first year courses, allowing me to minimize the problem of selection into courses. Secondly, during the first year students who attend different programs and departments have several courses in common. This provides a variation in the composition of the courses that each student attends during the first year that goes beyond the variation in the composition of the students enrolled in each program. Furthermore, this provides significant variation in the composition of classes within each course, since first year courses are large and each course is characterized by numerous students and numerous classes. Lastly, this is the first time that students meet each other, thus this allows me to study how behavior and performance are affected by the environment when students have an empty information set regarding each others, and thus base their beliefs on group specific performance mostly on priors rather than the signals that they get from observing their classmates' behavior and performance in exams and seminars[13].

A few programs are characterized by half-year courses that are scheduled for the second term. To limit the problem of endogenous choice of courses in the second term, the sample is restricted to first year courses that students attend during the first term, half-unit or full unit courses, excluding half-unit courses that students attend only in the second term (9.2% of observations).

The sample is restricted to class groups with a size between 6 and 28 students (excluding smallest and largest 0.5% of observations) to exclude unreasonable and unlikely class sizes[14]. Furthermore, since I do not observe the initial class group allocation, but only all the seminars each student has been allocated to during the first term, I exclude from the sample all the students who changed class group during the first term. This happens 5.09% of times[15]. Lastly, I exclude from the sample class groups where I see more than 50% of people changing the group. This occurrences correspond to class group "restructuring", for instance when a class group gets cancelled and students are re-shuffled to other class groups (2.5% of course-year-class group level observations).

Ultimately, since the empirical strategy relies on class group fixed effects and student fixed effects, the sample is restricted to courses with at least two class groups and students for which I can observe, after the sample selection explained above, a test score in at least two courses: 54.603 course-year-class group level observations, corresponding to information on 14.313 students (99% of the original sample), who attend on average 3.8 courses in their first year [16]. As we can see from Table 2, the sample is made of 512 courses, with an average course size of 138.44 students, split in 9.36 class groups of 13.43 students each.

3.2 Main outcome variables

Overall course performance

Students are required to get 4 credits during each year of undergraduate programs by attending courses that are worth 0.5 or 1 credit. At the end of each course students get a grade between 0 and 100 that assesses what they have learned during the course. This grade can be the result of a final exam, or the

[13] As a potential extension, second or third year data could be used to study belief updating after having observed the performance of female or male classmates during the first year, but at the moment this is outside the scope of this paper.

[14] The university regulations fix a cap to 17 students per class group. There are frequent exceptions, but seminars with more than 28 students seems very unlikely, and thus are excluded from the sample.

[15] In Appendix A I present the results of tests that show that the decision to change class group is not driven by the composition of the group.

[16] Excluding an interdisciplinary course that carries no credits and that is excluded from the analysis.

combination of final exam and essays or take-home assignments during the year. A student is deemed to have failed a course if his grade is below 40, a third class honor is awarded if the grade is between 40 and 49, a lower second class honor if the grade is between 50 and 59, an upper second class honor if the grade is between 60 and 69 and a first class honor if the grade is 70 or above. Students can also decide to drop-off from the course by not attending the final year exam or not submitting a part of the summative assessments. In this case, a grade of 0 is assigned by the university.

Final year grades represent a good measure of performance since every piece of assignment (exams, essays or take home assignments) is based on absolute grading. Grades are based on the performance of each student in the exam, without any ranking of students and grades are not curved[17]. Furthermore, LSE is characterized by a blind marking system: students do not indicate their names in any type of assessment, but only a candidate number which is secret to examiners and only known to the student[18].

A student registered on a BA or BSc programme who has completed the first year of the programme and who has passed assessments in courses to the value of at least three credits will be eligible to progress to the second year[19]. All courses contribute to the final degree classification, even though not all courses count to the same extent. The 'year one average' counts for 1/9 of the final classification grade. The 'year one average' is calculated by adding together and averaging the best six out of eight grades in first year courses. All first-year one-unit credits will be counted twice, and any half unit credits are counted once to make a total of eight first year grades.

Table 1 shows some descriptive statistics regarding first year grades. The average grade is 60.32, with a standard deviation across students of 16.35 points. Furthermore, students do not seem to perform in the same way in all the exams, as a matter of fact the within student standard deviation is 8.61.

Class participation

In order to test the model predictions, I analyse data on teachers' evaluation of students' participation in class. Teaching assistants are required to assess students' participation in class at the end of each term. The participation grade is based on the contributions that each student gives in class during the ten weeks of term. Each teaching assistant is asked to "please mark the student's overall participation in class during the term" and he/she can give a score from 0 to 3, where 0 stands for *"No contribution"*, 1 for *"Occasional contribution"*, 2 for *"Reasonable and alert interest shown"*, and 3 for *"Lively interest and frequent contributions"*. Teachers' evaluations of students participation in class can provide us with an indication of class dynamics and students interactions. However, since they are grades that teachers give to students, they are not objective measures of students' participation. Thus, results can be considered as indicative of class dynamics conditional on the assumption that teaching assistants do not discriminate or evaluate underrepresented groups differently when they are in a minority.

Teaching assistants are required to give a grade to students in Michaelmas and Lent term. However, even if assessment is in principle compulsory, not all the teaching assistants give a feedback to the students. Attrition increases during the academic year: in Michaelmas term, participation is missing for 16.75%

[17] For reference: https://www.lse.ac.uk/social-policy/Current-Students/BScProgrammesMarkingframe.pdf

[18] For reference: https://info.lse.ac.uk/Assessment-Toolkit/Marking-and-moderation, https://info.lse.ac.uk/current-students/challenging-results-and-appeals

[19] With the only exception of the Bachelor of Laws in which students progress to the second year if they have passed all four credits

of course-year-class group level observations, while 40.68 % are missing in Lent term. For this reason, the analysis with participation grades as outcome variable is restricted to Michaelmas term. Missing participation information are due to teaching assistants providing no information for everybody in the class. In Appendix A I report the results of a test that missing participation grades are independent on individual characteristics or the composition of the class group. Thus, given the sample restriction, participation grades are able to shed light on the dynamics that characterize classes in the first half of the academic year. While on the one hand this can represent a limitation since exam grades are the result of students' effort during the whole academic year, on the other hand we can argue that first term measures are more indicative of how students' behavior is affected by stereotypical distortions and priors, since this is the first time students meet and interact with each other.

The sample for the analysis on class dynamics consists of students for which I can observe a participation grade in at least two class groups: 44.771 course-year-class group level observations, corresponding to information on 13.424 students (93.8% of the sample)

Table 1 shows that the average participation grade received by students is 2.04, with a between students standard deviation of 0.85, and a within student standard deviation of 0.58. Figure 3 shows a histogram of the within student participation gap. I define the participation gap as the difference between student i's highest and lowest grades across all the seminars he/she attended during Michaelmas term of the first year. The variation is significant since the difference between the highest and the lowest participation grade for the median student is 1, and 30% of students experience a difference of at least 2 grades between the highest and the lowest participation grade.

3.3 Additional key variables

Ex-ante measure of ability

I construct a measure of individual ability at entry based on the information that students provide to the School during the admission process. The School bases its admission decisions on personal statement, academic achievement, and references. Every program has minimum entry requirements, which are publicly available and clearly stated in the guidelines. They are based on A-level qualifications or equivalents. The A Level is a subject-based qualification conferred as part of the General Certificate of Education, as well as a school leaving qualification offered by the educational bodies in the United Kingdom and the educational authorities of British Crown dependencies to students completing secondary or pre-university education. Students typically study three A levels in different subjects, and the majority of universities set their entry requirements according to this measure. A levels are graded on a scale of A*/A/B/C/D/E. Each A-level grade is worth 30 QCA (Qualifications and Curriculum Authority) points.

Following Campbell et al. (2019), I construct a measure of individual ability at entry based on the best three exam results among the A-level qualification scores students declared when applying to LSE. Some students take courses that are equivalents to A-Levels. In these cases I calculate their A-Level equivalence scores based on the university conversion tables for foreign students[20].

Using this criterion, I am able to construct a qualification score for a total of 9.449 students, 90.57% of

[20]Different ways to construct the qualification score are discussed in appendix B.2.

the students enrolled in undergraduate programs in LSE between academic years 2011/12 and 20117/18[21]. Figure 4 displays the resulting qualification score. Due to the high demand for places, the mean qualification score of students enrolled in undergraduate programs at LSE is high: 503.9 QCA points (which corresponds to a score in between a person that got two A-levels with A* and one A-level with A, and a person that has one A-level with A* and two A-levels with A) with a standard deviation of 34.26 (which corresponds to one A-level grade, i.e. 30 QCA points).

Information on previously attended schools

The university administrative records contain information on the school students attended before enrolling in LSE. I matched these data with the UK Government registers of schools and colleges. These register contains information on schools and colleges in England, Wales, Scotland, Northern Ireland, or overseas establishments of UK institutions. I managed to recover information on the characteristics of the previous school of enrolment for 63% of the students in my sample.

Global Gender Gap Index (World Economic Forum)

The university administrative records contain information on the country of origin of students enrolled in undergraduate programs. I match the information on the student's country of origin with information on the World Economic Forum Overall Global Gender Gap Index for the country between 2006 and 2018[22]. The Global Gender Gap Index measures the level of gender equality in the country for 130 countries around the world. It ranks countries according to calculated gender gaps between women and men in four key areas: health and survival probability, education attainment, economic participation and opportunities, and political empowerment and representation to gauge the state of gender equality in a country. I am able to match the student's country of origin with the Global Gender Gap Index for the country for 92.44% of students in the sample.

4 Empirical Strategy

The only two criteria used to allocate students to classes for each course are scheduling constraints and limits on the number of consecutive hours of teaching, thus I am going to argue that class allocation for each course is as good as random, conditional on the combination of courses that students attend during the year. This exogenous class allocation will allow me to identify the effect of being in a minority on students' performance. I am going to leverage this identifications strategy to assess how selection into fields interact with the effect of being in a minority. To do so, I am going to exploit three key features of the environment: (i) LSE offers a very diverse portfolio of programs, which allows me to define a measure of stereotypical selection, (ii) class allocation is orthogonal to the department of enrollment of the student and (iii) students attend several courses outside their department of enrollment, which combined provide me with substantial common support in class composition and within student variation in class composition across programs of enrollment.

[21] I don't have admission information for students who enrolled in LSE before 2011

[22] Source: The World Bank data

4.1 Causal effect of being in a numerical minority

I estimate the causal effect of being in a minority by comparing the performance of the same student across the courses c that he/she attends in the same academic year a, where he/she has been assign to a class g with exogenous peers' characteristics.

$$y_{iacg} = \alpha_{ac} + \alpha_i + \beta \times SLM_{iacg} + \epsilon_{iacg} \tag{1}$$

where the independent variable y_{iacg} is students' course grades. SLM_{iacg} is the *share of students like me*, i.e. the share of same gender classmates: the share of females for women and the share of males for men. Thus β captures the effect of an increase in the share of same gender students in the class[23].

Course $\times$ year fixed effects (α_{acg}) are essential for obtaining exogenous variation in peer characteristics as I exploit the exogenous variation in class composition within each course that is obtained by allocating the students that attend the course to different classes (small groups of maximum 15-20 students) in a way that is orthogonal to their individual characteristics. Course $\times$ year fixed effects also control for all the characteristics that make a course different from another and might affect the performance of students in that course. For instance, statistics and math courses might be less conducive to interactions and discussions with respect to courses as history or international relations, and thus class composition might matter less. Moreover, courses have different types of assessment or different levels of difficulty. Several courses are common to different programs of enrolment, thus course fixed effects capture also differences in overall course gender composition, which would lead to a systematically different probability of being exposed to female peers for the same student across courses. For example, John is a student who is enrolled in a BSc in Economics. John attends a Math course, MA100, and an Economics course, EC100. Since the Economics course is compulsory also for students enrolled in BSc in Accounting, Government, Economic History, etc., economics will be attended by a higher number of women with respect to math. Thus John will be more likely to have more women in class in Economics rather than in Math. However, given the overall course composition, the share of females in each class within the course is as good as random since class allocation is orthogonal to individual characteristics. Thus, the share of females that John is exposed to is exogenous once we control for course fixed effects. Course fixed effects also control for other potential characteristics that might make students attending different courses different and that can be correlated with the overall course gender composition and might affect performance in the course.

I also control for individual fixed effects α_i, which capture students' course selection and scheduling constraints, accounting for the fact that students who are enrolled in the same program and/or make the same constrained choices are more likely to be assigned to the same class, since they share similar schedules for lectures. Furthermore, individual fixed effects control for the fact that students enrolled in different programs have a different probability of being exposed to women due to the differences in the overall gender composition of students enrolled in each program and in the combination of courses that are part of each program. They also control for all those individual characteristics that are student-specific and common across courses, and are related to program or course selection (e.g. the fact that student A is a certain type of student, interested in economics and passionate about history, who enrolls in Economics,

[23]The approach follows the empirical strategy of Anelli and Peri (2017), Feld and Zölitz (2017), and Brenøe and Zölitz (2020).

and as a consequence attends EC100, MA100, ST102, and chooses EH101). Lastly, by controlling for student fixed effects, I am controlling for the average share of same gender classmates that the student experiences in the courses he attends solving the the problem of considering classes as independent from each other, even though we observe the same student in different classes. This assumption becomes important in the moment in which there are spillovers. In this case, the performance of a student in a course is not only affected by the peers he/she is exposed to in the class for that particular course, but also by what happens in the classes of the other courses he/she attends. I discuss the extent to which spillovers affect my estimates in Section 5.2.

Specification 1 allows me to identify the effect of being in a minority on students' performance β, exploiting the variation from the average share of same gender classmates that the student experiences in the courses he/she attends (due to the program of enrollment), where he/she has been assigned to a class g with exogenous classmates' characteristics. The underlying assumptions are that (i) conditional on attending a course, students are assigned to classes in a way that is orthogonal to their individual characteristics, conditional on scheduling constraints (student fixed effects). (ii) There are no factors that are correlated with class gender composition that differentially affect men and women. In the next two sections I will provide evidence towards the validity of these assumptions.

I am not worried about the results being driven by discrimination, or differential treatment of minority students during the examination process since grading of exams, essays, group projects, etc. is characterized by blind marking[24].

Under the assumption of no zero-sum game, I can identify the effect of being in a minority on the performance of men and women separately. The assumption of non-zero sum game doesn't seem unreasonable in the LSE setting. Marking is based on absolute grading, so grades are based on the performance of each student in the exam, without any ranking of students[25].

4.2 Selection into fields

In order to assess the impact of selection into fields on the effect of being in a minority on performance, I define *"stereotypical selection"* as the choice of a student who is enrolled in a program in line with gender norms and stereotypes. As a proxy for stereotypical selection, I use the average share of women and men enrolled in undergraduate programs in each department over the period 2008-2017. A man's choice will be considered as in line with stereotypes and gender norms if he is enrolled in a program that belongs to majority male departments, e.g. Mathematics, Statistics, Economics, Finance, while against stereotypes and gender norms if he is enrolled in a department such as Anthropology and Sociology, which are majority female departments. In the same way, a woman level of stereotypical selection increases the higher is the share of women enrolled in her program's department between 2008-2017. A graphical description of the measure of stereotypical selection used can be found in Figure 9.

[24]Any piece of assessment is marked by a first marker and a second marker, in most of the cases without seeing the first marker's grades/comments. Where there are any differences in mark, the two markers discuss and agree the final mark. The process is completely blind: students do not indicate their names in the exams, but only a candidate number which is secret to examiners and only known to the student.

[25]Regarding participation in class, grades are based on class interactions over a 10 weeks period. A zero-sum game assumption would require that each week 50 minutes class is fully saturated, i.e. students are racing to answer or ask questions, so that each student's intervention will take from other students' participation time. Although this is possible, from personal experience and consultations with teaching staff, this is quite unlikely, especially in first year courses.

The share of female as indicator of friendliness/stereotypes of the sector or field has been extensively used in the literature (for example Hebert 2020; Bostwick and Weinberg 2021; Kugler et al. 2021). The average share of women enrolled in undergraduate programs in the department over the period 2008-2017 can be considered a good measure of the extent to which student's choices are in line (against) stereotypes and gender norms for four reasons: (i) the distribution of women and men across departments barely changed between 2008 and 2017 (Figures A1); (ii) it closely mirrors the distribution of men and women across subjects in Higher Education across the overall UK university system (Figure A2); (iii) it is the result of men and women applying to systematically different programs, rather than the School's selection process (Figure A4) ; (iv) it reflects stereotypes regarding group-specific skills and roles. In line with lab and field experiments in the academic setting documenting a widespread belief that women are worse than men in mathematics and science while being better at reading (Carlana 2019; Reuben et al. 2014; ellemers2018; Lane 2012)), majority male departments are primarily characterized by Math-intensive programs, while majority female departments are characterized by programs related to Humanities[26].

I exploit two definitions of stereotypical selection based on the average share of men and women enrolled in each department over the period 2008-2017: a continuous measure and a categorical measure. Exploiting the continuous measure, I estimate the following specification:

$$y_{iacg} = \alpha_{ac} + \alpha_i + \beta_1 \times SLM_{iacg} + \beta_2 \times SLM_{iacg} \times STS_i + \epsilon_{iacg} \tag{2}$$

where SLM_{iacg} is the *share of students like me*, i.e. the share of same gender classmates that student i experiences in class g, course c and academic year a, and STS_i stands for *stereotypical selection*, measured as the average share of same gender students in student i's department of enrolment across academic years 2008-2017. The standard errors are clustered at the class level. β_2 provides us with an indication of the extent to which being surrounded by same gender classmates has a different effect on performance for students who made choices that are more in line with stereotypes regarding gender specific skills and norms with respect to students who made a choice against stereotypes. A positive coefficient implies that the performance of students who are enrolled in departments that are stereotypically-congruent (women in Humanities and men in Mathematics) is more sensitive to the composition of the class with respect to students who are enrolled in departments that are stereotypically associated with the opposite gender. A negative coefficient, on the other hand, implies that those whose performance is more affected by being in a minority are those students who are enrolled in departments stereotypically associated to the opposite gender (women in Mathematics and men in Humanities).

The continuous measure of stereotypical selection relies on an assumption of linearity in the effect of selection into fields on the effect of class composition on performance. In order to relax this assumption, I perform a second analysis, employing a categorical measure of stereotypical selection, where I define students who make stereotypical and counter-stereotypical choices using a definition that becomes gradually more extreme. I start by considering as students making stereotypical choices, students who are enrolled in the top five departments with the highest average share of same gender students, while students who are enrolled in the five departments with the lowest share of same gender students as students who made

[26]The relationship between stereotypes and race and gender segregation in the workforce has been documented in psychology(e.g. He et al. 2019; Garg et al. 2018).

a choice not in line with stereotypes regarding gender roles and skills. I then replicate the same analysis by defining stereotypical and counter stereotypical choices by considering the top and bottom 2 and 3 departments in terms of share of same gender students among undergraduates [27]. I estimate the following specification:

$$y_{iacg} = \alpha_{ac} + \alpha_i + \beta_c \times SLM_{iacg} + \beta_n \times SLM_{iacg} \times NF_i + \beta_s \times SLM_{iacg} \times SF_i + \epsilon_{iacg} \tag{3}$$

where the *share of students like me* (SLM_{iacg}) is the share of same gender classmates that student i experiences in class g, course c and academic year a, and *stereotypical fields* (SF_i) and *neutral fields* (NF_i) and are a dummy equal to one if the student is enrolled in the top 2,3,and 5 departments with the highest share of same gender students among undergraduates, and a dummy equal to one for students who are not enrolled in either top 2,3, and 5 nor bottom 2,3, and 5 departments respectively. This way, β_c provides us with an estimate of the effect of a change in the share of same gender classmates for students enrolled in counter-stereotypical departments, while β_n and β_s provide us with a measure of the extent to which the effect of a change in gender composition of classmates differs if a student is enrolled in a "neutral" or stereotypical department. By estimating the effect with a progressively more restrictive measure of stereotypical and counter-stereotypical choices, this measure allows me to capture potential non-linearities in the effect. The standard errors are clustered at the class level.

4.3 Variation in class composition

Figure 5 and Table 3 present descriptive evidence on the variation in share of the same gender students in class. Figure 5 shows the variation in the share of same gender classmates and the within student variation in the share of same gender classmates. The latter is obtained by taking the difference between the highest and lowest share of same gender classmates for each student.

The average share of same gender students in the classroom is 0.561, with a standard deviation of 0.162. In Table 3 we can see that the within course variation in the share of same gender classmates, indicated by the standard deviation of the residualized share of females after controlling for course fixed effects, is equal to 0.158, i.e. 97% of the variation in the overall share of same gender classmates, indicating that the most of the variation is across classes within courses. This is primarily due to the fact that first-year courses are large, with an average number of classes for each course equal to 9.

Lastly, the within student standard deviation in the share of same gender classmates is 0.112, thus controlling for course and students fixed effects, the variation within students I exploit represents 68.75% of the initial raw variation between students[28]. The within student variation I exploit for the analysis is sizable: on average students experience a variation in the share of same gender classmates equal to 26%, with a standard deviation of 12%.

The impact of selection into majors on the effect of being in a minority on performance can be estimated thanks to the fact that the allocation of students to classes is independent on the program of enrolment. As a matter of fact, once student enroll into a program, they attend the courses that are scheduled for

[27] When I consider top and bottom 5 departments, I am considering the top and bottom tercile of departments given that the total number of departments in 16.

[28] Following Olivetti et al. (2020)

their first year, and in each of them, they are assigned to classes considering only scheduling constraints. Furthermore, during the first year, students attend common courses, often outside their department of enrolment. This implies that they can be assigned to classes with students that do not belong to their program, as it can be seen from Table 2, which shows that the average share of same program classmates is equal to 0.49. Lastly, given that first-year courses are large and allocation of students to classes is as good as random conditional on scheduling constraints, students who are in the same class in a course are not necessarily allocated to the same class in other courses. Thus I can observe a variation in class composition for each student that goes beyond the variation within the program of enrollment, allowing me to exploit a substantial common support in class composition and within student variation in class composition across programs of enrollment.

Figure 10 and Figure 11 display the within student variation in the share of same gender students in the class and the share of same gender students in the class for students enrolled in stereotypical and counter-stereotypical departments. The within student variation in the share of same gender students is obtained by taking the difference between student i's highest and lowest share of same gender students across all the classes attended during the first year. We can see that both the within student variation in the share of same gender classmates and the share of same gender classmates for students enrolled in different types of departments share significant common support[29].

4.4 Validity of the identification strategy

Specification 1 allows me to identify the effect of being in a minority on students' performance under two assumptions: (i) students are assigned to classes within a course in a way that is orthogonal to their individual characteristics, conditional on scheduling constraints (student fixed effects). (ii) there are no factors that are correlated with class gender composition that differentially affect men and women.

I perform two checks to test that students are not systematically assigned to particular classes. I test that class group allocation does not predict students' individual characteristics. Furthermore, I test that being a woman does not predict the share of same gender classmates. Second, I perform a series of balance checks to provide evidence that the variation in the share of same gender classmates is not related to the variation in predetermined student characteristics. Lastly, I test that selection into courses does not systematically differ for men and women by performing a permutation test where I simulate 1000 unconstrained random allocations, and I test that the distribution of the course variation in the observed share of female students across classes is not statistically different from the distribution obtained with the simulated unconstrained random allocation.

Test 1: Class group allocation does not predict students' characteristics

Following Feld and Zölitz (2017) and Braga et al. (2016), I test that class group allocation does not predict students' characteristics, to make sure that students with different characteristics are not systematically

[29] In section 5.2, I provide evidence that the results are not driven by differences in support across different types of departments.

assigned to particular classes. I follow the specification below:

$$y_{ig} = \sum_{g=1}^{n_g} \alpha_g \times G_{i,g} + \sum_{p=1}^{n_a} \gamma_p \times PC_{i,p} + \epsilon_{ig},\ \forall a, c \tag{4}$$

where the dependent variables are pre-determined individual characteristics of student i enrolled in course c in year t allocated to class g: gender, ethnicity, age at enrollment. The explanatory variables are dummies for each class group g in course c in academic year a. The dummy for class group g is equal to one if student i is assigned to class group g and zero otherwise ($G_{gi} = \mathbb{1}(i\text{'s group}=g)$). I run one regression for each combination of course $c \times$ academic year a to cover all the courses that first year undergraduate students attend in the academic years in sample [30]. The sample for each regression consists in all the students enrolled in course c in the same academic year a that didn't change class during Michaelmas term [31]. Furthermore, the sample is restricted to all the courses that have at least 2 class groups. The allocation is constrained by the fact that students that attend more than one course in the same term cannot attend two classes at the same time, so I control for a dummy for each course that the student takes during the academic year ($\sum_{p=1}^{n_a} PC_{i,p}$).

I test that class dummies are jointly significantly different from zero:

$$H_0 : \alpha_g = 0,\ \forall g = \{1; n_c\}$$

i.e. that students who take the same combination of courses are allocated to classes independently from their individual characteristics. According to Murdoch et al. (2008), if class allocation is random, the P-values of the test across all courses and years should uniformly distributed with mean 0.5. In this case, courses have different sizes, the number of classes is not fixed, and class belonging to the same course might be of different size. In order to check that also in this case P-values converge to a uniform distribution with mean 0.5, I Perform a Monte-Carlo simulation where I randomly allocate the students enrolled in first year courses, that didn't change class group during the term, to class groups 1000 times, under the assumptions that course size, number of seminars and class size is equal to the observed one. Figure A5 shows the result of the simulation. Indeed p-values converge to a uniform distribution with mean 0.5. This will represent the reference point against which I will check under which conditions the observed allocation of students can be considered as good as random.

Figure 6 shows the p-values obtained from the tests of joint significance of the class dummies for the observed sample. For the regressions regarding gender, age at entry, we can see that conditional on clashes, less or equal to 5% of tests display a p-value smaller than 0.05, and less than 10% of tests display a p-value smaller than 0.10, in line with what we would obtain if students were randomly allocated to classes. Regarding ethnicity, I aggregated Chinese, Indian and Other Asians in a unique category called Asian in order to have a big enough sample to be able to perform a meaningful test[32], and I test that

[30] All first year courses plus 15 second year courses, among which 7 are language courses. Students can choose second year courses as elective courses. These correspond to 0.57% of the observations

[31] I am excluding students that changed class group since I can't observe their initial allocation. Tests of randomness of the decision to change class can be found in the appendix.

[32] We need a big enough sample of students that share characteristic t to be able to test if class allocation is as good as random. As a matter of fact, if the number of students is too small, even if allocated randomly, class allocation might still predict students' characteristics. Let me consider the extreme case in which there is only one Chinese student enrolled in

being White and being Asian cannot be predicted by class group allocation. Regarding the White dummy, slightly more than 5% of tests display a p-value smaller than 0.05, but less than 10% of tests display a p-value smaller than 0.10. Regarding the Asian dummy, slightly less than 5% of tests display a p-value smaller than 0.05, and less than 10% of tests display a p-value smaller than 0.10. More details on the randomization tests and the simulation performed can be found in appendix.

Test 2: Being a woman does not predict the share of same gender classmates

Following Feld and Zölitz (2017), Brenøe and Zölitz (2020), and Guryan et al. (2009), I test that female (male) students are not systematically assigned to classes where there are more female (male) students, conditional on having a certain share of same gender peers among the students enrolled in a course. The specification used is the following:

$$SGP_{-i,acg} = \alpha_{ca} + \beta \times F_i + \gamma \times SGP_{-i,ca} + \sum_{a=1}^{n_a} \sum_{p=1}^{n_{p,a}} \delta_{p,a} \times PC_{i,ap} + \epsilon_{iacg} \tag{5}$$

For each course c in academic year a I test that being a woman (F_i) does not predict the gender composition of peers in the class g (SGP_{iacg}). I control for the share of same gender peers enrolled in the course ($SGP_{-i,ca}$) to control for the fact that if there are more women than men enrolled in the course, the probability of being in a class group with a student of the same gender will be higher for female students than for male students. Let's assume that there are 7 females and 4 males enrolled in a course. The share of same gender peers in the course for female students will be 6/10, while for male students will be 4/10. Thus the probability for a women to be assigned to a class group with another woman is higher with respect than the probability that a man will be assigned to a class with another man. Lastly, I control for a series of dummies that are equal to one for all the students that attend the course in the same year, and zero otherwise ($\sum_{a=1}^{n_a} \sum_{p=1}^{n_{p,a}} PC_{i,ap}$). This is because the allocation is constrained by the fact that students attend more than one course in the same term and they cannot attend two classes at the same time. I perform this test for all the courses where there are at least two classes and standard errors are clustered at the class level.

Table 4 reports the result of the above regression. Students are not assigned to class group systematically based on their sex. As a matter of fact, women do not have a higher probability to be in class with same gender peers than men.

Test3 : Balance checks

The tests presented above provide evidence that students are as good as randomly allocated to class groups, conditional on their course choices. In Table 5, I produce an array of "balancing tests" to assess whether the variation in the share of same gender students in the class a student is allocated to is related to the variation in a number of predetermined student characteristics. I do so by testing that the share of females in the class is not systematically correlated with ethnicity, previous school characteristics, age at entry, and qualification score at entry. As shown in the table, only one of the estimated correlations

the course, class assignment will predict students' ethnicity even if the Chinese student is allocated randomly to the class.

appear to be significantly different from zero at 10% level of significance for the sample of analysis. This represents 7% of the tests performed. As expected when running a large number of regressions testing multiple hypotheses, some coefficients are statistically significant. In the absence of a systematic relation between the share of female classmates and other individual characteristics, we would expect 10% of coefficients to be statistically significant at the 10% significance level, 5% at the 5% level, and 1% at the 1% level simply as a result of chance. This is consistent with our results, providing supportive evidence that the estimated effects are due to a change in class group composition along gender lines, rather than other unobserved factors that are correlated with gender and student outcomes and that could confound our estimates.

Test 4: Systematic gender differences in selection into courses

Following Lavy and Schlosser (2011), I perform a permutation test. I Perform a Monte-Carlo simulation where I randomly allocate the students enrolled in first year courses, that didn't change class during the term, to classes 1000 times, under the assumptions that course size, number of seminars and class size is equal to the observed one. This is an unconstrained random allocation, that does not take into account the allocation constraint deriving from the fact that students cannot be allocated to certain classes due to clashes with other courses they attend during the same academic year. As such, this represents a test for the assumption that students of different gender do not select systematically different courses among the first year optional courses.

For each course c in academic year a, I compute within course variation in the share of female students (WCV_{gca}) across classes for both the observed sample allocation and the 1000 simulated random allocations:

$$WCV_{gca} = \textit{Class share of female students}_{gca} - \textit{Course share of female students}_{ca},\ \forall g, c, a, t$$

This is the variation in share of female students that I exploit to identify the effect of class composition on students' performance. Let me define $Diff_o$ the statistics for the observed sample, and $Diff_s$, the statistics for the simulated sample. I perform the Two-sample Kolmogorov-Smirnov test to test the null hypothesis that the observed distribution of the statistics $Diff_o$ and the distribution of the statistics $Diff_s$ for the randomly allocated simulated samples are not significantly different

$$Ho : Diff_o = Diff_s$$

The results of the test are shown in Figure 7. As we can see, we fail to reject the null hypothesis that the distribution of the observed statistics and the distribution of the simulated statistics are different at every significance level (1, 5, and 10%).

Alternatively, I perform the Two-sample Kolmogorov-Smirnov test to test the null hypothesis that the observed distribution of the within course standard deviation in the share of females and the randomly simulated distribution are not significantly different. The results can be found in 8. They confirm that the observed variation in the within course variation in the proportion of females across classes resembles the variation that would result if the gender composition of each class was randomly generated.

5 Results

5.1 Effect of stereotypical selection

Table 6 displays the results of Specification 2 in (Column 1) and Specification 3 in Columns (2)-(4). The coefficient of *Share of students like me* is negative and significant, while the coefficient of the interaction between the share of same gender students and the measure of conformism to gender roles and stereotypes is positive and significant in all specifications. This indicates that selection against stereotypes moderates the importance of being in a minority in shaping students' performance. The students whose performance is negatively affected by being in a minority are students who chose to enrol in programs in line with the stereotypes regarding gender skills and roles, i.e. women in Humanities and men in Math and Science-intensive fields. On the other hand, students who selected against stereotypes do not suffer from being in a minority, but if anything perform better when there are few students similar to them in the class (this can be seen from the negative and significant coefficient for *Share of students like me*). Interestingly, the performance of students who are enrolled in departments with a balanced gender ratio is not affected by class composition. This hints towards the fact that social identity considerations and preferences for the composition of the environment affect students way before they sit in the classroom. Since they are internalized in decisions regarding the field of occupation, they impact students enrolled in different departments to a different extent.

In line with the estimated effect using the continuous definition, the effect of an increase in the share of students like me decreases when we include in the definition of counter-stereotypical choice departments with a higher share of same gender students enrolled in the department. The same is true for the effect of an increase in the share of same gender students for students enrolled in stereotypical departments, which decreases when we include in the definition of stereotypical choice departments with a lower share of same gender students enrolled in the department.

In terms of magnitude of the effect, the paper estimates that for students who are enrolled in stereotypical departments, such as a man who is enrolled in Economics, Finance or Mathematics, and a woman enrolled in Anthropology, Sociology or International Relations, a 10% increase in the share of same gender classmates increases course grades by 0.325 points, equivalent to 2.0% of a standard deviation (Column 3). On the other hand, for a man enrolled in Anthropology, Sociology or International Relations and a woman enrolled in Mathematics, Economics and Finance, a 10% increase in the share of same gender classmates decreases final course grades by 0.288 points, i.e. 1.76% of a standard deviation (Column 3).

Table 7 provides evidence of the effect at different points of the grade distribution. I am defining a series of dummies that are equal to one if grades are greater or equal to 40, 50, 60, and 70, respectively. These represent important thresholds for students. A student is deemed to have failed a course if his grade is below 40. The student has achieved a third class honor if the grade is between 40 and 49, a lower second class honor if the grade is between 50 and 59, an upper second class honor if the grade is between 60 and 69 and a first class honor if the grade is 70 or above. Lastly, I define a dummy equal to one if students drop-out from the course and zero otherwise. Being in a minority does not affect the probability of dropping out from the course. The effect on average grades is driven by being in a minority affecting performance in the course, with the effect increasing at the top the grades distribution.

5.2 Is this due to stereotypical selection?

In the previous section, I provided evidence that students who are enrolled in stereotypical fields are negatively affected by being in a minority in the class, while this is not the case for other students. In particular, students who are enrolled in counter-stereotypical departments appear to benefit from being surrounded by students with different characteristics (in some specifications). In this subsection, I will provide evidence that the patterns observed are due to the effect of selection into fields, and in particular that whether students made a stereotypical or counter-stereotypical selection when choosing their major significantly moderates the effect of being in a minority on performance. In order to do so, I start by providing evidence that the results are not driven by differences in support in the share of same gender classmates and within student variation in the share of same gender classmates. Second, I show that the results are not driven by differences in teaching assistants or peers' characteristics for students enrolled in different departments. Third, I test whether the results could be explained by spillovers across courses or mechanical effects. Lastly, I provide evidence that the heterogeneity in effect for students enrolled in different departments is related to patterns of selections linked to stereotypes regarding gender skills and norms.

Differences in support of share of same gender classmates

In Section 4.2, I provided evidence of significant common support in the share of same gender classmates and within student variation in the share of same gender classmates across students enrolled in different departments. Despite the significant common support, the share of same gender classmates variation is different for students enrolled in different departments, and in particular it is higher for students who are enrolled in stereotypical departments. This could be able to explain the different effects of class composition estimated for students enrolled in different departments if the effect of being in a minority is non linear. Figure A6 shows that there is no evidence of non-monotonicity in the effect of a change in the share of same gender classmates. The estimates of a local polynomial regression are plotted for each value of the share of same gender classmates[33]. This provide evidence in support to the fact that the results cannot be explained by potential differences in the effect of being in a minority across departments due to students being exposed to a different variation in the share of same gender classmates or a different overall share of same gender students.

Difference in teachers and peers' characteristics across departments

Students enrolled in different departments might be exposed to different teachers or peers with different characteristics. In particular, as there are more female students in majority-female departments, there might be more female teachers in these departments. Furthermore, academic regulations are different across programs: the number of compulsory courses are different and the same is true for courses that students can attend outside the program or department of enrollment. Furthermore, math-intensive departments might attract students with different characteristics with respect to disciplines that are related to Humanities. In order to explore if this might be affecting my results, I estimate Specifications 2

[33] The Figure displays residual course grades and share of same gender classmates obtained by regressing them on course $\times$ year fixed effects and student fixed effects as in Specification 1

and 3 controlling for teaching assistant fixed effects, share of same ethnicity and same background students (defined as students coming from State funded or Independent schools), share of same program students, and average peers ability, defined based on qualification scores at entry. The results are robust to the introduction of these controls.

Spillovers across courses and mechanical effects

The estimated effects could represent an overestimation in the presence of spillovers across courses. For instance, we can hypothesise the case in which being in a minority in a course induces students to perform worse in the course, but also to perform better in other courses because there are more students of their gender in the class, despite the share being low. This could rationalize the stronger effect for students enrolled in stereotypical departments considering that the within-student variation in the share of same gender classmates for these students is greater than the within-student variation for students enrolled in counter-stereotypical departments.

I can test if this is the case by re-estimating the effects by exploiting the within course variation in the share of same gender students (not including student fixed effects). This allows me to estimate the effect of being in a minority by comparing the performance of students who are enrolled in the same course, but have been as good as randomly assigned to classes with a different share of same gender classmates. This identification strategy exploits the exogenous allocation of students across classes within the same course conditional on scheduling constraints (I provide evidence of the validity of this identification strategy in the Empirical Strategy section). Under the assumption that assignment to classes is independent across courses conditional on scheduling constraints, i.e. students who are assigned to a class with a low share of same gender classmates in a course are not systematically assigned to classes with a higher share of same gender students in other courses, the effect estimated by exploiting the within course variation represents a counterfactual to assess the extent to which spillovers across courses induce to overestimate the effect when exploiting the within-student variation.

On the other hand, spillovers across courses could also induce us to overestimate the effects when exploiting the within-course variation. For instance, if being in a minority in the Economics course has such a demotivating effect that students perform worse not only in Economics, but also in the other courses they attend, not controlling for student fixed effects would lead me to overestimating the effect. Table A2 displays the results of the two specifications. Column (1) displays the result of Specification 2, where I exploit the within-student variation, while Columns (3) and (4) display the results obtained by exploiting the within-course variation. Column (4) exploits one observation per student, which controls for the fact that observations for the same student in different courses are not independent. We can see that the estimates exploiting the within student-variation are smaller in magnitude with respect to the estimated effects obtained by exploiting the within-course variation, confirming that spillover effects are not leading me to overestimate the impact of stereotypical selection on the minority effect.

Lastly, Column (2) displays the result of Specification 2 without controlling for course $\times$ year fixed effects, confirming that the results are not driven by mechanical effects arising because, controlling for course fixed effects, I am forcing the average grades in the course to be equal to 0.

Evidence on stereotypical selection

To support the hypothesis that the results are due to *stereotypical* selection, and in particular whether students made a stereotypical or counter-stereotypical selection when choosing their major, I provide three pieces of evidence.

First, I perform a placebo test by estimating specifications 2 and 3 controlling for the interaction between the measure of stereotypical selection and the share of same ethnicity classmates, share of same program classmates, share of same background classmates and peers' average ability at entry. Table A3 shows that the results are robust to the introduction of these controls. Furthermore, none of the coefficients of the interaction between the measure of stereotypical selection and other peers' characteristics are significant, indicating that the coefficient of stereotypical selection is capturing the heterogeneity in the effect of being in a minority caused by students who selected into different fields having different characteristics along gender specific dimensions.

Second, Table A4 shows that the results are robust to other proxies of stereotypical selection related to gender stereotypes: the share of women and men among applicants to undergraduate programs at LSE, the share of men and women enrolled in different subjects in higher education in UK, and the share of men and women among the staff working in each subject in higher education in UK[34].

Lastly, Table A6 provides suggestive evidence that stereotypes play a role. I exploit the Global Gender Gap Index (GGI) of the country of origin of the student as a proxy for the strengths of gender roles and norms for the student. The GGI is a measure created by the World Economic Forum to measure the level of gender equality in the country for 130 countries around the world. It ranks countries according to calculated gender gaps between women and men in four key areas: health and survival probability, education attainment, economic participation and opportunities,and political empowerment and representation. Guiso et al. (2008) provide evidence that country's with lower GGI have bigger math gender gaps in favor to men, while countries with high GGI have bigger reading gender gaps in favor to women. As such, it can provide us with suggestive evidence towards the importance of stereotypes regarding gender skills and roles and stereotypical selection in explaining the effects. Table A6 displays the estimates of Specification 1 where I interact the share of same gender classmates with the GGI of each student's country of origin. I split students in three categories based on the terciles of the GGI of students' countries of origin. A higher tercile implies a higher GGI, indicating that the student comes from a country with more equal gender norms. I estimate this specification for the sample of students who are enrolled in counter-stereotypical fields (Column 1) and for the sample of students who are enrolled in stereotypical departments (Column 2)[35]. Focusing on students who are enrolled in stereotypical departments, those who benefit the most from being surrounded by same gender classmates are students who come from countries with low GGI, i.e. students who come from countries with more unequal gender roles. However, students coming from countries with low GGI are those who benefit the most from being in a minority if they made a counter-stereotypical selection. This provides suggestive evidence that selection into fields in a way that is related to stereotypes regarding gender roles and norms plays a role in moderating the effect of being in a minority on performance.

[34]details regarding the measures used can be found in Table A5.

[35]I am using here the most conservative definition of stereotypical and counter-stereotypical choices: top and bottom 5 departments. This allows me to have a big enough sample size to deter significant effects.

5.3 Gender differences in the effect of stereotypical selection

Is the effect of stereotypical selection different for men and women? In order to give an answer to this question I estimate Specifications 2 and 3 interacting the share of students like me and the share of students like me × stereotypical selection with a dummy equal to one if the student is a woman and a dummy equal to one if the student is a man. Table 8 displays the results. We can see in Panel A that the coefficient of the interaction between the Share of same gender classmates and stereotypical selection is positive and significant for men, indicating that men who selected in line with stereotypes and gender norms benefit more from having classmates of their own gender with respect to men who selected against stereotypes. The effect for women is smaller in magnitude and not statistically significant. However, this does not mean that we don't see the same pattern of selection against stereotypes mitigating the effect of being in a minority for women. As a matter of fact, Panel B shows that when we define the measure of stereotypical selection to include only departments that are very male and female dominated (bottom and top 2 and 3) the coefficients become significant also for women. Furthermore, the coefficient is not statistically significantly different from the effect estimated for men using the same definition of stereotypical selection. On the other hand, the effects estimated for men and women become statistically significantly different when we consider the definition of stereotypical selection that includes bottom and top five departments. This indicates that both men and women are affected by the composition of the environment, but men's performance is affected more with respect to women's performance since the effect is significant and strong also for students who didn't enroll in extreme departments in terms of gender composition.

Panel B also provides us with a quantifiable estimate for the effect of being in a minority on performance for men and women who are enrolled in female fields versus male fields. Let's consider Column 3, for example. For men who are enrolled in male fields (stereotypical selection), a 10% increase in the share of men increases course grades by 0.376 points, i.e. 2.3% of a standard deviation in course grades. On the other hand, women who are enrolled in male fields (counter-stereotypical selection), do not suffer from being surrounded by men. As a matter of fact, a 10% increase in the share of women (equivalent to a 10% increase in the share of men) decreases course grades by 0.234 points, i.e. 1.43% of a standard deviation in course grades. In a mirroring way, for women who are enrolled in female fields (stereotypical selection), a 10% increase in the share of women increases course grades by 0.217 points, i.e. 1.33% of a standard deviation in course grades. On the other hand, men who are enrolled in female fields (counter-stereotypical selection), do not suffer from being surrounded by women, as a 10% increase in the share of men (equivalent to a 10% increase in the share of women) decreases course grades by 0.435 points, i.e. 2.67% of a standard deviation in course grades. This implies that being in a minority can explain the performance gaps we observe across fields, but the effect is due to the over-represented group benefiting from being in a majority, not the under-represented group performing worse because in a minority.

6 Mechanisms

How does stereotypical selection intervene to moderate the effect of being in a minority on performance?

Being in a minority affects students' performance via two channels. Studies in psychology and sociology show that minority status can affect performance by reducing opportunities for social interactions and mutual academic assistance, which are factors directly related to persistence in college (Tinto 1975). This is due to the fact that people prefer to affiliate with those who share their attitudes and beliefs or demographic traits, since we have positive affective responses for those who are similar to us, and we also expect increased comfort and trust when interacting with them (Inzlicht and Good 2006).

The second channel through which minority status can impact students' performance is by affecting expectations regarding returns and confidence about personal achievement through its effect on beliefs about self and others' ability. Previous work in psychology, sociology and economics suggests that differences in performance can be partially explained by biased beliefs regarding own-self and others' ability caused by stereotypes (e.g. Bordalo et al. 2019; Spencer et al. 2016; Coffman 2014). For instance, Bordalo et al. (2019) shows that people tend to overestimate their own ability and the ability of other people of their gender in categories that are judged to be stereotypically congruent with their group (stereotypically male domains for men or stereotypically female domains for women), and underestimate their own ability and the ability of other people of their gender in categories that are judged to be stereotypically in-congruent with their group. The effect is stronger when individuals are paired with people of the other gender (Bordalo et al. 2019) or when individuals are in groups where their gender is over-represented (Karpowitz and Stoddard 2020; Born et al. 2020; Chen and Houser 2019). As a matter of fact, stereotyping is exacerbated by minority status, which reminds people about their social identity and their belonging to the group that makes them distinct (Hoff and Pandey 2006; Inzlicht et al. 2006). In the education setting lab and field experiments document a widespread belief that women are worse than men in math and science, while are better at literature (Carlana 2019; Reuben et al. 2014; Ellemers 2018). Thus, according to this channel, being in a minority is expected to depress beliefs for female students in math-intensive fields, where on the contrary it should inflate believed relative ability for men. On the other hand, being in a minority is expected to depress male students beliefs regarding relative ability in fields related to humanities, where on the contrary it should inflate women's believed relative ability.

The extent to which minority status can affect performance depends on the strengths of stereotypical associations and of the cost of interacting with the opposite gender. This is where stereotypical selection might play a role. Recent literature on selection into occupations and majors provide evidence that negative stereotypes regarding group-specific skills affect beliefs about expected returns, driving individuals out of counter-stereotypical occupations (Kugler et al. 2021; Del Carpio and Guadalupe 2018; Oxoby 2014). Furthermore, individuals incorporate their preferences toward the fraction of women and men in the occupation when making choices regarding the type of field to specialize in (Pan 2015; Pan 2015). As a consequence, students who selected in a field dominated by the opposite gender in spite of the negative stereotypes regarding their group (women in math-intensive fields and men in humanities) might have weaker stereotypical associations and might face lower costs in interacting with students of the opposite gender. Thus, they might be less affected by being in a minority.

I test the extent to which this is the case by building a theoretical framework. This allows me to rationalize the effect through which being in a minority affects performance and derive predictions of the effect of relaxing it. I will then test these predictions using rich administrative data and auxiliary evidence gathered through the survey.

6.1 Theoretical Framework

Students are risk neutral and choose educational investments (e_i) to maximize $U(e_i, a_i^b, a_{-i}^b, g, s_g, \beta_i^T, \beta_i^S)$

$$\max_{e_i} \quad \overbrace{\beta_i^P[f(a_i^b, e_i)]}^{\textbf{Course Performance}} \quad + \overbrace{\beta_i^S g(e_i, a_i^b - a_{-i}^b, g)}^{\textbf{Image concerns}} - c(e_i, \delta_i s_g) \tag{6}$$

Students' choice of effort depends on two factors (following Bursztyn et al. 2019 and Ashraf et al. 2014: (i) learning motives -$f(.)$, students benefit from investing more effort since they want to maximize their course performance, and (ii) image concerns -$g(.)$, since students care about appearing smart in front of their peers. The latter will be more important (higher β_i^S) when effort is visible to the peers. In the case of undergraduate students at LSE, an example of public investments in education is participation in class. For instance, students might refrain from participating to avoid appearing not smart enough in front of their peers, or they might participate only to appear as smart[36]. The classical assumptions of returns to schooling are assumed: $f_a > 0$, $f_{aa} < 0$, $f_e > 0$,$f_{ee} < 0$, thus course performance is increasing and concave in ability and effort. In the same way, I assume that the utility that students derive from social image is increasing and concave in effort: $g_e > 0, g_{ee} < 0$. Peers' ability enters students' utility function because students care about being of higher ability than their peers rather than having higher grades per se (Ashraf et al. 2014): $g(a_i^b - a_{-i}^b > 0) > 0$, $g(a_i^b - a_{-i}^b < 0) < 0$, $g_{a_i^b - a_{-i}^b} \geq 0$[37]. The benefit of effort in terms of image is higher the higher is students' relative ability: $g_{e, a_i^b - a_{-i}^b} \geq 0$. This implies that students of higher perceived relative ability get higher utility from image if they make higher investments in effort, and that conditional on investing in effort students with higher perceived relative ability get higher utility. This is a key assumption of the model and evidence for its validity can be found in the Section 6.2. Lastly, following Spence (1974), the cost function is convex and increasing in effort: $c_e > 0$ and $c_{ee} > 0$.

I model beliefs on ability building on the framework of Bordalo et al. (2019). Students hold imperfect information regarding their ability and the ability of their peers. Beliefs about their and their peers' ability in the subject rely on stereotypes and are affected by stereotypical distortions.

$$a_i^b = A_g + \mu_i + \theta_i \sigma_g (A_g - A_{-g}) \tag{7}$$

$$E(a_i^b - a_{-i}^b) = (A_g - A_{-g})(1 - s_g)(1 + 2\theta_i \sigma_g) \tag{8}$$

A_g is the average ability of group g, and μ_i is individual specific ability, such that $E_i(\mu_i) = 0$ and $E_i(A_g + \mu_i) = A_g$. $\theta_i \sigma_g (A_g - A_{-g})$ are stereotypes driven distortions. The distortion in beliefs that derive from stereotypes contain a kernel of truth since they exaggerate true differences in ability between groups. If a student belongs to the "better" performing group, stereotypical distortions will lead him/her to overestimate his/her own absolute ability. On the contrary, if a student belongs to the "worse" performing group, stereotypical distortions will lead him/her to underestimate his/her own absolute ability. The size of the bias depends on how much stereotypes are top of mind (σ_g) for the student. If stereotypes are top of mind, differences in ability between the two groups are overestimated. Changes in class composition change the extent to which stereotypes are salient in the students' minds. In particular, stereotyping

[36] Evidence regarding the importance of image concerns for participation is discussed in the section 6.2

[37] This is a framework where social comparison enters additively in the utility function (Ashraf et al. 2014; Kandel and Lazear 1992)

is exacerbated by minority status, $\sigma_{s_g)} \leq 0$, i.e. the extent to which stereotypes are top of mind for a member of group g is decreasing in the size of his/her group s_g.

The second channel through which class composition affects students' choices of effort is through their costs. This is in line with minority status limiting opportunities for social interactions. In particular, I assume that the cost of effort decreases in the share of own group students, $C_{s_g} \leq 0$ and $C_{es_g} \leq 0$. This assumption implies that students feel more comfortable participating in class when they are surrounded by students that are "similar" to them. This can be due to the fact that we expect increased comfort, trust and positive affective responses from those who are similar to us. But this can also have to do with potential language barriers. Regarding private forms of effort, such as hours spent studying, this might happen because class composition influences students networks formation, and as a consequence their academic support.

I assume that individuals are heterogeneous along two key dimensions: the strength of stereotypical associations θ_i and their cost of interacting with students of the opposite gender δ_i. The former determines the strength of stereotypical distortions, while the latter determines the extent to which students benefit from being surrounded by students similar to them in terms of marginal cost of effort. These are the dimensions through which stereotypical selection might intervene to moderate the effect of being in a minority on performance.

Effect of changes in class composition on effort

Given the assumptions on concavity of g and f and convexity of the cost functions in effort, there exist at least an interior solution such that

$$e_i^* : \beta_i^P f_e + \beta_i^S g_e - C_e = 0 \tag{9}$$

Given the equilibrium first order conditions described above, the effect of a change in class composition is described by the following expression:

$$\frac{\partial e_i^*}{\partial s_g} = -\frac{\beta_i^P \overbrace{f_{ea}}^{?} \frac{\partial a_i^b}{\partial s_g} + \beta_i^S \overbrace{g_{e,a-a_{-i}}}^{\geq 0} \frac{\partial a_i^b - a_{-i}^b}{\partial s_g} - \delta_i \overbrace{c_{es_g}}^{\leq 0}}{\underbrace{\beta_i^P f_{ee} + \beta_i^S g_{ee} - c_{ee}}_{\leq 0}} \tag{10}$$

The effect of a change in class composition on effort depends on three components. A learning component, an image component and a cost of effort component. Regarding the learning component, the effect depends on the sign of f_{ae}, i.e. whether ability and effort are complement or substitute in learning. Assuming that relaxing numerical minority generates a positive shock on beliefs on ability, if ability and effort are complement, students will invest more in effort. If ability and effort are substitute, they will decrease the amount of effort they invest in the course. Concerning the image component, the prediction is straightforward: students will start investing more in effort since they received a confidence boost. Lastly, relaxing numerical minority will have an effect on the cost of effort, and in particular, it will induce student to invest more when the share of "similar" people increases. Thus, if ability and effort are complement, a positive shock on beliefs regarding relative ability will induce students to invest more, since image and learning components reinforce each others. On the contrary, if effort and ability are substitute in learning, the effect will depend on the weight that learning and image concerns have in the utility function.

Whether students receive a positive or negative shock on beliefs regarding relative ability when relaxing minority status depends on the nature of stereotypes in the field.

$$\frac{\partial a_i^b}{\partial s_g} = \overbrace{\theta_i \sigma_{s_g}}^{\leq 0}(A_g - A_{-g}) \tag{11}$$

$$\frac{\partial E(a_i^b - a_{-i}^b)}{\partial s_g} = (A_g - A_{-g})\overbrace{[-1 - 2\theta_i\sigma + 2\theta_i(1-s_g)\sigma_{s_g}]}^{\leq 0} \tag{12}$$

If students are enrolled in departments in line with stereotypes ($A_g - A_{-g} > 0$), an increase in the share of students of their gender depresses their beliefs regarding absolute and relative ability. An increase in the share of same gender classmates reduces the extent to which stereotypes are top of mind for the student, thus weakening the stereotypical distortions that were leading him/her to overestimate his/her own absolute ability. At the same time, an increase in the share of same gender classmates increases the average perceived ability of the peers, depressing the student's perceived relative ability. This for instance would be the case for men (women) in math-intensive (humanities) departments when the share male (female) students in class increases. On the other hand, if students are enrolled in counter-stereotypical departments ($A_g - A_{-g} < 0$), an increase in the share of same gender classmates improves their beliefs regarding absolute and relative ability. As a matter of fact, an increase in the share of same gender classmates, by reducing the extent to which stereotypes are top of mind,reduces stereotype threat, which was leading them to underestimate their own absolute ability. In the same way, an increase in the share of same gender classmates decreases the average perceived ability of the peers, improving the student's perceived relative ability. This is the case for women (men) in math and science-intensive (humanities) fields when the share of women (men) in class increases.

$$\begin{aligned}
&\text{if } (A_g - A_{-g}) > 0 \rightarrow \frac{\partial e_i^*}{\partial s_g} = -\frac{\beta_i^P \overbrace{f_{ea}}^{?} \overbrace{\frac{\partial a_i^b}{\partial s_g}}^{\leq 0} + \beta_i^S g_{e,a-a_{-i}} \overbrace{\frac{\partial E(a_i^b - a_{-i}^b)}{\partial s_g}}^{\leq 0} - \delta_i \overbrace{c_{es_g}}^{\leq 0}}{\underbrace{\beta_i^P f_{ee}^e + \beta_i^S g_{ee} - c_{ee}^e}_{\leq 0}} \\
&\text{if } (A_g - A_{-g}) < 0 \rightarrow \frac{\partial e_i^*}{\partial s_g} = -\frac{\beta_i^P \overbrace{f_{ea}}^{?} \overbrace{\frac{\partial a_i^b}{\partial s_g}}^{\geq 0} + \beta_i^S g_{e,a-a_{-i}} \overbrace{\frac{\partial E(a_i^b - a_{-i}^b)}{\partial s_g}}^{\geq 0} - \delta_i \overbrace{c_{es_g}^e}^{\leq 0}}{\underbrace{\beta_i^P f_{ee}^e + \beta_i^S g_{ee} - c_{ee}^e}_{\leq 0}}
\end{aligned} \tag{13}$$

Prediction 1 (Counter-stereotypical departments) *Relaxing minority status increases effort for students that are are enrolled in counter-stereotypical departments ($A_g - A_{-g} < 0$) whenever effort and ability are complement, or effort and ability are substitutes but the effect on image and cost of effort prevails on the effect on learning.*

Prediction 2 (Stereotypical departments) *For students enrolled in fields that are stereotypically con-*

gruent with the group identity ($A_G - A_{-G} > 0$), relaxing minority status generates an increase in effort for students if the negative effect on image is small and ability and effort are substitute. On the other hand, a decrease in effort if the positive effect on the cost of effort is small and ability and effort are complement.

It can be seen from equations 14 that the effect of relaxing minority status on effort choices is stronger the stronger is the effect that relaxing minority status has on beliefs regarding relative and absolute ability and the stronger is the effect on the marginal cost of effort. Equations 12 and 13 show that the effect of relaxing numerical minority on beliefs on ability is stronger the stronger are stereotypical associations for the students (θ_i). On the other hand, the strength of the effect of relaxing minority status on the marginal cost of effort depends on δ_i, the individual cost of interacting with students of the opposite gender. Thus, the model delivers a third prediction:

Prediction 3 (Stereotypical selection) *The effect of changes in class composition on effort choices are stronger the stronger are stereotypical associations for students (θ_i) and the higher is the individual cost of interacting with students of the opposite gender (δ_i).*

6.2 From Theory to Empirics

In order to test the model predictions, I exploit rich administrative data and a novel survey. LSE requires teaching assistants to evaluate students' participation in class during the term. Lab and field experiments provide clear evidence that, by reducing the daunting effect of negative stereotypes, relaxing numerical minority increases participation and willingness to contribute to discussions for individuals in counter-stereotypical domains (Coffman and Shurchkov 2021; Karpowitz and Stoddard 2020; Chen and Houser 2019; Bordalo et al. 2019; Coffman 2014). I exploit teachers' evaluations of students' participation in class as a counterfactual to estimate the effect of a change in group composition on participation and willingness to contribute to discussions in a real-life setting where selection against stereotypes plays a role[38].

Furthermore, participation in class can be considered as forms of public effort, since it is observable to peers. Thus, we can expect choices of participation to be motivated primarily by image concerns rather than learning motives. Figure 12 displays the relationship between exam grades and participation in class (Panel A), and participation and individual and peers' ex-ante ability (Panels B and C), controlling for student and class group fixed effects. Participation is beneficial for students' learning, since we can see that it is positively correlated with exam grades: students who participate more in the first term obtain higher exam grades at the end of the year. However, the students who participate the most are high ability students, and participation appears to be negative correlated with the ability of the peers in the class group. This is in line with participation in class being primarily motivated by image concerns and

[38]These data have two caveats. First of all, they are not objective measures of students' participation and performance, but they are grades that teachers give to students. Thus, results can be considered as indicative of class dynamics conditional on the assumption that teaching assistants do not discriminate or evaluate underrepresented groups differently when they are in a minority. Secondly, they only concern Michaelmas term (due to attrition problems, I consider only Michaelmas term grades, not Lent term evaluations). As a consequence, they are able to shed light on the dynamics that characterize classes in the first half of the academic year. This on the one hand represents a limitation, since exam grades are the result of students' effort during the whole academic year. On the other hand, we can argue that first term measures are more indicative of how students' behavior is affected by stereotypical distortions, since this is the first time students meet and interact with each other.

in particular with the idea that students care about being better than their peers. This is confirmed also by the evidence gathered through the survey. Figure 13 displays that students are significantly more comfortable answering questions in class rather than asking questions. Furthermore, they admitted that the worry of not looking “smart enough” has refrained them from participating at least once. On the contrary they disagree with the statement that they refrained from participating at least once for the worry of appearing "too know-it-all".

Evidence for students who made a counter-stereotypical choice

When social image represents the primary concern and effort is public, the model predicts that relaxing minority status induces students who are enrolled in counter-stereotypical departments to participate more, by reducing stereotypical distortions, which were causing them to underestimate their absolute and relative ability, and by allowing them to benefit from a reduction in the marginal cost of effort

Figure 14 shows the results of Specification 3 on participation in class considering the least restrictive and most conservative definition of stereotypical selection: bottom and top 5 departments. There is no evidence of an effect of changes in class composition on participation for students who are enrolled in counter-stereotypical fields. This is not due to the fact that participation is not affected by class composition since students who are enrolled in departments in line with stereotypes display significant effects. Furthermore, the results would be consistent with the findings in the literature that minority status impacts performance of minorities in stereotypically in-congruent domains through stereotype threat (inducing the "worse" performing group to perform worse by depressing their believes regarding their relative ability) only if we assume that the threat is so strong that not even a change in class group composition improves students' beliefs regarding their ability. However, this does not seem to be the case. Table A8 displays the gender gap in class participation across departments. We observe a significantly smaller gender gap in participation grades in female fields with respect to male fields, indicating that students who selected against stereotypes are more vocal on average with respect to same gender students who selected against stereotypes. This indicates that the channels traditionally used to explain the effect of being in a minority on performance do not seem to apply in a real world environment where selection plays a role.

Evidence for students who made a stereotypical choice

On the other hand, Figure 14 shows that men and women who are enrolled in stereotypical fields modify their participation with class composition. However, while women participate more in classes where there are more women, men participate less when surrounded by more men. This indicates that the effects for men and women who are enrolled in stereotypical departments are driven by different channels. Interpreted through the lenses of the model, these results imply that the effect for women is driven by them benefiting from greater comfort and support when surrounded by more women. On the other hand, the effect for men can be reconciled with positive stereotypes regarding men's performance in stereotypically male departments inducing them to be less confident when surrounded by men, participating less to the discussion.

This would be consistent with suggestive evidence indicating that the cost of participating for women in higher. Women have lower participation grades with respect to men in the same class for every level of ability at entry. Furthermore, evidence from the auxiliary survey in Figure 17 displays that women are significantly less comfortable asking and answering questions in class with respect to men. An additional piece of suggestive evidence in line with these findings is presented Table 9, where I estimate the effect of an increase in the share of same gender classmates for the subsample of students for which I have information regarding their previous school[39]. In particular, I define students based on whether their previous school was a single vs mixed sex school. I use this as a proxy for the strength of the cost of interacting with opposite gender peers. The underlying assumption is that students who studied in schools with only students of their own gender would be less used and less comfortable interacting with opposite gender students. In line with the effect for women being driven primarily by the cost of interacting with opposite gender students, increasing the share of female classmates always increase participation for women, but the effect is stronger for women who studied in single sex schools. On the contrary, for men, increasing the share of male classmates reduces participation, consistently with a reduction in perceived relative ability when men are surrounded by other men in stereotypically male departments. However, this effect disappears for men who studied in single sex schools, who, according to our assumption, are the men for which the cost of interacting with the opposite gender is stronger. For these men the negative effect of stereotypes is counteracted by them benefiting from a lower share of women in class reducing the cost of participating.

In light of this finding, the results on course performance could be reconciled with men in stereotypically male departments underestimating their relative ability due to an increase in the share of men , as a consequence investing less in participation (image channel), but investing more in learning to improve their course performance. Through the lenses of my model, this would imply that effort and relative ability are substitute in the learning function. This could be plausible if we consider that students have a fixed amount of time to allocate to effort across different courses, and as a consequence they might want to allocate less time to study to courses where they believe their subject specific ability is higher or their peers are on average less competitive.

6.3 What makes students who made stereotypical choices different from students who made counter-stereotypical choices?

In this last section, I shed some light on the characteristics that make students who decided to enroll in stereotypical departments different from students who decided to enroll in counter-stereotypical departments by exploiting evidence from the auxiliary survey I administered and administrative data on admission and the gender of the teaching assistants.

Figure 15 displays the results of an implicit association test (Greenwald et al. 1998) to elicit students' associations between female-humanistic and male-scientific[40]. A score of 0 indicates no association between male-Scientific and female-Humanistic. A positive score indicates that the student unconsciously associates women with humanities and men with science and math. Lastly, a negative score indicates that the student unconsciously associates men with humanities and women with science and math. We

[39]Students whose previous school was in UK (or oversees but related to a UK institution) and for whom I managed to match the information with the UK government register of school and colleges

[40]Details on the survey can be found in Appendix E

can see that students on average associate men with math and science and women with humanities, but this implicit association is significantly stronger for students who enrolled in departments in line with stereotypes[41]. In line with this finding, Table 10 provides suggestive evidence that the performance of students who are enrolled in counter-stereotypical departments is not affected by the gender of the class teacher, contrary to the performance of students who made a stereotypical selection. Since class teachers act as role models, breaking stereotypes regarding gender roles and skills (see for example Breda et al. 2021; Porter and Serra 2020; Olsson and Martiny 2018; Carrell et al. 2010), this result confirms that students who are enrolled in counter-stereotypical departments are less affected by gender stereotypes.

Furthermore, students who are enrolled in counter-stereotypical fields nominate significantly more people of the opposite gender when asked about their friends, people they study with, and people they ask questions on the material to, as it can be seen from Figure 16. While this might be partially explained by a different availability of students of the opposite gender to interact with, the difference between students enrolled in stereotypical and counter-stereotypical departments is significantly bigger when it concerns students to ask questions on the material to. This seems to indicate that students who are enrolled in counter-stereotypical departments have a lower cost of engaging with opposite gender peers, allowing them to benefit from academic support from their peers independently on their gender. However, additional research is needed to be able to conclusively say that this is due to differences in the cost of engaging with students of the opposite gender rather than, for example, the availability of peers that are perceived as high ability and that students believe can help them in understanding the course material.

Lastly, I can provide evidence that students who are enrolled in stereotypical and counter-stereotypical departments have equal potential and ability at entrance, indicating that differences in ability do not seem to be able to explain the results. Even though Math-intensive departments are the most competitive and selective, with the higher overall rejection rates, there is no evidence of a gender gap in qualifications at entry for students who are enrolled in different departments. Figure 18 shows the distribution of qualification scores for men and women across departments. There is no significant difference in average qualification scores at entrance between men and women, nor in the distributions of qualification scores at entry for men and women enrolled in the same type of departments.

This is in line with suggestive evidence indicating that the unbalanced gender composition of departments is related to preferences or strategic behavior of students at the application stage, rather than the university selection process, represented by the fact that that patterns in applications across departments exactly mirror the distribution of men and women enrolled in different programs (Figure A4). Interestingly, these preferences seem to be stronger for men. Figure A7 shows the number of applicants for each offer made in the same year by each department by gender. While we don't see a strong difference in applications for women, for the same number of available places, a disproportionately higher number of men apply to departments that end up being male-majority. This is in line with findings from Card and Payne (2021) that the gender gap in STEM readiness can be explained by the lower rate of university entry by non-STEM-oriented males. Furthermore, this can reconcile the stronger effect I find for men with respect to women.

[41]The result is confirmed also when I restrict the sample to first year students. Furthermore, the very same pattern can be found when analysing the data from a gender-scientific implicit association test carried out by Project Implicit. The evidence can be found in appendix E.

7 Beyond gender-specific dynamics

Are these patterns specific to gender or do they concern being in a minority more in general? In order to provide an answer to this question, I replicate the analysis along ethnic lines. The institution is characterized by an exceptionally diverse environment: only 37% of students are White, while 47% of the population of undergraduates are are Asian (primarily Chinese and South Asian). Furthermore, also ethnic groups are distributed unequally across departments. The pattern along ethnic lines is exactly the opposite with respect to the distribution of traits that characterize departments along gender lines. The fields where ethnic minorities (in this case Asian students) represent the majority of enrolled students are Math and Science-intensive fields, which are also the fields where women are under-represented. As for gender, this reflects stereotypes regarding group-specific skills and roles. As a matter of fact, lab and field experiments in the academic setting document a widespread belief that Asians are better at math and science with respect to white students (see for example the review by spencer2016).

In this section I am going to study if stereotypical selection along ethnic lines affects the effect of classmates' ethnic composition on students' course performance. I am going to estimate the following specification:

$$y_{iacg} = \alpha_{ac} + \alpha_i + \sum_{e=1}^{3} E_{i,e} \times [\beta_{1,e} \times SLM_{iacg} + \beta_{2,e} \times SLM_{iacg} \times STS_i] + \epsilon_{iacg} \quad (14)$$

where students are divided in three groups $E_{i,e} = \mathbb{1}(\text{i's ethnic group} = e)$, Asian, White, and Other students, which is a residual category that includes other ethnicity students and students who provided no information on their ethnicity[42]. The *share of students like me* (STS_{iacg}) is the share of same ethnicity classmates that student i experiences in class g, course c and academic year a, and *stereotypical selection* (STS_i) is the average share of same ethnicity students in student i's department of enrolment across academic years 2008-2017. Figure 19 provides a graphical description of stereotypical selection along ethnic lines. The average share of same ethnicity students the department of enrolment for the residual groups is calculated as one minus the share of Asian and White students enrolled in each department[43]. $\beta_{2,e}$ provides an indication of the extent to which being surrounded by same ethnicity classmates has a different effect on performance for students who made choices that are more in line with stereotypes regarding ethnic specific skills and norms with respect to students who made a choice against stereotypes, for each ethnic group e. The standard errors are clustered at the class level.

This exercise is based on the assumption that students are not systematically allocated to different classes because they belong to particular ethnic groups. I provide evidence for the validity of this assumption by replicating for ethnicity the same tests performed for gender. Evidence and a detailed explanation on the results can be found in Appendix D.

Table 11 displays the results of this exercise. Stereotypical selection moderates the effect of being

[42]This categorization is motivated by the necessity of having large enough groups to perform the analysis. Table A19 in Appendix D provides evidence that pulling students coming from different Asian countries together is not such a strong assumption given that the performance of Asian students coming from different countries is affected by an increase in the share of classmates coming from other Asian countries in the same qualitative way as an increase in the share of Asian classmates who were born in the same subset of Asian countries (dividing students in Chinese, India, Other Asian).

[43]The results are robust to restricting the sample to only Asian and White students (Table A7 for evidence)

in a minority also along ethnic lines. Both White and Asian students benefit from being surrounded by more classmates of their ethnicity when they made a stereotypical selection of major. This is robust to controlling for the share of same gender classmates (Column 2). These results confirm that the estimated patterns concern the interaction between being in a minority and selection into fields, and are not only related to gender-specific dynamics.

8 Discussion

This paper aims at empirically testing if selection into fields plays a role in moderating the effect of being in a numerical minority on performance. I consider a particular type of selection: whether individuals made a choice in line or against stereotypes regarding their group. This is relevant as the individuals that we observe in a numerical minority are often individuals who decided to bear the cost of making a choice against stereotypes. As they internalized social identity considerations and the composition of the environment in their choices, they might react very differently to being in a minority with respect to individuals who made choices in line with stereotypes.

I find that the only students whose performance is negatively affected by being under-represented are students who made stereotypical choices, and, as such, are part of the (stereotypical) majority group in the field. These students are also those who hold stronger implicit stereotypical associations and seem to be more affected by stereotypes, hinting towards the majority group being the perpetrator of stereotypes. These results have important policy implications as they suggest that targeting underrepresented groups with initiatives such as training or mentoring once they self-selected into counter-stereotypical fields not only might not be enough to address imbalances, but it might also not be the most efficient use of resources if they do not suffer when in a minority. Policies that aim at fostering minority inclusion should target the majority.

This is especially important when the environment is very selective and the presence of a person from an under-represented group is the result of a series of strategic choices. This is very likely to be the case at LSE. Application to undergraduate programs is centralized in the UK, and students can only apply to 5 programs (across all universities in UK) in the same year. Furthermore, applications at LSE are very competitive: 75% of students who apply are rejected every year. Thus students who apply at LSE are very motivated and very confident.

This implies that the findings of the paper cannot be easily generalized to other educational environments since LSE and its students are not comparable to the average university. However, given the competitive nature of the environment and the strategic decision-making process that applying to undergraduate programs in the UK entails, these findings might be informative for selective and competitive working environments. For instance, the findings of the paper might be useful to inform policies aiming at addressing the under-representation of women in decision-making bodies or leading positions.

References

Akerlof, G. A. and R. E. Kranton (2000, 08). Economics and Identity*. *The Quarterly Journal of Economics 115*(3), 715–753.

Anelli, M. and G. Peri (2017). The effects of high school peers' gender on college major, college performance and income. *The Economic Journal*.

Ashraf, N., O. Bandiera, and S. S. Lee (2014). Awards unbundled: Evidence from a natural field experiment. *Journal of Economic Behavior Organization 100*(C), 44–63.

Austen-Smith, D. and J. Fryer, Roland G. (2005, 05). An Economic Analysis of "Acting White"*. *The Quarterly Journal of Economics 120*(2), 551–583.

Avilova, T. and C. Goldin (2018, May). What can uwe do for economics? *AEA Papers and Proceedings 108*, 186–90.

Bandiera, O., V. Larcinese, and I. Rasul (2010). Heterogeneous class size effects: New evidence from a panel of university students*. *The Economic Journal 120*(549), 1365–1398.

Beede, D. N., T. Julian, D. Langdon, G. McKittrick, B. Khan, and M. Doms (2011). Women in stem: A gender gap to innovation. *Sexuality & Gender Studies eJournal*.

Bertrand, M. (2011). Chapter 17 - new perspectives on gender. Volume 4 of *Handbook of Labor Economics*, pp. 1543–1590. Elsevier.

Bertrand, M. (2020, May). Gender in the twenty-first century. *AEA Papers and Proceedings 110*, 1–24.

Blau, F. D., J. M. Currie, R. T. A. Croson, and D. K. Ginther (2010, May). Can mentoring help female assistant professors? interim results from a randomized trial. *American Economic Review 100*(2), 348–52.

Booth, A. L., L. Cardona-Sosa, and P. Nolen (2018). Do single-sex classes affect academic achievement? an experiment in a coeducational university. *Journal of Public Economics 168*, 109–126.

Bordalo, P., K. Coffman, N. Gennaioli, and A. Shleifer (2016). Stereotypes. *Quarterly Journal of Economics 131*(4), 1753–1794.

Bordalo, P., K. Coffman, N. Gennaioli, and A. Shleifer (2019). Beliefs about gender. *American Economic Review 109*(3), 739–73.

Born, A., E. Ranehill, and A. Sandberg (2020). Gender and willingness to lead: Does the gender composition of teams matter? *The Review of Economics and Statistics 0*(ja), 1–46.

Bostwick, V. and B. Weinberg (2021). Nevertheless she persisted? gender peer effects in doctoral stem programs. *Journal of Labor Economics 0*(ja), null.

Braga, M., M. Paccagnella, and M. Pellizzari (2016). The Impact of College Teaching on Students' Academic and Labor Market Outcomes. *Journal of Labor Economics 34*(3), 781–822.

Breda, T., J. Grenet, M. Monnet, and C. van Effenterre (2021, March). Do Female Role Models Reduce the Gender Gap in Science? Evidence from French High Schools. PSE Working Papers halshs-01713068, HAL.

Brenøe, A. A. and U. Zölitz (2020). Exposure to more female peers widens the gender gap in stem participation. *Journal of Labor Economics 38*(4), 1009–1054.

Bursztyn, L., G. Egorov, and R. Jensen (2019, 05). Cool to be Smart or Smart to be Cool? Understanding Peer Pressure in Education. *The Review of Economic Studies 86*(4), 1487–1526.

Bursztyn, L., T. Fujiwara, and A. Pallais (2017, November). 'acting wife': Marriage market incentives and labor market investments. *American Economic Review 107*(11), 3288–3319.

Bursztyn, L. and R. Jensen (2017). Social image and economic behavior in the field: Identifying, understanding, and shaping social pressure. *Annual Review of Economics 9*(1), 131–153.

Card, D., A. Mas, and J. Rothstein (2008, 02). Tipping and the Dynamics of Segregation*. *The Quarterly Journal of Economics 123*(1), 177–218.

Card, D. and A. A. Payne (2021). High school choices and the gender gap in stem. *Economic Inquiry 59*(1), 9–28.

Carlana, M. (2019, 03). Implicit Stereotypes: Evidence from Teachers' Gender Bias*. *The Quarterly Journal of Economics 134*(3), 1163–1224.

Carrell, S. E., M. E. Page, and J. E. West (2010, 08). Sex and Science: How Professor Gender Perpetuates the Gender Gap*. *The Quarterly Journal of Economics 125*(3), 1101–1144.

Chen, J. and D. Houser (2019). When are women willing to lead? the effect of team gender composition and gendered tasks. *The Leadership Quarterly 30*(6), 101340.

Coffman, Katherine B., C. B. F. and O. Shurchkov (2021). Gender stereotypes in deliberation and team decisions. Harvard Business School Working Paper No. 19-069.

Coffman, K. B. (2014). Evidence on Self-Stereotyping and the Contribution of Ideas. *The Quarterly Journal of Economics 129*(4), 1625–1660.

Del Carpio, L. and M. Guadalupe (2018, October). More Women in Tech? Evidence from a field experiment addressing social identity. CEPR Discussion Papers 13234, C.E.P.R. Discussion Papers.

Ellemers, N. (2018). Gender stereotypes. *Annual Review of Psychology 69*(1), 275–298. PMID: 28961059.

Feld, J. and U. Zölitz (2017). Understanding peer effects: On the nature, estimation, and channels of peer effects. *Journal of Labor Economics 35*(2), 387–428.

Garg, N., L. Schiebinger, D. Jurafsky, and J. Zou (2018). Word embeddings quantify 100 years of gender and ethnic stereotypes. *Proceedings of the National Academy of Sciences 115*(16), E3635–E3644.

Giorgi, G. D., W. G. Woolston, and M. Pellizzari (2012). Class size and class heterogeneity. *Journal of the European Economic Association 10*(4), 795–830.

Goldin, C. (2014, April). A grand gender convergence: Its last chapter. *American Economic Review 104*(4), 1091–1119.

Goldin, C., L. F. Katz, and I. Kuziemko (2006, December). The homecoming of american college women: The reversal of the college gender gap. *Journal of Economic Perspectives 20*(4), 133–156.

Greenwald, A. G., D. E. McGhee, and J. L. K. Schwartz (1998). Measuring individual differences in implicit cognition: the implicit association test. *Journal of personality and social psychology 74 6*, 1464–80.

Griffith, A. L. and J. B. Main (2019). First impressions in the classroom: How do class characteristics affect student grades and majors? *Economics of Education Review 69*, 125–137.

Guiso, L., F. Monte, P. Sapienza, and L. Zingales (2008). Culture, gender, and math. *Science 320*(5880), 1164–1165.

Guryan, J., K. Kroft, and M. J. Notowidigdo (2009, October). Peer effects in the workplace: Evidence from random groupings in professional golf tournaments. *American Economic Journal: Applied Economics 1*(4), 34–68.

He, J. C., S. K. Kang, K. Tse, and S. M. Toh (2019). Stereotypes at work: Occupational stereotypes predict race and gender segregation in the workforce. *Journal of Vocational Behavior 115*, 103318.

Hebert, C. (2020). Gender stereotypes and entrepreneur financing. 10th miami behavioral finance conference, available at ssrn: https://ssrn.com/abstract=3318245 or http://dx.doi.org/10.2139/ssrn.3318245.

Hill, A. J. (2017). The positive influence of female college students on their male peers. *Labour Economics 44*, 151–160.

Hoff, K. and P. Pandey (2006, May). Discrimination, social identity, and durable inequalities. *American Economic Review 96*(2), 206–211.

Huntington-Klein, N. and E. Rose (2018). Gender peer effects in a predominantly male environment: Evidence from west point. *AEA Papers and Proceedings 108*, 392–395.

Inzlicht, M., J. Aronson, C. Good, and L. McKay (2006, May). A particular resiliency to threatening environments. *Journal of Experimental Social Psychology 42*(3), 323–336.

Inzlicht, M. and C. Good (2006). How environments can threaten academic performance, self-knowledge, and sense of belonging. *In S. Levin and C. van Laar (Eds.), The Claremont symposium on Applied Social Psychology. Stigma and group inequality: Social psychological perspectives*, 129–150.

Kandel, E. and E. P. Lazear (1992). Peer pressure and partnerships. *Journal of Political Economy 100*(4), 801–817.

Karpowitz, Chris, J. P. and O. Stoddard (2020). Strength in numbers: A field experiment on gender, influence and group dynamics. IZA Discussion Paper No. 13741.

Kugler, A. D., C. H. Tinsley, and O. Ukhaneva (2021). Choice of majors: are women really different from men? *Economics of Education Review 81*, 102079.

Lane, K. A., G. J. X. . D.-L. E. (2012). Implicit science stereotypes mediate the relationship between gender and academic participation. *Sex Roles: A Journal of Research 66(3-4)*, 220–234.

Lavy, V. and A. Schlosser (2011, April). Mechanisms and impacts of gender peer effects at school. *American Economic Journal: Applied Economics 3*(2), 1–33.

McNally, S. (2020). Gender differences in tertiary education: What explains stem participation. CEP Discussion Paper No. 1721.

Murdoch, D. J., Y.-L. Tsai, and J. Adcock (2008). P-values are random variables. *The American Statistician 62*(3), 242–245.

OECD (2020). *Education at a Glance 2020.*

Olivetti, C., E. Patacchini, and Y. Zenou (2020). Mothers, Peers, and Gender-Role Identity. *Journal of the European Economic Association 18*(1), 266–301.

Olsson, M. and S. E. Martiny (2018). Does exposure to counterstereotypical role models influence girls' and women's gender stereotypes and career choices? a review of social psychological research. *Frontiers in Psychology 9*, 2264.

Oosterbeek, H. and R. van Ewijk (2014). Gender peer effects in university: Evidence from a randomized experiment. *Economics of Education Review 38*, 51–63.

Oxoby, R. J. (2014). Social inference and occupational choice: Type-based beliefs in a bayesian model of class formation. *Journal of Behavioral and Experimental Economics 51*, 30–37.

Pan, J. (2015). Gender segregation in occupations: The role of tipping and social interactions. *Journal of Labor Economics 33*(2), 365–408.

Porter, C. and D. Serra (2020, July). Gender differences in the choice of major: The importance of female role models. *American Economic Journal: Applied Economics 12*(3), 226–54.

Reuben, E., P. Sapienza, and L. Zingales (2014). How stereotypes impair women's careers in science. *Proceedings of the National Academy of Sciences 111*(12), 4403–4408.

Russell, L. (2017). Can learning communities boost success of women and minorities in stem? evidence from the massachusetts institute of technology. *Economics of Education Review 61*, 98–111.

Shan, X. (2020). Does minority status drive women out of male-dominated fields? Working paper.

Spencer, S. J., C. Logel, and P. G. Davies (2016). Stereotype threat. *Annual Review of Psychology 67*(1), 415–437. PMID: 26361054.

Spencer, S. J., C. M. Steele, and D. M. Quinn (1999). Stereotype threat and women's math performance. *Journal of Experimental Social Psychology 35*(1), 4–28.

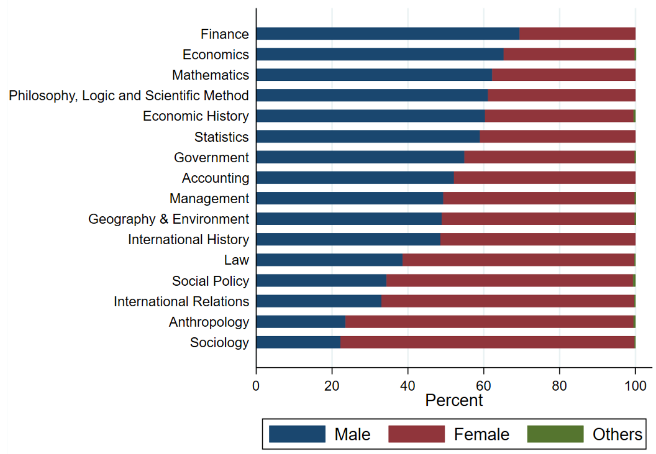
Steele, C. and J. Aronson (1995, November). Stereotype threat and the intellectual test performance of african americans. *Journal of Personality and Social Psychology 69*(5), 797–811. Copyright: Copyright 2018 Elsevier B.V., All rights reserved.

Tinto, V. (1975). Dropout from higher education: A theoretical synthesis of recent research. *Review of Educational Research 45*(1), 89–125.

Zölitz, U. and J. Feld (2018). The effect of peer gender on major choice. ECON - Working Papers No. 270, Department of Economics - University of Zurich.

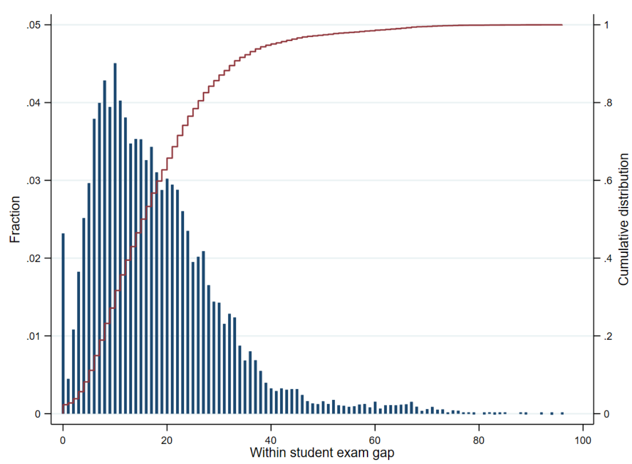
9 Figures

Figure 1: Departments gender composition



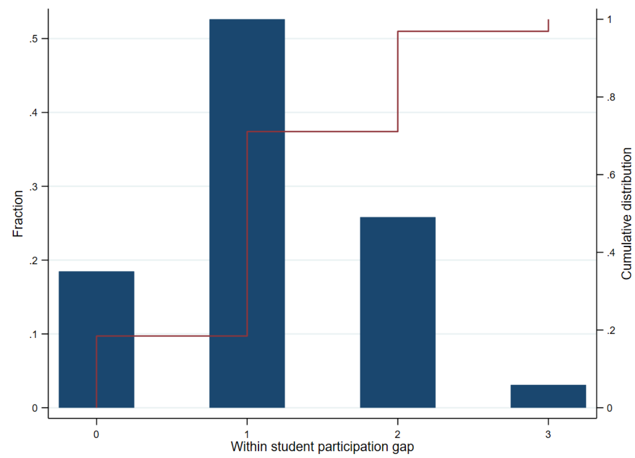
Notes: This figure illustrates the gender composition of each department. It is constructed based on the number of first year undergraduate students that are enrolled in bachelor programs offered by the department between 2008/09 and 2017/18. The figure shows the average across academic years 2008/09 to 2017/18.

Figure 2: Within student exam gap



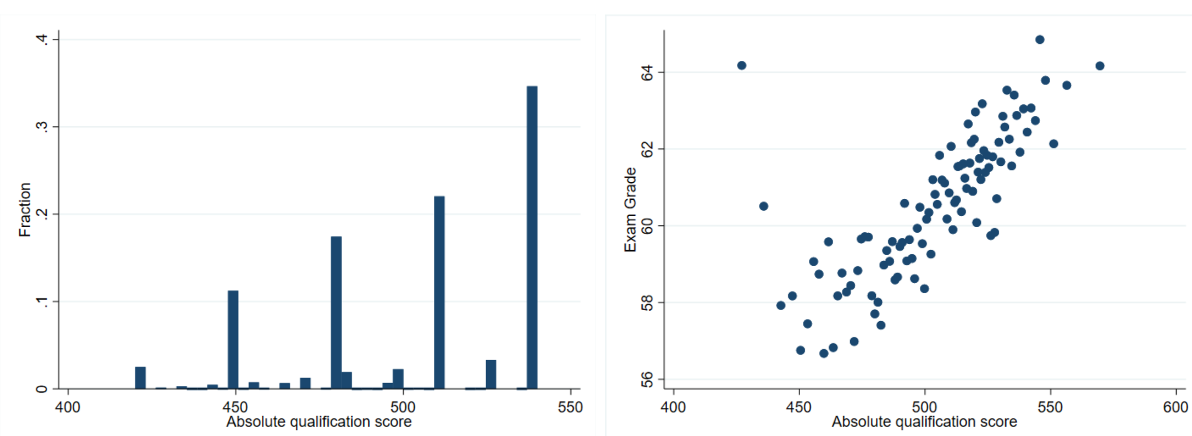
Notes: Following Bandiera et al. (2010). The figure displays the within student exam gap. This is defined as the difference between student i's highest and lowest exam mark across all the courses attended during Michaelmas term of the first year. The sample considered in the graph is the sample in analysis: 54.603 course-year-class group level observations, corresponding to information on 14.313 students.

Figure 3: Within student class participation gap



Notes: Following Bandiera et al. (2010). The figure displays the within student participation gap. This is defined as the difference between student i's highest and lowest participation grade across all the classes attended during Michaelmas term of the first year. The sample consist of the sample of analysis restricted to all the students for which I can observe a participation grade in at least two class groups: 44.771 course-year-class group level observations, corresponding to information on 13.485 students.

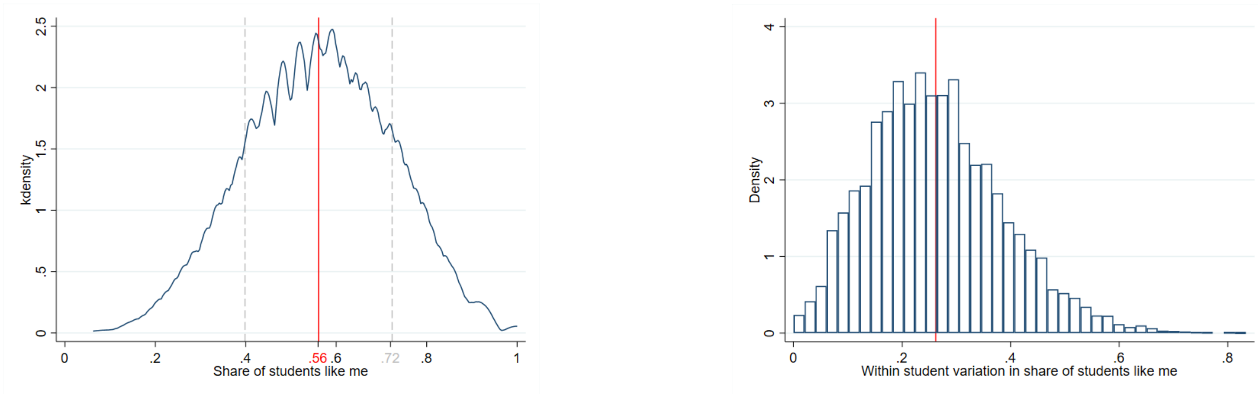
Figure 4: Qualification scores at entry



Notes: Panel A displays qualification scores at entry for 9.449 students, 90% of the students enrolled in undergraduate programs in LSE between academic years 2011/12 and 20117/18 (students for which I have information regarding qualifications at entry). Following Campbell et al. (2019), I construct a qualification score based on the best three exam results among the A-level qualification scores students declared when applying to LSE. Some students take courses/programs that are equivalents to A-Levels. In these cases I calculate their A-Level equivalence scores based on the university conversion tables for foreign students. A levels are graded on a scale of A*/A/B/C/D/E. Each A-level grade is worth 30 QCA (Qualifications and Curriculum Authority) points. Panel B displays the correlation between qualification scores at entry and course grades controlling for qualification type, individual characteristics (program of enrolment, gender, ethnicity, social background), and course fixed effects

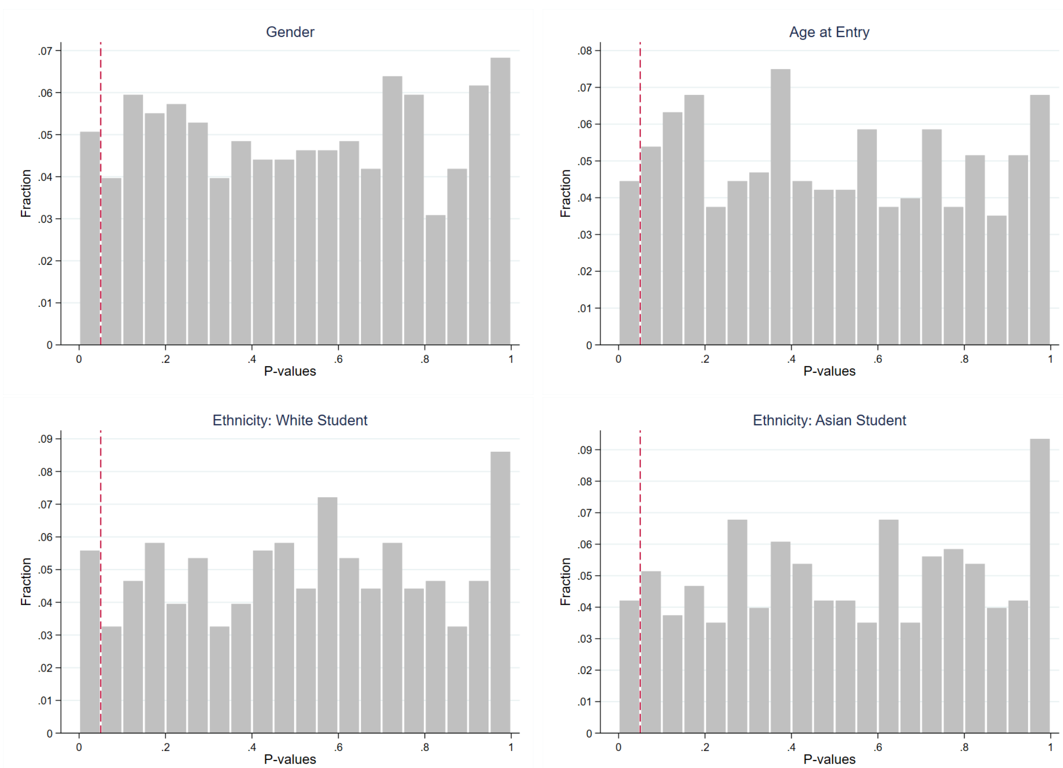
Figure 5: Within student variation in share of same gender students

Panel A **Panel B**



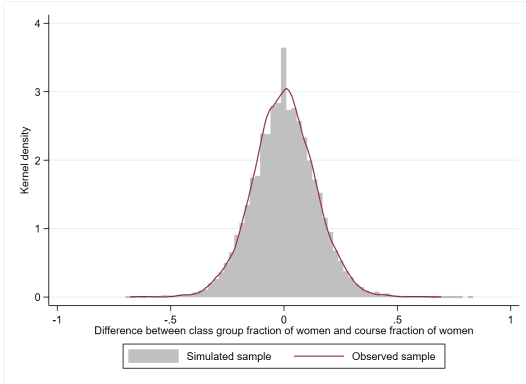
Notes: Panel A displays the distribution of the share of students like me, defined as the share of same gender classmates. The red vertical line indicates the average, while the two grey dashed lines indicate the average plus and minus one standard deviation. Panel B displays the distribution of the within student variation in the share of students like me. This is defined as the difference between the maximum and minimum share of same gender classmates experienced by each student during the first academic year. The red line indicates the average variation.

Figure 6: Observed sample P-values



Notes: This graph show the p-values of a test of joint significance of class dummies from a regression of gender (age at entry, a dummy for being White, and a dummy for being Asian, one at the time) on class dummies and dummies for each one of the courses taken by students in the academic years in analysis. A total of 454 regressions were performed. The sample is restricted to the courses that have at least 2 classes. The test is performed on all the students that attend courses attended by the students in the sample of analysis and that did not change classes (which are the students for whom I can recover the initial class allocation). More information on the text can be found in Appendix C.

Figure 7: Statistics distributions

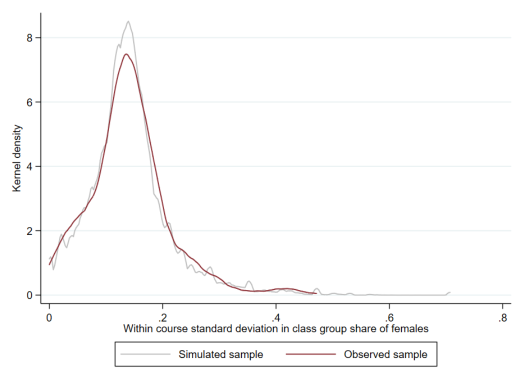


Two-sample Kolmogorov-Smirnov test

Smaller group	D	P-value
0:	0.0130	0.193
1:	-0.0116	0.271
Combined K-S:	0.0130	0.384

Notes: The Figure displays in dark grey the distribution of the difference between the share of women in each class and the share of women in the course for 1000 simulations of an unconstrained (not considering scheduling constraints) random allocation of students to classes. This is compared with the same statistics for the observed allocation (in red). The result of a two-sample Kolmogorov-Smirnov test shows that the distribution of the observed statistics is not significantly different from the simulated statistics.

Figure 8: Within course standard deviation in class groups share of females

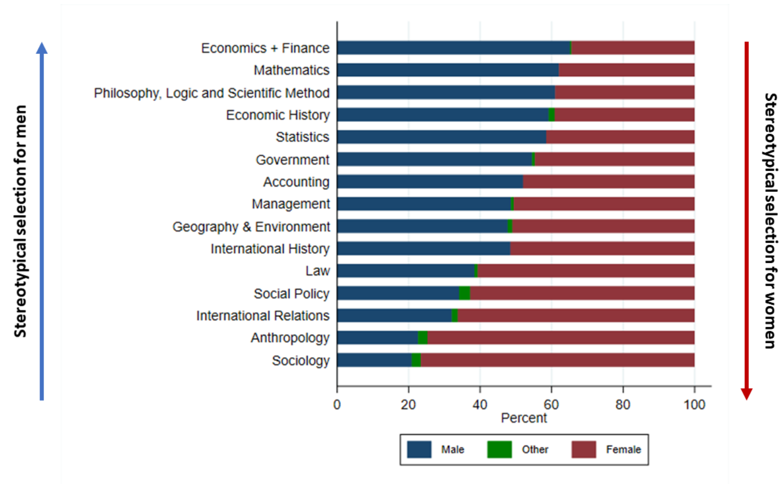


Two-sample Kolmogorov-Smirnov test

Smaller group	D	P-value
0:	0.0286	0.410
1:	-0.0272	0.446
Combined K-S:	0.0286	0.764

Notes: The Figure displays in dark grey the distribution of the within course standard deviation in the class share of females for 1000 simulations of an unconstrained (not considering scheduling constraints) random allocation of students to classes. This is compared with the same statistics for the observed allocation (in red). The result of a two-sample Kolmogorov-Smirnov test shows that the distribution of the observed statistics is not significantly different from the simulated statistics.

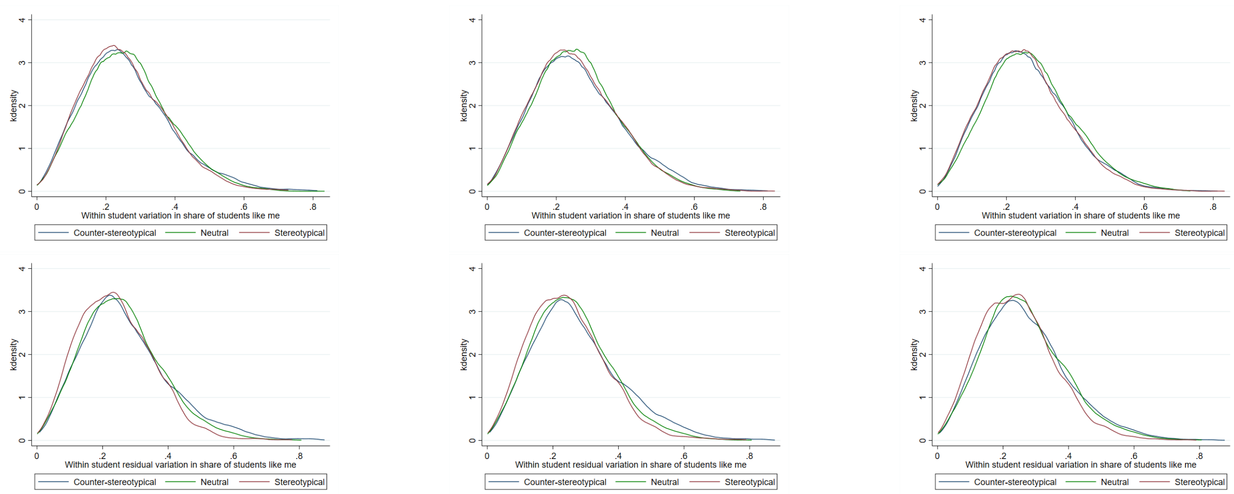
Figure 9: Conformism to gender norms and stereotypes



Notes: The Figure displays the distribution of men and women enrolled in the first year of undergraduate programs across departments. The statistics is the average of academic years 2008-2017. The blue and red arrows at the sides display the direction of choices of majors that would be in line with stereotypes and gender norms for men and women respectively.

Figure 10: Within student variation in share of same gender classmates across departments

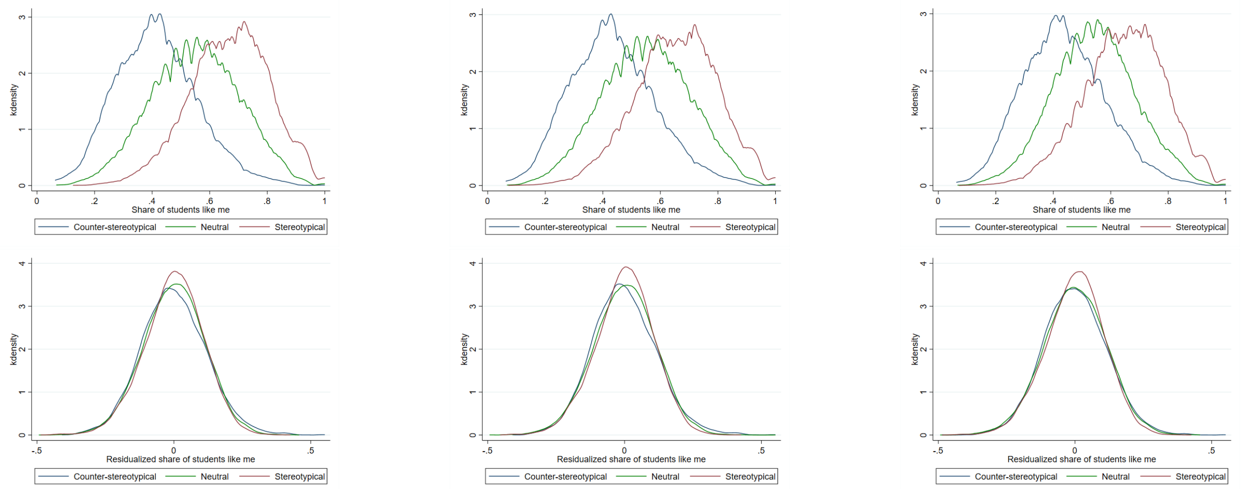
Panel A: Top & Bottom 2 **Panel B: Top & Bottom 3** **Panel C: Top & Bottom 5**



Notes: The figure displays the within student variation in the share of same gender classmates (top) and the within student variation in the residual share of same gender classmates (bottom) for students enrolled in stereotypical and counter-stereotypical departments, according to the three definitions used. The within student variation in the share of same gender classmates is obtained by taking the difference between student i's highest and lowest share of same gender classmates across all the classes attended during the first year. The within student variation in the residual share of same gender classmates is obtained by taking the difference between student i's highest and lowest residual share of same gender classmates across all the classes attended during the first year, obtained after regressing the share of same gender classmates on course $\times$ year fixed effects. Kolmogorov-Smirnov Test of equality in distribution for Stereotypical vs Against-stereotypes P-value: Variation - 0.526, 0.208, 0.139; Residual variation - 0.000, 0.000, 0.000.

Figure 11: Share of same gender classmates across departments

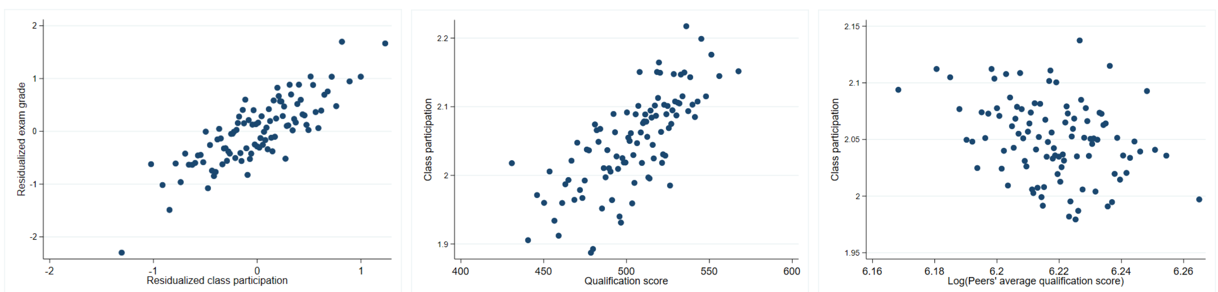
Panel A: Top & Bottom 2 **Panel B: Top & Bottom 3** **Panel C: Top & Bottom 5**



Notes: The figure displays the share of same gender classmates and the residual share of same gender classmates for students enrolled in stereotypical and counter-stereotypical departments, according to the three definitions used. The residual share of same gender classmates is obtained by taking the residuals of the regression of same gender classmates on course × year fixed effects and student fixed effects. Kolmogorov-Smirnov Test of equality in distribution for Stereotypical vs Against-stereotypes P-value: Share - 0.000, 0.000, 0.000; Residual share - 0.000, 0.000, 0.000.

Figure 12: Class participation

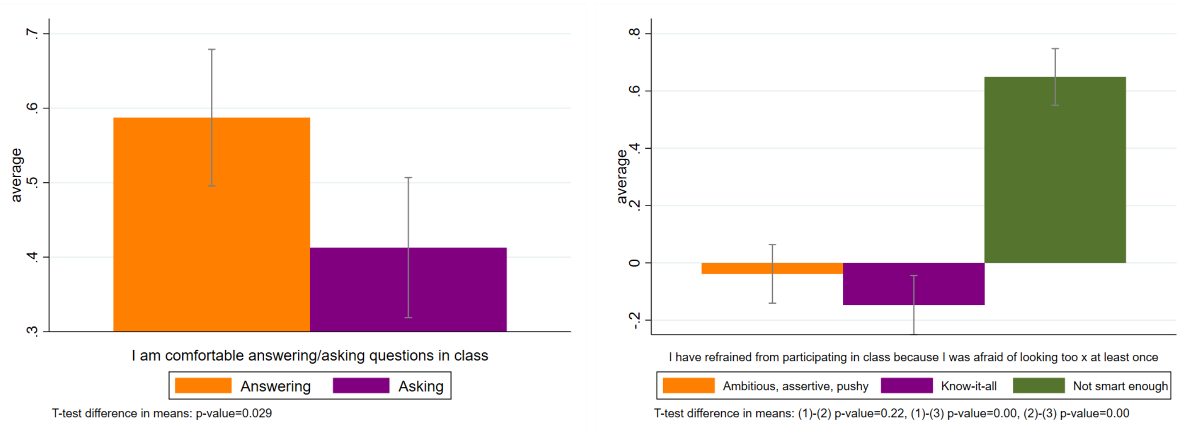
Panel A Panel B Panel C



Notes: Panel A displays a binned scatterplot of residualized exam grades on residualized participation in class. Each variable is the residual of a regression on class group and students fixed effects. Panel B displays a binned scatterplot of participation grades on students' ability controlling for class group and individual characteristics (gender, program of enrollment, school of origin, ethnicity). Panel C displays a binned scatterplot of participation grades on class group peers' ability controlling for class size, course and students fixed effects.

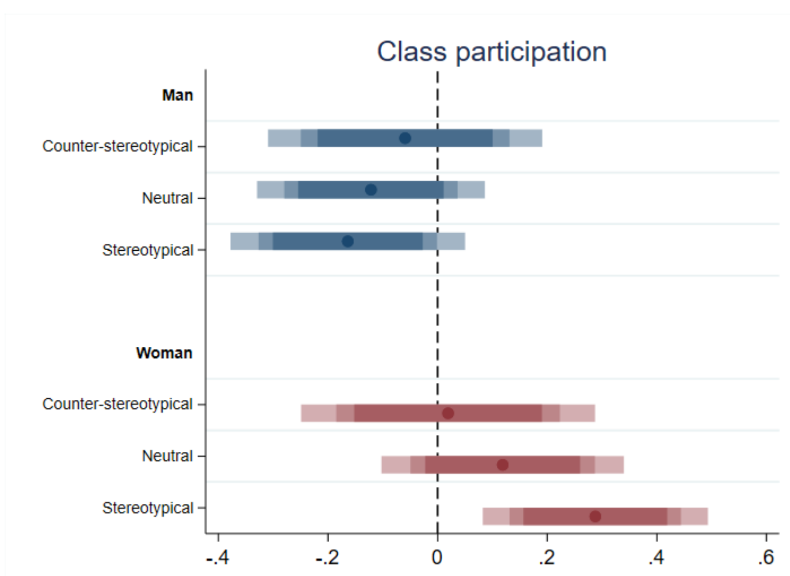
Figure 13: Image concerns and class participation

Panel A Panel B



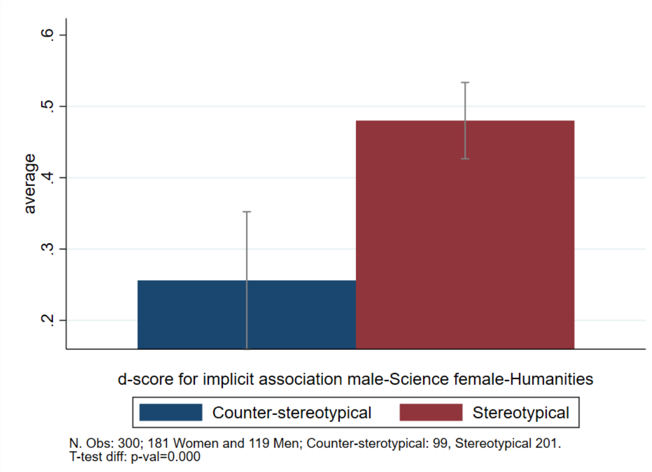
Notes: Following Bursztyn et al. (2017). Panel A displays the answers to the following questions: "Thinking about the courses you have taken in your career at LSE, how much do you agree or disagree with the following statements? (-2: strongly disagree, +2: strongly agree) (i) I am comfortable answering questions or contributing to the discussion in class; (ii) I am comfortable answering questions or contributing to the discussion in class". Panel B displays the answers to the following questions: "Thinking about the courses you have taken in your career at LSE, how much do you agree or disagree with the following statements? (-2: strongly disagree, +2: strongly agree) (i) I have refrained from participating in class because I was afraid of looking too ambitious, assertive, or pushy at least once (ii) I have refrained from participating in class because I was afraid of looking too “know-it-all” at least once (iii) I have refrained from participating in class because I was afraid of looking “not smart enough” at least once".

Figure 14: Minority status effect on class participation



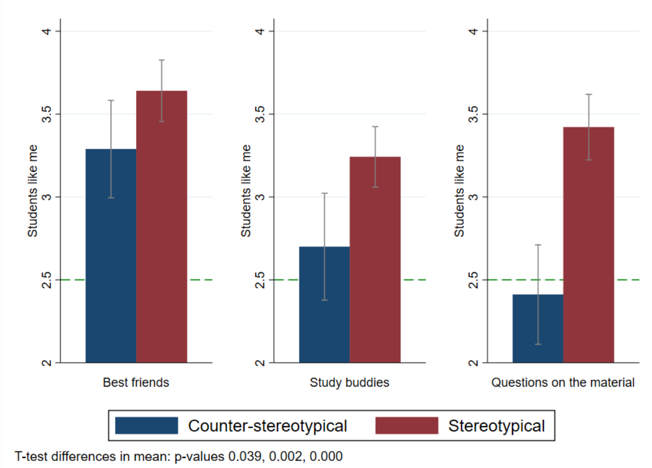
Notes: The Figure displays the results of specification 3. The outcomes variable are participation grades. Stereotypical and counter-stereotypical departments are defined based on the top and bottom 5 departments in terms of share of students like me enrolled in the department. Standard errors are clustered at the class group level.

Figure 15: Scientific-Male, Humanistic-Female IAT - Survey on LSE students



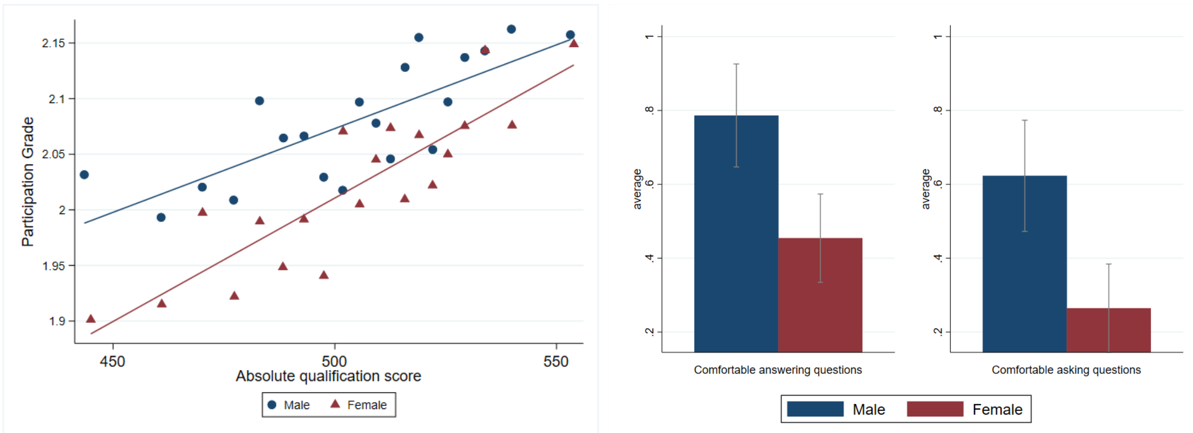
Notes: Results of an implicit association test (Greenwald et al. 1998) to elicit students' associations between female-humanistic and male-scientific. A score of 0 indicates no association between male -scientific and female-humanistic; a positive score indicates that the student associates women with humanities and men with science and math; lastly a negative score indicates that the student associates men with humanities and women with science and math.

Figure 16: Social network



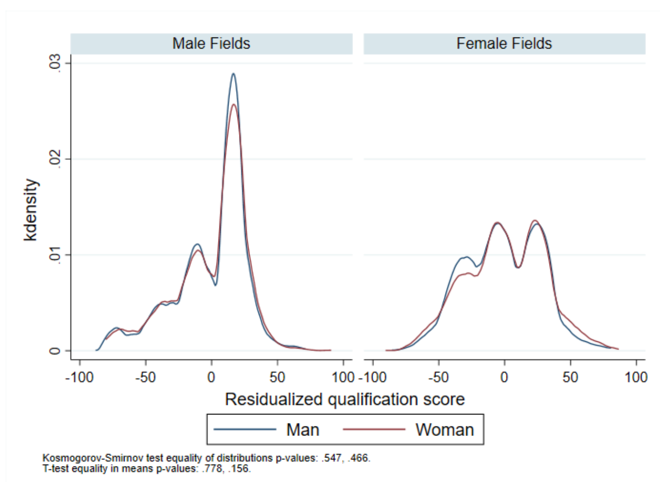
Notes: The figure displays students' replies to the following questions: "Thinking about 5 of your best friends/people you study with/people you ask questions on the material to, how many of them are women?. The answers were standardized in order to display on the y-axis the number of same gender people they nominated. An answer equal to 2.5 indicates that they interact with peers independently on their gender. The P-values for the T-test for the difference in means between Stereotypical and Counter-stereotypical are: 0.039, 0.002, 0.000. The p-value for the difference in mean between "best friends vs questions on the material" and "study buddies and questions on the material" for students enrolled in counter-stereotypical departments are 0.000 and 0.156. The p-values for the difference between the gaps for "best friends vs questions on the material" and "study buddies and questions on the material" are 0.061 and 0.008.

Figure 17: Cost of participating



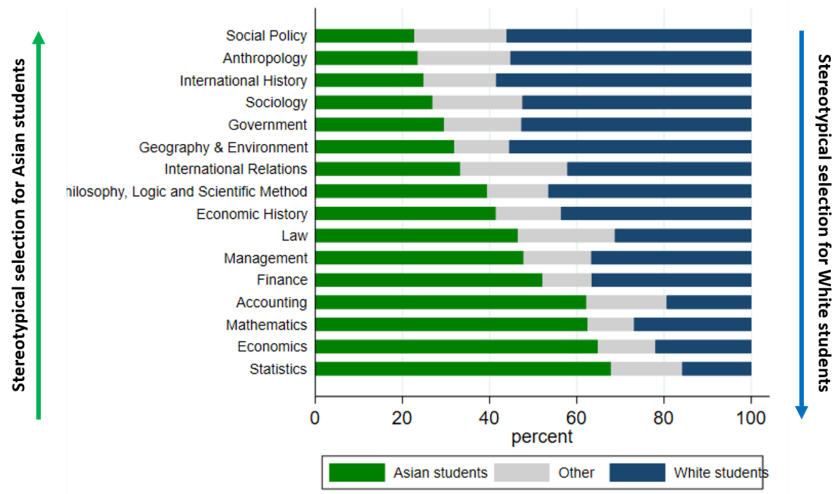
Notes: Panel A displays a binned scatterplots of class participation controlling for class group fixed effects and individual characteristics (program of enrollment, school of origin, ethnicity). Panel B displays the answers to the survey questions: "Thinking about the courses you have taken in your career at LSE, how much do you agree or disagree with the following statements? (-2: strongly disagree, +2: strongly agree) (i) I am comfortable answering questions or contributing to the discussion in class; (ii) I am comfortable answering questions or contributing to the discussion in class".

Figure 18: Qualification scores at entry by department and gender



Notes: The graph displays the residualized qualification score, residuals of regression of qualification score on qualification type and program x year fixed effects, for men and women enrolled in Male and Female fields. Male and Female fields are the 5 departments with the highest share of men and women among undergraduates students, respectively. The statistics include the undergraduate students enrolled in LSE between 2011 and 2017 for whom I was able to reconcile information at entry with qualifications requirements at LSE: 9.449 students, 90% of the students enrolled in undergraduate programs in LSE between academic years 2011/12 and 20117/18. Following Campbell et al. (2019), I construct a measure of individual quality based on the best three exam results among the A-level qualification scores students declared when applying to LSE. Some students take courses that are equivalents to A-Levels. In these cases I calculate their A-Level equivalence scores based on the university conversion tables for foreign students. A levels are graded on a scale of A*/A/B/C/D/E. Each A-level grade is worth 30 QCA (Qualifications and Curriculum Authority) points. P-values of two-sided Kosmogorov-Smirnov tests of equality of distributions: Male Fields - 0.547, Female Fields - 0.466. P-values of ttes of equality in means: Male Fields - 0.778, Female Fields - 0.156.

Figure 19: Ethnicity: Stereotypical Selection



Note: The figure displays the distribution of Asian, White, and other ethnicity students enrolled in undergraduate programs across departments. The statistics is the average of academic years 2008-2017. The green and blue arrows at the sides display the direction of choices of majors that would be in line with stereotypes and norms for Asian students and White students respectively. Other students include other ethnicity students and students who don't disclose their ethnic group. Other ethnicity students is a residual category that includes students of other ethnic groups, but also students who provided no information regarding their ethnicity.

10 Tables

Table 1: Outcome measures

	N.	Mean	SD
Panel A: Course grades			
Raw	54603	60.32	16.35
Residual grades after controlling for Course FEs	54603	0.00	15.84
Residual grades after controlling for Course and Student FEs	54603	0.00	7.94
Panel B: Participation grades			
Raw	44771	2.04	.85
Residual grades after controlling for Course FEs	44771	0.00	.82
Residual grades after controlling for Course and Student FEs	44771	0.00	.56

Notes: Panel A - The sample of the analysis on performance: students for which I can observe an exam grade in at least two courses: 54.603 course-year-class group level observations, corresponding to information on 14.313 students. The residual variation is obtained by taking the residuals of a regression of exam grades on course fixed effects, and course and student fixed effects respectively. Panel B - The sample is the sample of analysis restricted to all the students for which I can observe a participation grade in at least two class groups: 44.771 course-year-class group level observations, corresponding to information on 13.485 students. The residual variation is obtained by taking the residuals of a regression of participation grades on course fixed effects, and course and student fixed effects respectively.

Table 2: Sample Characteristics

	N.	Mean	SD	Min	Max
Students' Characteristics:					
Females	14313	.49	.50	0	1
Age at entry	14313	18.55	1.224551	16	56
White	14313	.36	.48	0	1
Asian	14313	.47	.50	0	1
Black	14313	.04	.20	0	1
Other	14313	.04	.19	0	1
Missing	14313	.09	.28	0	1
Single sex school	9154	.33	.47	0	1
Qualification score at entry	9449	503.90	34.27	420	540
Classes and courses:					
Course size	512	138.44	163.91	12	1011
N. classes per course	512	9.36	10.77	1	69
Class size	4886	13.43	2.45	4	23
N. classes per student	14313	3.81	0.60	2	7
Class composition:					
Share of same gender class mates	54603	.56	.16	.06	1
Share of co-ethnic class mates	54603	.35	.18	.04	1
Share of same program class mates	54447	.49	.32	.04	1
Average peers qualification score at entry	35935	501.89	15.57	420	540
Outcomes:					
Course Grade	54603	60.32	16.35	0	100
Pr(complete course)	54603	.97	.17	0	1
Participation grade	44771	2.04	.85	0	3

Notes: The descriptive statistics concern the sample of the analysis on performance: students for which I can observe an exam grade in at least two courses: 54.603 course-year-class group level observations, corresponding to information on 14.313 students. The maximum number of classes for each students are 7. Students for which we observe more than 4 classes are 5%, 85% of which attend 5 courses. These are students who attend language courses or half-unit courses during Michaelmas term.

Table 3: Variation in share of same gender students in the class

	N.	Mean	SD
Raw	54603	0.56	0.162
Residual share after controlling for Course FEs	54603	0.00	0.158
Residual share after controlling for Student and Course FEs	54603	0.00	0.112

Notes: Following Olivetti et al., (2020). The table displays the share of same gender students in class and the residual share of same gender students in class obtained by taking the residuals of a regression of the class share of same gender classmates on course fixed effects, and course and student fixed effects respectively.

Table 4: Effect of student characteristics on the share of same gender peers in class

	Share of same gender peers	
	(1)	(2)
Panel A: Gender		
Female	0.003	0.001
	(0.004)	(0.004)
Course leave-out-mean	0.993***	0.994***
	(0.016)	(0.018)
Observations	54603	44771
Course fixed effects	Y	Y
Parallel course dummies	Y	Y

Notes: Standard errors are clustered at the class group level. For each course c in academic year t I test that individual characteristics cannot predict the share of same gender peers in the class g the student was assigned to. The dependent variable is the share of same gender peers. *leave-out mean*$_{ict}$ is the share of same gender peers (dependent variable) in the course for each student. Parallel course dummies are a series of dummies that are equal to one for all the students that attend the course in the same year, and zero otherwise. The omitted category are men. Column (1) sample is the sample of the course performance analysis, while column (2) restrict the sample to the analysis on participation.

Table 5: Class group composition and Students' characteristics

	Independent Variable: Share of females	
Dependent Variables	(1)	(2)
White	-0.005	-0.004
	(0.015)	(0.017)
Asian	0.014	0.005
	(0.016)	(0.017)
Other Ethnicity	-0.003	-0.002
	(0.009)	(0.010)
Unknown Ethnicity	-0.005	0.002
	(0.010)	(0.011)
Independent School	-0.029*	-0.036**
	(0.015)	(0.017)
State School	0.014	0.011
	(0.014)	(0.016)
Other School	0.015	0.025
	(0.017)	(0.019)
Mixed School	0.005	0.000
	(0.017)	(0.019)
Single Sex	-0.006	-0.015
	(0.014)	(0.016)
Not applicable	0.001	0.015
	(0.017)	(0.018)
Age at entry	-0.027	-0.051
	(0.040)	(0.044)
Qualification Score at entry	-0.374	-0.604
	(0.873)	(0.956)
Course Fixed Effects	Y	Y
Parallel Course Dummies	Y	Y
N	54603	44771
N. Tests performed	12	12
N. Tests significant at 1%	0	0
N. Tests significant at 5%	0	1
N. Tests significant at 10%	1	1
Share Tests significant at 1%	0	0
Share Tests significant at 5%	0	0.08
Share Tests significant at 10%	0.08	0.08
Total N. Tests performed	24	
Total Share Tests significant at 1%	0	
Total Share Tests significant at 5%	0.04	
Total Share Tests significant at 10%	0.08	

Notes: Standard errors are clustered at the class group level. For each course c in academic year t I test that individual characteristics cannot predict the share of female in the class g the student was assigned to. Column (2) restricts the sample to the sample for the analysis on participation. Each row corresponds to a separate regression where the independent variable is the share of females in the class and the dependent variable is the individual characteristic, controlling for course fixed effects, a dummy for each course the student attends during the academic year, and a female dummy. When the dependent variables are age at entry and qualification score at entry, a dummy for missing values is included in the regression.

Table 6: Selection into fields

	Course grade			
	Continuous	Top and Bottom 2	Top and Bottom 3	Top and Bottom 5
	(1)	(2)	(3)	(4)
Share of students like me	-5.937***	-3.555***	-2.884***	-1.167
	(1.701)	(1.232)	(1.042)	(0.725)
Share of students like me × Neutral		3.757***	3.154***	1.028
		(1.300)	(1.132)	(0.954)
Share of students like me × Stereotypical selection	12.390***	7.759***	6.138***	3.447***
	(3.166)	(1.555)	(1.313)	(0.944)
Course fixed effects	Y	Y	Y	Y
Student fixed effects	Y	Y	Y	Y
Observations	54603	54603	54603	54603
Mean Dependent Variable	60.320	60.320	60.320	60.320
	(16.345)	(16.345)	(16.345)	(16.345)

Notes: This table provides evidence of the results of Specification 2 in Column (1) and Specification 3 in Columns (2)-(4). In Column (1) stereotypical selection is defined as the average share of same gender students in the student i department of enrolment across academic years 2008-2017. In Columns (2) I consider as students making stereotypical choices, students who are enrolled in the top two departments with the highest average share of same gender students, while students who enrolled in the two departments with the lowest share of same gender students, as students who made a choice not in line with stereotypes regarding gender roles and skills. In Columns (3) and (4), I replicate the same analysis by defining stereotypical and counter stereotypical choices by considering the top and bottom 3 and 5 departments in terms of share of same gender students among undergraduates. The outcome variable is course grades, with incomplete courses coded as 0. Standard errors are clustered at the class group level.

Table 7: Selection into fields - Grades distribution

	Course grade	Pr(Drop-out)	Grade ≥ 40	Grade ≥ 50	Grade ≥ 60	Grade ≥ 70
	(1)	(2)	(3)	(4)	(5)	(6)
Share of students like me	-5.937***	0.015	-0.056*	-0.131***	-0.198***	-0.089
	(1.701)	(0.016)	(0.031)	(0.047)	(0.066)	(0.056)
Share of students like me × Stereotypical Selection	12.390***	-0.023	0.117**	0.276***	0.386***	0.207**
	(3.166)	(0.030)	(0.058)	(0.086)	(0.124)	(0.103)
Course fixed effects	Y	Y	Y	Y	Y	Y
Student fixed effects	Y	Y	Y	Y	Y	Y
Observations	54603	54603	54603	54603	54603	54603
Mean Dependent Variable	60.320	0.029	0.931	0.843	0.628	0.232
	(16.345)	(0.167)	(0.254)	(0.364)	(0.483)	(0.422)

Notes: This table provides evidence of the results of Specification 2. The outcome variable is course grades, with incomplete courses coded as 0 in Column (1). In Column (2) the dependent variable is a dummy equal to one if students drop-out from the course and zero otherwise. In Columns (3) to (6) the outcome variables are a series of dummies that are equal to one if grades are greater or equal to 40, 50, 60, and 70, respectively. Standard errors are clustered at the class group level.

Table 8: Selection into fields - Gender differences

	Course grade			
	Continuous	Top and Bottom 2	Top and Bottom 3	Top and Bottom 5
	(1)	(2)	(3)	(4)
Panel A: Continuous definition of Stereotypical Selection:				
Female x Share of students like me	-2.432			
	(2.169)			
Female x Share of students like me × Stereotypical Selection	5.252			
	(3.866)			
Male x Share of students like me	-10.508***			
	(2.535)			
Male x Share of students like me × Stereotypical Selection	21.279***			
	(4.838)			
Panel B: Categorical definition of Stereotypical Selection:				
Female x Share of students like me		-2.982**	-2.344*	-0.449
		(1.332)	(1.215)	(1.022)
Female x Share of students like me × Neutral		3.722**	2.985**	0.811
		(1.462)	(1.380)	(1.368)
Female x Share of students like me × Stereotypical Selection		5.536***	4.509***	1.186
		(2.120)	(1.635)	(1.196)
Male x Share of students like me		-5.910*	-4.348**	-2.238**
		(3.135)	(2.006)	(0.957)
Male x Share of students like me × Neutral		5.555*	4.233**	1.573
		(3.195)	(2.107)	(1.298)
Male x Share of students like me × Stereotypical Selection		10.655***	8.112***	5.664***
		(3.311)	(2.256)	(1.319)
Course fixed effects	Y	Y	Y	Y
Student fixed effects	Y	Y	Y	Y
Observations	54603	54603	54603	54603
Mean Dependent Variable	60.320	60.320	60.320	60.320
	(16.345)	(16.345)	(16.345)	(16.345)
Gender differences in effect:				
Share of students like me	-8.008**	-2.876	-1.974	-1.790
	(3.254)	(3.346)	(2.314)	(1.390)
Share of students like me × Stereotypical Selection	15.906***	5.071	3.576	4.463**
	(6.041)	(3.710)	(2.703)	(1.760)
Effect for students who made a stereotypical selection:				
Female		2.554	2.165*	.737
		(1.633)	(1.106)	(0.639)
Male		4.745***	3.765***	3.426***
		(1.069)	(1.008)	(0.895)

Notes: This table provides evidence of the results of Specification 2 (Panel A) and Specification 3 (Panel B) interacting Share of students like me and Share of students like me × Stereotypical Selection by a dummy equal to one if the student is female and a dummy equal to one if the student is male. In Panel A stereotypical selection is defined as the average share of same gender students in the student's department of enrolment across academic years 2008-2017. In Panel B I consider as students making stereotypical choices, students who are enrolled in the top two departments with the highest average share of same gender students,while students who enrolled in the two departments with the lowest share of same gender students, as students who made a choice not in line with stereotypes regarding gender roles and skills in Column (2). In Columns (3) and (4), I replicate the same analysis by defining stereotypical and counter stereotypical choices by considering the top and bottom 3 and 5 departments in terms of share of same gender students among undergraduates. The outcome variable is course grades, with incomplete courses coded as 0. Standard errors are clustered at the class group level. The additional tests at the bottom of the table display a test of the differences between the estimated coefficient for men and women for each specification (Gender differences in effect), and the estimated effect of an increase in the share of same gender classmates for students who made a stereotypical selection: sum of the coefficient of the Share of students like me and Share of students like me interacted with Stereotypical Selection for men and women (Effect for students who made a stereotypical selection).

Table 9: Selection into fields - Minority effect by gender

	Participation Grade		
	All	Counter-Stereotypical	Stereotypical
	(1)	(2)	(3)
Panel A: Woman			
Share of students like me	0.185**	0.074	0.155
	(0.074)	(0.147)	(0.116)
Single Sex × Share of students like me	-0.094	-0.242	0.234
	(0.104)	(0.206)	(0.175)
Panel B: Man			
Share of students like me	-0.159**	-0.088	-0.190*
	(0.069)	(0.144)	(0.108)
Single Sex × Male x Share of students like me	0.217**	0.390	0.273
	(0.110)	(0.252)	(0.172)
Observations	29062	6596	12153
Course Fixed Effects	Y	Y	Y
Student Fixed Effects	Y	Y	Y
Effect if Single Sex = 1			
Woman	0.091	-0.168	0.389**
	(0.093)	(0.178)	(0.162)
Man	0.058	0.302	0.083
	(0.100)	(0.225)	(0.153)

Notes: This table provides evidence of the results of Specification 2, interacting Share of students like me with a dummy equal to 1 if the student attended a single-sex school. The sample is restricted to students for which I have information on previous schools attended. In Column (1) I am considering all students, in Column (2) students who are enrolled in counter-stereotypical departments, in Column (3) students who are enrolled in stereotypical departments. The definition of Stereotypical selection is based on top and bottom 5 departments in terms of share of same gender students enrolled.

Table 10: Teaching assistant's gender

	Course Grade			
	Continuous	Top and Bottom 2	Top and Bottom 3	Top and Bottom 5
	(1)	(2)	(3)	(4)
Same gender TA	-1.309*	-0.461	-0.417	-0.002
	(0.775)	(0.558)	(0.462)	(0.376)
Same gender TA × Neutral		0.192	0.105	-0.421
		(0.594)	(0.512)	(0.457)
Same gender TA × Stereotypical selection	2.635*	2.105***	1.669***	0.664
	(1.461)	(0.764)	(0.629)	(0.538)
N	26669	26669	26669	26669
Course Fixed Effects	Y	Y	Y	Y
Student Fixed Effects	Y	Y	Y	Y

Notes: This table provides evidence of the results of Specification 2, interacting Share of students like me with a dummy equal to 1 if the teacher's gender is the same as the student's gender. The sample is restricted to classes where I have information on the gender of the teaching assistant. In Column (1) I am considering all students, in Column (2) students who are enrolled in counter-stereotypical departments, in Column (3) students who are enrolled in stereotypical departments. The definition of Stereotypical selection is based on top and bottom 5 departments in terms of share of same gender students enrolled.

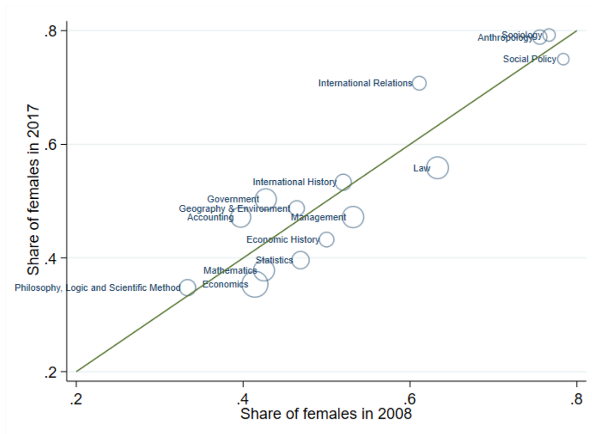
Table 11: Ethnicity: Effect of stereotypical selection

	Course grade	
	(1)	(2)
Panel A: White students:		
Share of students like me	-2.129	-2.122
	(1.828)	(1.827)
Share of students like me × Stereotypical Selection	9.144**	9.143**
	(4.065)	(4.062)
Panel B: Asian students:		
Share of students like me	-5.203***	-5.205***
	(1.723)	(1.723)
Share of students like me × Stereotypical Selection	12.899***	12.911***
	(3.375)	(3.375)
Panel C: Other students:		
Share of students like me	-11.288**	-11.242**
	(4.507)	(4.504)
Share of students like me × Stereotypical Selection	59.670***	59.438***
	(22.131)	(22.117)
Share of students like me		0.551
		(0.368)
Share of students like me × Stereotypical selection		
Course fixed effects	Y	Y
Student fixed effects	Y	Y
Observations	54603	54603

Notes: This table provides evidence of the results of Specification 14. The outcome variable is course grades, with incomplete courses coded as 0. Stereotypical selection is defined as the average share of same ethnicity students in the student i department of enrolment across academic years 2008-2017. In Column (2) I additionally control for the share of same gender classmates. Standard errors are clustered at the class group level.

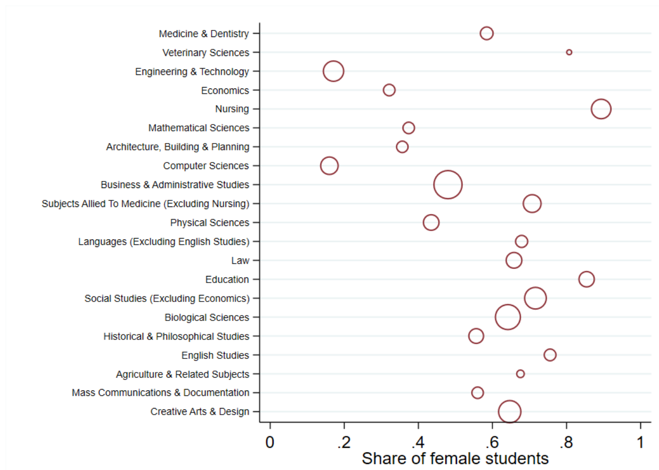
Appendix A Additional Tables and Figures

Figure A1: Departments gender composition over the years



Notes: This figure illustrates the change in gender composition of LSE departments between 2008/09 and 2017/18. It is constructed based on the number of first year undergraduate students that are enrolled in bachelor programmes offered by each department in the two academic years.

Figure A2: Enrollment in Higher Education by subject of study



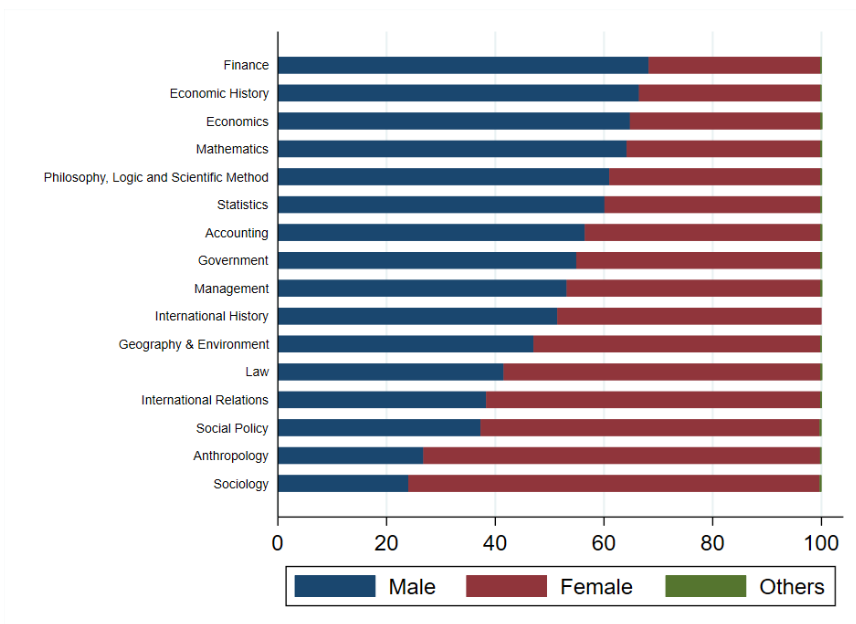
Notes: Information on the share of women among the overall population of undergraduate students enrolled in UK Universities. Source: HESA Higher Education Student Data, academic year 2018-2019.

Figure A3: Share of courses outside the department of enrolment

	Academic year										
Department of Enrolment	**2008/09**	**2009/10**	**2010/11**	**2011/12**	**2012/13**	**2013/14**	**2014/15**	**2015/16**	**2016/17**	**2017/18**	**2018/19**
Accounting	0,75	0,75	0,75	0,75	0,75	0,80	0,80	0,80	0,80	0,80	0,75
Anthropology	0,44	0,44	0,44	0,44	0,44	0,38	0,38	0,38	0,38	0,38	0,50
Economic History	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,67	0,67	0,57	0,61
Economics	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75
Finance									0,80	0,80	0,80
Geography & Environment	0,50	0,50	0,50	0,44	0,38	0,38	0,41	0,44	0,44	0,44	0,44
Government	0,67	0,67	0,67	0,67	0,67	0,67	0,67	0,55	0,65	0,55	0,58
International History	0,88	0,88	0,88	0,88	0,88	0,88	0,88	0,88	0,67	0,78	0,56
International Relations	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,50
Law	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Management	0,79	0,79	0,79	0,79	0,67	0,67	0,67	0,67	0,67	0,67	0,71
Mathematics	0,50	0,50	0,50	0,50	0,50	0,50	0,50	0,50	0,50	0,50	0,50
Mathematics, Statistics										0,25	0,25
Philosophy, Logic and Scientific Method	0,58	0,58	0,64	0,58	0,58	0,58	0,58	0,67	0,67	0,67	0,67
Social Policy	0,52	0,52	0,52	0,52	0,52	0,52	0,52	0,55	0,43	0,38	0,38
Sociology	0,50	0,50	0,50	0,50	0,50	0,25	0,25	0,25	0,25	0,40	0,25
Statistics	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75	0,75

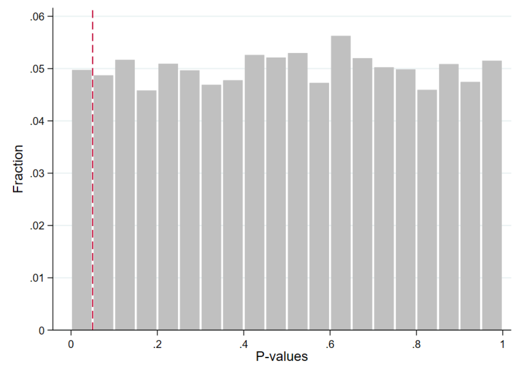
Notes: The table displays the share of courses outside the department of enrollment among courses in program for first year undergraduate students. Information are gathered from LSE Course Guides and Program Regulations for each academic year. When students can choose more than one course, the course is considered as outside the department if one of the choices is a course outside the department of enrolment. E.g. EC100 is considered outside the department for all the students who are enrolled in programs of study that do not fall under the Economics department.

Figure A4: Gender composition of applicants



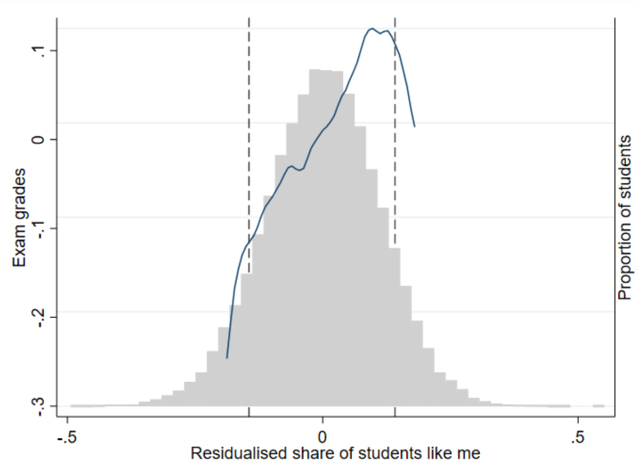
Notes: This figure illustrates the gender composition of each department. It is constructed based on the number of men and women that apply for bachelor programs at the university every year. The figure shows the average across academic years 2007/08 to 2019/20.

Figure A5: Simulated sample P-values



Notes: This graph show the p-values of a test of joint significance of the class dummies from a regression of gender on class dummies for each first year course in each academic year for each of the 1000 randomly simulated allocations. The sample is restricted to the courses that have at least 2 classes. The test is performed on all the students that attend first year courses and that did not change classes (which are the students for whom I can recover the initial class allocation).

Figure A6: Functional form of effect of share of females



Notes: Local polynomial plot of the relationship between residualised course grades on the residualised share of same gender classmates. These are obtained by regressing course grades and the share of samge gender classmates on course and student fixed effects, respectively. The vertical lines display the 5st and 95th percentile of the share of same gender classmates. The grey histogram displays the support of the residualised share of same gender classmates.

Table A1: Selection into fields - Robustness

	Course grade				
	(1)	(2)	(3)	(4)	(5)
Panel A: Continuous definition					
Share of students like me	-5.937***	-4.033**	-5.999***	-3.175*	-6.549***
	(1.701)	(1.933)	(1.701)	(1.703)	(2.094)
Share of students like me × Stereotypical Selection	12.390***	8.757**	12.515***	6.953**	13.191***
	(3.166)	(3.619)	(3.164)	(3.171)	(3.905)
Panel B: Top & Bottom 2:					
Share of students like me	-3.555***	-2.173	-3.610***	-2.420**	-4.524***
	(1.232)	(1.353)	(1.232)	(1.230)	(1.606)
Share of students like me × Stereotypical Selection	7.759***	5.570***	7.803***	5.186***	8.848***
	(1.555)	(1.765)	(1.554)	(1.552)	(2.023)
Panel B: Top & Bottom 3:					
Share of students like me	-2.884***	-2.135*	-2.926***	-1.914*	-3.626***
	(1.042)	(1.153)	(1.042)	(1.045)	(1.303)
Share of students like me × Stereotypical Selection	6.138***	4.911***	6.165***	3.962***	7.081***
	(1.313)	(1.485)	(1.312)	(1.321)	(1.663)
Panel B: Top & Bottom 5:					
Share of students like me	-1.167	-0.649	-1.204*	-0.596	-1.182
	(0.725)	(0.813)	(0.724)	(0.722)	(0.888)
Share of students like me × Stereotypical Selection	3.447***	2.447**	3.489***	2.208**	3.187***
	(0.944)	(1.077)	(0.942)	(0.940)	(1.176)
Course fixed effects	Y	Y	Y	Y	Y
Student fixed effects	Y	Y	Y	Y	Y
TA fixed effects	X	Y	X	X	X
Share of same ethnicity students	X	X	Y	Y	X
Share of same school students	X	X	Y	Y	X
Share of same program students	X	X	X	Y	X
Classmates' average qualification score at entry	X	X	X	X	Y
Observations	54603	51622	54603	54447	35883

Notes: This table provides evidence of the results of Specification 2 (Panel A) and Specification 3 (Panel B). In Panel A stereotypical selection is defined as the average share of same gender students in the student's department of enrolment across academic years 2008-2017. In Panel B I consider as students making stereotypical choices, students who are enrolled in the top two departments with the highest average share of same gender students,while students who enrolled in the two departments with the lowest share of same gender students, as students who made a choice not in line with stereotypes regarding gender roles and skills. I replicate the same analysis by defining stereotypical and counter stereotypical choices by considering the top and bottom 3 and 5 departments in terms of share of same gender students among undergraduates (Top Bottom 3, Top Bottom 5). The outcome variable is course grades, with incomplete courses coded as 0. Standard errors are clustered at the class group level. Column (1) contains the basic specification, Column (2) includes teaching assistants fixed effects, Column (3) includes controls for the share of same ethnicity and same previous school classmates, Column (4) adds the share of same program students to Column (3) controls, Column (5) includes a control for the classmates' average qualification score at entry.

Table A2: Selection into fields - Robustness spillovers and mechanical effects

	Course Grade			
	(1)	(2)	(3)	(4)
Share of students like me	-5.321***	-4.598**	-9.757***	-9.308**
	(1.566)	(1.818)	(2.067)	(4.511)
Stereotypical Selection			-6.365***	-6.294
			(2.093)	(4.538)
Share of students like me × Stereotypical Selection	11.116***	9.886***	18.920***	18.321**
	(2.892)	(3.399)	(3.802)	(8.211)
Observations	54603	54603	54603	14313
Course × year FEs	Y	X	Y	Y
Student FEs	Y	Y	X	X
Parallel Courses	X	X	Y	Y

Notes: This table provides evidence of the results of Specification 2 in Column (1). Column (2) displays the results of Specification 2 with no course fixed effects. Columns (3) and (4) display the results obtained by exploiting the within-course variation: Specification 2 with no student fixed effects, but with controls for the other courses attended by each student during the academic year. Column (3) includes all the observations, while (4) exploits one observation per student. Standard errors are clustered at the class level.

Table A3: Selection into fields - Placebo tests

	Course grade		
	(1)	(2)	(3)
Share of students like me	-5.937***	-6.006***	-3.097*
	(1.701)	(1.701)	(1.701)
Share of students like me × Stereotypical Selection	12.390***	12.534***	6.919**
	(3.166)	(3.165)	(3.170)
Share of co-ethnic classmates		1.987	
		(1.860)	
Share of co-ethnic classmates × Stereotypical Selection		-0.537	
		(3.422)	
Share of same program classmates			4.707***
			(0.967)
Share of same program classmates × Stereotypical Selection			-2.291
			(1.770)
Course fixed effects	Y	Y	Y
Student fixed effects	Y	Y	Y
Observations	54603	54603	54447

Notes: This table provides evidence of the results of Specification 2 in Column (1). Column (2) displays the results of Specification 2 with additional controls for Stereotypical selection interacted with the share of same ethnicity classmates (Column 2), adn the share of same program classmates (Column 3). Standard errors are clustered at the class level.

Table A4: Selection into fields - Different measure of Stereotypical Selection

	Course grade			
	LSE Undergraduates	LSE Applications	UK HESA Undergraduates	UK HESA Staff
	(1)	(2)	(3)	(4)
Share of students like me	-5.937***	-4.890***	-7.409***	-4.125***
	(1.701)	(1.812)	(1.739)	(1.401)
Share of students like me × Stereotypical Selection	12.390***	10.410***	15.313***	8.934***
	(3.166)	(3.411)	(3.265)	(2.645)
Course fixed effects	Y	Y	Y	Y
Student fixed effects	Y	Y	Y	Y
Observations	54603	54603	54603	52623

Notes: This table provides evidence of the results of Specification 2 using the share of same gender students among students enrolled in undergraduate programmes at LSE as proxy for stereotypical selection in Column (1). Columns (2)-(4) display the results of Specification 2, using different proxies for stereotypical selection: the share of same gender students among students who applied to undergraduate programmes at LSE (Column 2), the share of same gender students among students enrolled in undergraduate programmes in UK universities (Column 3), the share of same gender staff working in UK universities in each field (Column 4). Information on the data used to create the alternative proxies of stereotypical selection can be found in Table A5. Standard errors are clustered at the class level.

Table A5: Department categorization - Share of females

	LSE Undergraduate Enrolment	LSE Undergraduate Applications	UK HESA Undergraduate Enrolment	UK HESA Staff
	(1)	(2)	(3)	(4)
Finance	0.31	0.32	0.42	0.43*
Economics	0.35	0.35	0.33	0.30
Mathematics	0.38	0.36	0.39	0.23^{+}
Philosophy, Logic and Scientific Method	0.39	0.39	0.47	0.29
Economic History	0.39	0.33	0.53^{+}	
Statistics	0.41	0.40	0.43	0.23^{+}
Government	0.45	0.45	0.47*	0.37^{x}
Accounting	0.48	0.43	0.46	0.43*
Management	0.51	0.48	0.47	0.43*
Geography & Environment	0.51	0.53	0.56	0.40
International History	0.51	0.49	0.53^{+}	0.42
Law	0.61	0.58	0.63	0.51
Social Policy	0.66	0.62	0.69	0.65
International Relations	0.67	0.62	0.47*	0.37^{x}
Anthropology	0.76	0.73	0.74	0.51
Sociology	0.78	0.76	0.75	0.55

Notes: Columns (1)-(4) display the share of females among students enrolled in undergraduate programmes at LSE, students who applied to undergraduate programmes at LSE, students enrolled in undergraduate programmes in UK universities, staff working in UK universities respectively. In columns (1)-(3) the share is calculated as the average of the share of females in each subject across academic years 2008-2017. In column (4) the reported share is the share across academic years 2014-2018. *,+,x are symbols used to indicate that data come from aggregate statistics since the department isn't present as a separate voice.

Table A6: Stereotypes - Global Gender Gap Index

	Course Result	
	Counter-Stereotypical	Stereotypical
	(1)	(2)
Panel A: Men		
Share of students like me	-4.746*	5.260***
	(2.443)	(1.560)
GGI Tercile=2 × Share of students like me	4.965*	-0.588
	(2.985)	(2.215)
GGI Tercile=3 × Share of students like me	3.392	-5.234**
	(2.988)	(2.216)
Panel B: Women		
Share of students like me	0.306	0.112
	(1.617)	(1.307)
GGI Tercile=2 × Share of students like me	-0.671	-0.007
	(2.465)	(1.657)
GGI Tercile=3 × Share of students like me	1.099	0.315
	(2.891)	(1.785)
N	11290	20255
Course Fixed Effects	Y	Y
Student Fixed Effects	Y	Y

Notes: This table provides evidence of the results of Specification 1, interacting Share of students like me with a dummy for female and a dummy for male, and with a dummy equal to 1 if the student's country of origin belongs to the second tercile of the GGI distribution or the third tercile. The reference category are students whose country of origin belongs to the first tercile of the Gender Gap Index distribution (more unequal countries). The sample is restricted to students for which I have information on the Gender Gap Index of the country of origin. In Column (1) I consider students who are enrolled in counter-stereotypical departments, in Column (2) students who are enrolled in stereotypical departments. The definition of Stereotypical selection is based on top and bottom 5 departments in terms of share of same gender students enrolled. Standard errors are clustered at the class level.

Table A7: Ethnicity: Effect of stereotypical selection - No Other

	Course grade	
	(1)	(2)
Panel A: White students:		
Share of students like me	-1.856	-1.844
	(1.839)	(1.838)
Share of students like me × Stereotypical Selection	9.138**	9.123**
	(4.078)	(4.074)
Panel B: Asian students:		
Share of students like me	-5.739***	-5.736***
	(1.728)	(1.728)
Share of students like me × Stereotypical Selection	13.266***	13.272***
	(3.376)	(3.375)
Share of same gender classmates		0.771*
		(0.400)
Course fixed effects	Y	Y
Student fixed effects	Y	Y
Observations	45471	45471

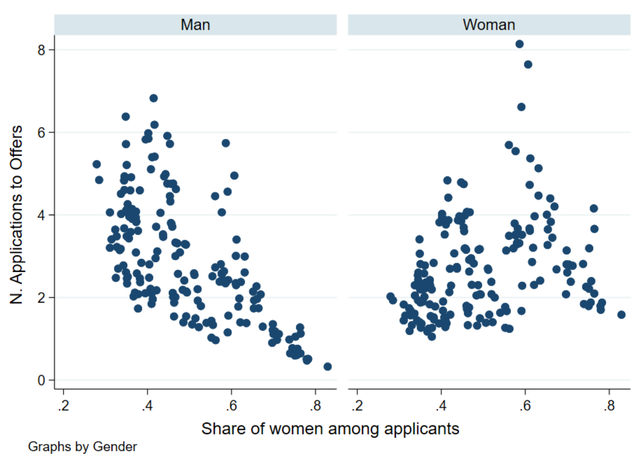
Notes: This table provides evidence of the results of Specification 14. The outcome variable is course grades, with incomplete courses coded as 0. Stereotypical selection is defined as the average share of same ethnicity students in the student i department of enrolment across academic years 2008-2017. In Column (2) I additionally control for the share of same gender classmates. The sample is restricted to students who declared Asian or White as their ethnic group. Standard errors are clustered at the class group level.

Table A8: Gender gap in class participation

	Class participation	
	(1)	(2)
Female	-0.089***	-0.091***
	(0.014)	(0.013)
Female × Balanced	-0.046**	-0.052***
	(0.020)	(0.019)
Female × Female Fields	-0.060***	-0.068***
	(0.021)	(0.021)
Balanced	0.023	0.006
	(0.017)	(0.017)
Female Fields	0.016	-0.009
	(0.024)	(0.025)
Observations	44771	44661
Course fixed effects	Y	X
Class group fixed effects	X	Y

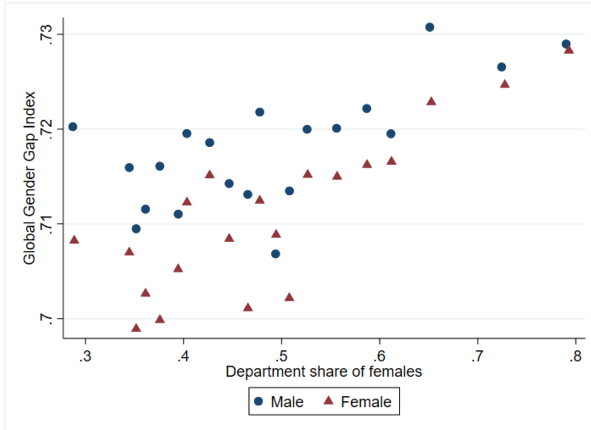
Notes: This table provides evidence of the results of a specification where class participation is regressed on course × year fixed effects (Column 1) the female dummy interacted with a dummy equal to one if the department the student is enrolled in is a balanced department and a dummy equal to one if the department the student is enrolled in is a female dominated department. The reference category are male dominated departments. The definition of female, balanced and male dominated departments is based on top and bottom 5 departments in terms of share of female students among undergraduate students. Standard errors are clustered at the class level. The outcome variable is participation grades. In Column (2) I control for class fixed effects instead of course × year fixed effects.

Figure A7: Number of applications by number of offers by gender



Notes: Information on undergraduate students applying to LSE in academic years 2007-2018. The y-axis displays the ratio of number of applications to number of offers in each academic year for each department. On the x-axis, departments are ordered based on the share of women among applicants, from lowest to highest.

Figure A8: Gender gap index and selection across departments



Notes: This is a binned scatter-plot that displays the relationship between the gender gap index in student's country of origin (y-axis) and the share of females in the departments the student is enrolled into (x-axis), controlling for year fixed effects. Sample: students enrolled in the first year of undergraduate programs for which I have information on the GGI of the country of origin.

Appendix B Students changing class groups

Students have the possibility to change class group during the term. Students are not allowed to change class group whenever they fancy, but changes are allowed only under particular circumstances, i.e. if the student is not able to follow the allocated seminar due to clashes with other courses that arose during the term, or external circumstances. In order to be able to change class group, they have to submit an official request. Considering the sample of analysis, this happens 5.9% of times. If students changed class group in a systematic way, class group allocation would not be exogenous anymore. In order to test that the decision to change class group does not depend on the gender composition of the class group, and that omitting students who changed class group does not generate bias, I perform two tests.

Table A9 and A10 show the results of regressions where a dummy equal to one when a student changed class group is regressed on gender. Columns (2) to (5) include also class group fixed effects, while Columns (3) and (5) include a control for parallel courses, a dummy for each course the student attend in Michaelmas term. In Table A9 the sample is restricted to all the students in analysis (first year undergraduate students who attended the courses for the first time), while Table A10 includes all the students that are allocated to a class group where a student in analysis is allocated, i.e. all the students that will contribute in defining class group gender composition. Both tables are divided into two panels. Panel A considers all the class groups the student has been allocated to during the term. If a student changed class group once during Michaelmas term, the student will be present in the sample twice for the same course. Panel B consider only one class group per student. If a student changed class group, I randomly select one of the groups to which he has been allocated.

In order to test whether the decision to change class group is independent on the group composition, I reconstruct the initial and final class group allocation for the students who changed class group. Since students normally keep the class group to which they have been allocated for all the three terms in the academic year, for 87.68% of students I am able to identify final and initial allocation by assuming that, among the two class groups observed, the final allocation is the class group the student is allocated to in Lent term. Table A11 shows the results of a regression on the sample of all students who change class group in Michaelmas term for which I am able to reconstruct initial and final allocation, of the share of females in the class group on a dummy equal to one when the class group corresponds to the reconstructed initial allocation and zero if it corresponds to the final allocation (Initial allocation), a dummy for whether the student is a female, and the interaction of the two.

We can see from Panel B of Table A10 that women have a slightly higher probability of changing class group. However, this probability is very small, between 0.04 and 0.07 percentage points higher with respect to a man in the same class group[44]. Furthermore, we can see from Table that the decision to change class group is independent to the gender composition of the class group. Since I am excluding all the students who changed class group when I construct the measure of class group composition, the share of female peers will be underestimated, but in an homogeneous way and independently to class group composition.

Lastly, Panel B of Table shows that once I control for parallel courses, the female dummy coefficient becomes insignificant, and Table shows that for the student in analysis, class group changes are independent on class group composition. This means that when I exclude the observation for students who change class group, I am creating an unbalanced sample, but this shouldn't generate a bias since, once I control for parallel courses (or equivalently student fixed effects) this does not vary with the gender of the student, and this is orthogonal to class group composition.

[44]To get a correct estimate of this probability we have to look at Panel B, since in Panel A people who changed class group are oversampled

Table A9: Decision to change class group - Analysis sample

	Dummy=1 if student changed class group				
	(1)	(2)	(3)	(4)	(5)
Panel A: All class groups					
Female	0.008**	0.008***	0.006**	0.013***	0.010**
	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)
Observations	61696	61696	61696	37584	37584
Panel B: Random class groups					
Female	0.004**	0.003*	0.003	0.006*	0.005
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Observations	58593	58593	58593	34481	34481
class group Fixed Effects		x	x	x	x
Parallel Courses			x		x

Notes: The Table shows the results of a regression where the independent variable is a dummy equal to one if the student changed class group. The sample is restricted to Michaelmas term, first year undergraduate students who attended the courses for the first time. Panel A considers all the class groups the student has been allocated to during the term. If a student changed class group, the student will be present in the sample twice for the same course. Panel B consider only one class group per student. If a student changed class group, I randomly select one of the groups to which he has been allocated. Columns (1)-(3) include all class groups, columns (4) and (5) only class groups where at least one student changed class group. t statistics from standard errors clustered at class group level in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A10: Decision to change class group - All students

	Dummy=1 if student changed class group				
	(1)	(2)	(3)	(4)	(5)
Panel A: All class groups					
Female	0.009***	0.011***	0.009***	0.018***	0.015***
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)
Observations	76280	76280	76280	47266	47266
Panel B: Random class groups					
Female	0.005**	0.005**	0.004**	0.008**	0.007**
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Observations	72031	72031	72031	43017	43017
class group Fixed Effects		x	x	x	x
Parallel Courses			x		x

Notes: The Table shows the results of a regression where the independent variable is a dummy equal to one if the student changed class group. The sample consists of all the students that have been allocated to a class group where a student in analysis has been allocated. Panel A considers all the class groups the student has been allocated to during the term. If a student changed class group, the student will be present in the sample twice for the same course. Panel B consider only one class group per student. If a student changed class group, I randomly select one of the groups to which he has been allocated. Columns (1)-(3) include all class groups, columns (4) and (5) only class groups where at least one student changed class group. t statistics from standard errors clustered at class group level in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A11: Decision to change class group - All students

	class group share of females					
	(1)	(2)	(3)	(4)	(5)	(6)
Initial allocation	0.007	0.007	0.007	0.010	0.010	0.010
	(0.009)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)
Initial allocation × Female	0.005	0.005	0.005	0.003	0.003	0.003
	(0.011)	(0.008)	(0.008)	(0.010)	(0.007)	(0.007)
Female	0.127***	0.072***	0.069***	0.125***	0.067***	0.064***
	(0.008)	(0.006)	(0.006)	(0.007)	(0.005)	(0.005)
Course Fixed Effects		x	x		x	x
Parallel courses			x			x
Included Students	Analysis	Analysis	Analysis	All	All	All
Observations	5222	5222	5222	7040	7040	7040

Notes: The Table shows the results of a regression where the share of females in the class group is regressed on "Initial allocation", a dummy equal to one when the class group corresponds to the reconstructed initial allocation and zero if it corresponds to the final allocation, a dummy for whether the student is a female, and the interaction of the two. The sample consists of all the students who changed class group once in Michaelmas term, for whom I was able to reconstruct the initial and final class group allocation (87.68% of cases). Since students normally keep the class group to which they have been allocated for all the three terms in the academic year, the final allocation is assumed to be the class group the student is allocated to in Lent term. t statistics from standard errors clustered at class group level in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.1 Participation grade attrition checks

Teaching assistants are required to give a performance and participation grade to all the students in the seminar. However, even if assessment is in principle compulsory, not all the teaching assistants give a feedback to the students. In Michaelmas term, participation is Missing for 16.75% of course-year-class group level observations, thus, the dataset is an unbalanced panel. However, the reason why class group participation is Missing is because the teaching assistant didn't give a grade to anybody in the class group.

As it can be seen in A12 in 75% of cases, participation is Missing for all the students in the class group, while in the remaining of the cases, it is Missing because the student dropped the course or changed class group before the term ended, or the student never attended the seminar. In Table A13 we can see that women have a slightly lower probability (1 percentage point) of having a participation grade, but this effect disappears when we control for course fixed effects and class group fixed effects. This indicates that women don't have a lower probability of having a participation grade, but the probability that teaching assistants give a participation grade to students is lower in courses where there are more women. The same is true for ethnicity. Regarding age of entry, even controlling for class group fixed effects, an additional year of age at entry decreases the probability of having a participation grade by 0.1 percentage points. Table A14 confirms the fact that the probability of having a participation grade does not depend on the share of females or the share of students from particular ethnic groups in the class group.

Table A12: Missing participation

Fraction of class groups based on presence of participation information

	MT	LT	ST
None or only general course students (compulsory)	0.34	0.19	0.95
Whole class	0.40	0.28	0.01
Whole class, except students who changed class group	0.05	0.13	0.00
Whole class, except students who were never present	0.04	0.06	0.02
Whole class, except students who dropped the course	0.01	0.06	0.00
Whole class, except combination of the above	0.16	0.28	0.02

Table A13: Participation grade attrition checks - Individual characteristics

	Pr(Participation grade)		
	(1)	(2)	(3)
Female	-0.011**	-0.003	-0.001
	(0.004)	(0.003)	(0.001)
Age on entry	-0.001	-0.001	-0.002*
	(0.001)	(0.001)	(0.001)
Arab	-0.010	0.016	0.012
	(0.022)	(0.018)	(0.008)
Asian	-0.023*	-0.010	-0.003
	(0.014)	(0.011)	(0.005)
Black	-0.020	-0.005	0.005
	(0.016)	(0.013)	(0.006)
Chinese	-0.028**	-0.002	0.002
	(0.014)	(0.011)	(0.005)
Missing	0.017	-0.008	-0.002
	(0.015)	(0.011)	(0.005)
Mixed	-0.035**	-0.017	-0.000
	(0.015)	(0.012)	(0.005)
White	-0.032**	-0.011	-0.005
	(0.014)	(0.011)	(0.005)
Observations	54603	54603	54603
Course Fixed Effects	X	Y	X
Class group Fixed Effects	X	X	Y

Notes: The Table shows the results of a regression where the independent variable is a dummy equal to one when the student has a participation grade and zero otherwise. The independent variables are background students' individual characteristics. The omitted category for ethnicity is Other. t statistics from standard errors clustered at class group level in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A14: Participation grade attrition checks - Class group composition

	Pr(Participation grade)		
	(1)	(2)	(3)
Panel A: Gender			
Share of females	-0.097***	-0.025	-0.003
	(0.031)	(0.031)	(0.027)
Panel B: Ethnicity			
Share of Indian	0.095*	-0.017	-0.020
	(0.055)	(0.053)	(0.046)
Share of Chinese	-0.027	0.016	0.007
	(0.037)	(0.042)	(0.038)
Share of Black	0.024	-0.093	-0.115
	(0.104)	(0.091)	(0.079)
Share of Other Asian	0.024	-0.008	-0.004
	(0.052)	(0.046)	(0.042)
Share of Other	0.031	-0.023	-0.059
	(0.096)	(0.078)	(0.069)
Share of Missing	0.218***	0.010	-0.013
	(0.041)	(0.052)	(0.046)
Observations	54603	54603	54603
Course Fixed Effects	X	Y	Y
Student Fixed Effects	X	X	Y

Notes: The Table shows the results of a regression where the independent variable is a dummy equal to one when the student has a participation grade and zero otherwise. In Panel A the independent variable is the share of females in the class group. In Panel B the independent variables are the share of students from different ethnic groups in the class group, and the omitted category is the share of white students. t statistics from standard errors clustered at class group level in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B.2 Qualification score at entry

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Best 3	1								
Best 3 Not-excluded	0.995***	1							
Best 3 Preferred	0.983***	0.987***	1						
Best 3 Most common	0.951***	0.954***	0.954***	0.976***	1				
Total Preferred	0.547***	0.553***	0.557***	0.390***	0.460***	1			
Average Preferred	0.922***	0.926***	0.936***	0.962***	0.930***	0.394***	1		
Best Math	0.664***	0.669***	0.672***	0.655***	0.640***	0.339***	0.658***	1	
Average Math	0.664***	0.668***	0.672***	0.655***	0.640***	0.338***	0.659***	0.999***	1
N.	9449								

Appendix C Identification strategy

C.0.1 class group allocation does not predict students' characteristics

Following Zoelitz and Feld (2017) and Braga et al. (2016), I perform the following regression:

$$y_{itcg} = \sum_{g=1}^{n_c} \alpha_g * \mathbb{1}(i\text{'s group} = g) + \epsilon_{itcg},\ \forall t, c \tag{15}$$

where the dependent variable is a dummy equal to one if student i enrolled in course c in year t allocated to class group g has characteristic t (female, asian, white, age at enrolment), and the independent variables are dummies for each class group g in course c in year t. The dummy for class group g is equal to one if student i is assigned to class group g and zero otherwise. I run one regression for each combination of course c x academic year t to cover all the courses that first year undergraduate students attend in the academic years in sample [45]. The sample for each regression consists in all the students enrolled in course c in the same academic year t that didn't change class group during Michaelmas term [46]. Furthermore, the sample is restricted to all the courses that have at least 2 class groups.

I test that class group dummies are jointly significantly different from zero:

$$H_0 : \alpha_g = 0,\ \forall g = \{1; n_c\}$$

Table A15 shows the results of the tests performed on the observed sample. The total number of combinations of courses x academic year are 576, 523 observations belong to first year courses, while 53 to second year courses. Column 'N.' displays the number of performed regressions, column 'P<0.05' displays the proportion of tests with a p-value smaller than 0.05, column 'P<0.10' displays the proportion of tests with a p-value smaller than 0.10. Columns (2) - (4) show the results of regression 15; columns (5) - (7) show the results of regression 15 in which I include a dummy for all the mandatory courses that students attend in the same academic year; columns (8) - (10) show the results of regression 15 with dummies for all the elective courses that students attend in the same academic year; and columns (11) - (13) show the results of regression 15 controlling for dummies for all the mandatory and elective courses that students attend in the same academic year. We can see that when I add the parallel course dummies to control for clashes the number of performed regressions decrease. This is due to the fact that these specifications are identified out of students that are allocated to the same class and attend the same combination of courses during the year. The more courses I include in the parallel course dummies, the higher becomes the number of courses and class groups in which I don't have enough students that attend the same combination of courses. In particular, when I control for clashes with mandatory and elective courses, I lose 99 observations (combination of courses $\times$ academic years). 85 of these courses correspond to language courses in different academic years. This makes sense if we think that language courses are not part of a bachelor program, but can be attended by students that come from different programs. In the last 3 columns (14-16), I report the results of the tests obtained from the regressions in

[45] All first year courses plus 15 second year courses, among which 7 are language courses. Students can choose second year courses as elective courses. These correspond to 0.57% of the observations

[46] I am excluding students that changed class group since I can't observe their initial allocation. Tests of exogeneity of the decision to change class group can be found in the appendix.

which I included dummies for mandatory and elective courses (columns 11-13), to which I add the results of the tests for the unconstrained regressions for all the Missing 109 combinations of courses × academic years.

We can see from the Table that the proportion of tests with a p-value smaller than 0.05 and 0.10 are respectively 5.8% and 12.1% in the unconstrained regressions, and remain slightly above the threshold (5% and 10%) also when I control for mandatory or elective courses separately. When I control for all the courses that the students contemporaneously attend during the year (mandatory and electives), the results of the tests seem to become consistent with random allocation of students into class groups, indicating that the exogenous allocation is conditional on course clashes. As a matter of fact, the fraction of p-values smaller than 5% is exactly 5% and the fraction of p-values smaller than 10% is 9%. In other words, students who take the same combination of courses are allocated to class groups independently from their gender. Lastly, the proportion of p-values below the thresholds remain below 5% and 0% also in columns (13) - (15).

Table A15: Gender - Observed sample P-values

	Unconstrained			Mandatory			Elective			Mandatory + Elective			Combination		
	N.	P<0.05	P<0.10	N.	P<0.05	P<0.10	N.	P<0.05	P<0.10	N.	P<0.05	P<0.10	N.	P<0.05	P<0.10
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
First year	505	0.061	0.125	505	0.071	0.119	501	0.064	0.113	441	0.050	0.091	505	0.048	0.085
Second year	48	0.02	0.083	48	0.042	0.104	48	0.042	0.063	13	0.077	0.077	48	0.021	0.0625
Total	553	0.0579	0.1211	553	0.0687	0.1175	549	0.0619	0.1093	454	0.0507	0.0903	553	0.0452	0.0832

Notes: The table shows the results of the tests of joint significance of the class group dummies in specification 15. The sample consists of all the students that are enrolled in courses attended by first year students in the academic years in analysis. The total number of combinations of courses x academic year are 553, 505 observations belong to first year courses, while 48 to second year courses. Column 'N.' displays the number of performed regressions, column 'P<0.05' displays the proportion of tests with a p-value smaller than 0.05, column 'P<0.10' displays the proportion of tests with a p-value smaller than 0.10. Columns (2) - (4) show the results of specification 15; columns (5) - (7) show the results of specification 15 in which I include a dummy for all the mandatory courses that students attend in the same academic year; columns (8) - (10) show the results of specification 15 with dummies for all the elective courses that students attend in the same academic year; and columns (11) - (13) show the results of specification 15 controlling for dummies for all the mandatory and elective courses that students attend in the same academic year. In the last 3 columns (14-16), I report the results of the tests obtained from the regressions in which I included dummies for mandatory and elective courses (columns 11-13), to which I add the results of the tests for the unconstrained regressions for all the missing 99 combinations of courses × academic years.

Table A16 shows the result of specification 15 controlling for clashes (mandatory and electives) when the dependent variable is age on entry, a dummy equal to 1 if the student is Asian, and a dummy equal to one if the student is white respectively. The results of the tests are consistent with random allocation of students into class groups, indicating that the exogenous allocation is conditional on course clashes. In other words, students who take the same combination of courses are allocated to class groups independently from their age on entry or ethnicity.

Table A16: Other characteristics - Observed sample P-values

	Mandatory + Elective								
	Age on Entry			Asian			White		
	N.	P<0.05	P<0.10	N.	P<0.05	P<0.10	N.	P<0.05	P<0.10
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
First year	405	0.040	0.094	407	0.044	0.096	409	0.056	0.090
Second year	22	0.136	0.182	21	0.00	0.048	21	0.048	0.048
Total	427	0.045	0.098	428	0.042	0.093	430	0.056	0.088

Notes: The table shows the results of the tests of joint significance of the class group dummies in specification 15. The sample consists of all the students that are enrolled in courses attended by first year students in the academic years in analysis. Column 'N.' displays the number of performed regressions, column 'P<0.05' displays the proportion of tests with a p-value smaller than 0.05, column 'P<0.10' displays the proportion of tests with a p-value smaller than 0.10. Columns (1) - (9) show the results of specification 15 controlling for dummies for all the mandatory and elective courses that students attend in the same academic year. The number of performed regressions are 427, 428 and 430 for Age on entry, Asian dummy and White dummy respectively.

Appendix D Analysis along ethnic lines

D.1 Validity of the identification strategy

In order provide evidence that students belonging to different ethnic groups are not systematically assigned to particular classes, I replicate the tests performed for gender. The first test I perform is discussed in Section . Following Feld and Zölitz (2017, 2018) and Braga et al. (2016), I test that class group allocation does not predict students' individual characteristics by regressing individual characteristics on class dummies for each course in each year. I then test that class group dummies are jointly significantly different from zero. Figure 6 shows the p-values obtained from the tests of joint significance of the class group dummies for the observed sample. Regarding the White dummy, slightly more than 5% of tests display a p-value smaller than 0.05, but less than 10% of tests display a p-value smaller than 0.10. Regarding the Asian dummy, slightly less than 5% of tests display a p-value smaller than 0.05, and less than 10% of tests display a p-value smaller than 0.10. More details on the exogeneity tests and the simulation performed can be found in appendix.
In the second test, I test that students are not systematically assigned to class groups where there are more (less) students of their own ethnic group, conditional on having a certain share of same ethnicity peers among the students enrolled in a course. The specification used is the following:

$$\begin{aligned}\textit{Share of same ethnicity peers}_{iacg} = \alpha_{ca} + \beta \times \mathbb{1}(\text{Ethnic group}_i = e) + \gamma \times \textit{leave-out mean}_{ica} + \\ \sum_{a=1}^{n_a}\sum_{p=1}^{n_{p,a}} \delta_{p,a} \times \mathbb{1}(\textit{i took course p}) + \epsilon_{iacg} \quad (16)\end{aligned}$$

For each course c in academic year a I test that individual characteristics (Ethnic group) do not predict the composition of peers in the class group g they are assigned to. I control for the share of same ethnicity peers enrolled in the course (*leave-out mean*$_{ica}$). Lastly, I control for a series of dummies that are equal to one for all the students that attend the course in the same year, and zero otherwise ($\sum_{a=1}^{n_a}\sum_{p=1}^{n_{p,a}} \delta_{p,a} \times \mathbb{1}(\textit{i took course p})$). This is because the allocation is constrained by the fact that students attend more than one course in the same term and they cannot attend two classes at the same time. I perform this test for all the courses where there are at least two class groups and standard errors are clustered at the class group level.

Table A17 reports the result of the above regression. Students are not assigned to class group systematically based on their ethnic group. As a matter of fact, Chinese, Asian, White, Black and other minority students do not have a higher probability of being assigned to a class group with more students of their ethnic group.

Lastly, I produce an array of "balancing tests" to study whether the variation in the share of ethnic classmates a student is allocated to is related to the variation in a number of predetermined student characteristics: gender, previous school characteristics, age at entry, and qualification score at entry. As shown in Table A18, only two of the estimated correlations appear to be significantly different from zero for the sample of analysis. They concern the characteristics of the previous attended school.

Table A17: Effect of student characteristics on the share of share of same ethnicity peers

Share of same ethnicity peers	(1)	(2)
Panel A: Ethnicity		
Chinese	0.006	0.007
	(0.004)	(0.004)
Other	-0.004	-0.006
	(0.004)	(0.004)
White	0.003	0.005
	(0.004)	(0.004)
Missing	-0.003	-0.002
	(0.005)	(0.005)
Course level leave-out-mean	0.992***	0.991***
	(0.012)	(0.013)
Observations	54603	44771
Course fixed effects	Y	Y
Parallel course dummies	Y	Y

Notes: Standard errors are clustered at the class group level. For each course c in academic year t I test that individual characteristics cannot predict the share of same ethnicity peers in the class group g (y_{itcg}) the student was assigned to. The dependent variable is the share of same ethnicity peers. Parallel course dummies are a series of dummies that are equal to one for all the students that attend the course in the same year, and zero otherwise. The check consists in testing that the students enrolled in these courses are allocated in class groups independently on their individual characteristics, after considering the other courses they selected. The omitted category is Other Asian. This sample includes also students that are not in their first year of a bachelor program at the university. I am excluding students that changed class group since I can't observe their initial allocation. Tests of exogeneity of the decision to change class group can be found in the appendix. Column (3) to the sample for the analysis on participation.

D.2 Effect of changes in ethnic composition of the class of students' performance

I estimate the effect of a change in class composition along ethnic lines on students' performance estimating the following specification:

$$y_{iacg} = \alpha_{ac} + \alpha_i + \sum_{e=1}^{n_{e-1}} [\beta_{1,e} \textit{Share of ethnic group e students}_{iacg} + \\ + \beta_{2,e} \times \textit{Share of ethnic group e students}_{iacg} \times \mathbb{1}(\text{Ethnic group}_i = e)] + \epsilon_{iacg} \quad (17)$$

where the unit of analysis is students (i) belonging to ethnic group e, who attends course c, in the academic year a, and who is assigned to class g, and the independent variables y_{iacg} are course grades. $\mathbb{1}(\text{Ethnic group}_i = e)$ is a dummy equal to one if the student belongs to ethnic group e. Students are divided in seven groups: White, Chinese, Indian, Other Asian, Black, other ethnic minorities, and students with missing ethnic group. This is the finest possible split that could be performed. Students with missing ethnic information are included in the regression so that the omitted category are White students and the coefficients estimate the effect of an increase in the share of Chinese, Indian, Black, Other Asian classmates with respect to having additional White classmates. $\textit{Share of ethnic group e students}_{iacg}$ is the share of classmates belonging to ethnic group e, thus $\beta_{1,e}$ will capture the effect of an increase in the share of ethnic group e classmates for students in the omitted (reference) group, White students, while $\beta_{2,e}$ will capture the effect of an increase in the share of type e classmates on the gap in course grades

Table A18: Effect of student characteristics on the share of share of same ethnicity peers

	Independent Variable: Share of Asian		Independent Variable: Share of White	
Dependent Variables	(1)	(2)	(3)	(4)
Female	0.001	-0.004	0.016	0.013
	(0.017)	(0.019)	(0.017)	(0.019)
Independent School	0.032**	0.029*	-0.039**	-0.027
	(0.015)	(0.017)	(0.016)	(0.017)
State School	-0.026*	-0.029*	0.036**	0.035**
	(0.014)	(0.016)	(0.014)	(0.016)
Other School	0.003	0.001	-0.000	-0.002
	(0.010)	(0.011)	(0.010)	(0.012)
Mixed School	-0.008	-0.001	-0.016	-0.007
	(0.016)	(0.017)	(0.017)	(0.019)
Single Sex	0.021	0.015	0.002	0.002
	(0.014)	(0.016)	(0.014)	(0.016)
Not applicable	-0.015	-0.007	0.014	0.005
	(0.016)	(0.017)	(0.016)	(0.017)
Age at entry	0.006	0.002	-0.059	-0.047
	(0.042)	(0.047)	(0.043)	(0.049)
Qualification Score at entry	0.438	0.024	-1.197	-1.361
	(0.871)	(0.938)	(0.916)	(0.989)
Ethnicity dummies	Y	Y	Y	Y
Course Fixed Effects	Y	Y	Y	Y
Parallel Course Dummies	Y	Y	Y	Y
Program of enrollment Fixed Effects	Y	Y	Y	Y
N	54603	44771	54603	44771

Notes: Standard errors are clustered at the class group level. For each course c in academic year t I test that individual characteristics cannot predict the share of Asian or White students in the class g (y_{itcg}) the student was assigned to. Column (2) and (4) restrict the sample to the sample for the analysis on participation. Each row corresponds to a separate regression where the independent variable is the share of Asian or White classmates and the dependent variable is the individual characteristic, controlling for course fixed effects, a dummy for each course the student attends during the academic year, ethnic group dummies, and a dummy for the program of enrollment (not included in the balance checks for gender). When the dependent variables are age at entry and qualification score at entry, a dummy for missing values is included in the regression.

between students belonging to ethnic group e and the reference group (White students). The specification follows the main empirical strategy of the paper, thus I include course fixed effects, α_{acg}, and student fixed effects, α_i. The assumptions underlying the identification strategy are the same as for the main empirical strategy. The validity is discussed in the previous section.

Table A19 display the results of Specification 17 with and without individual fixed effects (Column 2 and 3 respectively. Minority status affecting performance is not a phenomenon specific to gender, since it is able to explain part of the performance gap also for ethnic minorities. Chinese students' are the group for which performance appears to be more affected by class group composition, and the effect is robust to all the specifications. In particular, the gap in performance between Chinese and White students increases by 0.999 points when the share of Chinese students in the class group increases by 10%. This represents 22% of the raw gap between Chinese and White students in first year exams. Interestingly, Chinese do not benefit only from having more Chinese in the class, but also from having more Indian and Other Asian students with respect to White students in the class group. The effect is qualitatively the same for Indian and Other Asian students: their average performance gap with respect to white students decreases if the proportion of Asian students in the class group is higher. However, the effect is not significant. This is not very surprising for Other Asian students given that the category is a spurious category, including all Asian students who are not Chinese or Indian. Interestingly, the effect for white students mirrors exactly the effect for Asian students: white students' performance is significantly lower in class groups where there is a higher proportion of Asian students. In particular, a 10% increase in the share of Indian students decreases White students' performance by 0.368 points, significant at 1%, a 10% increase in the share of Chinese students in class decreases White students' performance by 0.240 points, significant at 1%, and a 10% increase in the share of Other Asian students decreases White students' performance by 0.192 points, significant at 5%. The proportion of Black students is very low, so it is not possible to estimate precisely an effect for this group.
Given that the effects of increasing the share of Chinese, Indian and Other Asian students are very homogeneous both for Asian students and White students, in the main analyses I aggregate students of Asian background in a composite category to increase the power of the estimates.

Table A19: Minority effect along ethnic lines

	Course grades	
	(1)	(2)
Share of Indian students	-1.121	-3.680***
	(1.451)	(1.141)
Share of Chinese students	-1.711	-2.403***
	(1.119)	(0.876)
Share of Other Asian students	-0.331	-1.912**
	(1.280)	(0.923)
Share of Black students	1.606	1.262
	(2.105)	(1.493)
Indian	0.235	
	(0.933)	
Indian × Share of Indian students	-4.166*	3.145
	(2.437)	(2.091)
Indian × Share of Chinese students	2.810	0.621
	(1.758)	(1.556)
Indian × Share of Other Asian students	-2.210	0.564
	(2.501)	(1.979)
Indian × Share of Black students	0.705	-4.848
	(4.556)	(3.531)
Chinese	-1.447*	
	(0.749)	
Chinese × Share of Indian students	7.815***	9.166***
	(1.991)	(1.830)
Chinese × Share of Chinese students	10.146***	7.526***
	(1.531)	(1.345)
Chinese × Share of Other Asian students	6.707***	6.595***
	(1.977)	(1.593)
Chinese × Share of Black students	3.897	3.545
	(3.415)	(2.812)
Other Asian	-1.349*	
	(0.818)	
Other Asian × Share of Indian students	-0.029	4.629**
	(2.362)	(1.983)
Other Asian × Share of Chinese students	0.316	1.342
	(1.652)	(1.507)
Other Asian × Share of Other Asian students	1.100	1.310
	(2.199)	(1.708)
Other Asian × Share of Black students	-2.772	-2.885
	(3.809)	(2.779)
Black	-1.280	
	(1.344)	
Black × Share of Indian students	-0.631	1.090
	(3.749)	(3.295)
Black × Share of Chinese students	-4.292*	-3.000
	(2.585)	(2.572)
Black × Share of Other Asian students	-2.981	-0.393
	(3.699)	(3.003)
Black × Share of Black students	-0.940	-2.983
	(4.995)	(4.233)
N.	54603	54603
Class size	Y	Y
Course fixed effects	Y	Y
Student fixed effects	X	Y

Notes: The table displays the results of Specification 17 in Column (2). In Column (1), the results of the same specification without student fixed effects are presented. The outcome variable is course grades, with non-takers coded as 0. The regressions also contain the share of students with missing information on ethnicity and the share of other ethnic minorities, a dummy for missing information and other residual ethnic minorities, and their interactions with all the other ethnic dummies and share. This is done so that the omitted category are white students, and the increase in the share of each ethnic minority can be read as an increase in the share of the ethnic minorities with respect to white students. Standard errors are clustered at the class group level.

Appendix E Survey

During the academic year 2020/2021 I administered a complementary online survey to students (June-July 2021). The survey was designed using Qualtrics and was sent to students to their institutional email address through the university system. The survey included 4 sections. In the first section, I asked students some questions regarding their experience at the university, disregarding as much as they could the last year of remote teaching. Following Burztyn and Jensen (2019), I asked students questions regarding the extent to which they think image is important, and what elements contribute to being popular. Moreover, following Bursztyn et al. (2017), I asked students questions regarding how much they felt comfortable participating in class. This section was meant to be used to micro-found the theoretical model.

In the second section, I asked students to perform a double-target Implicit Association Test (Greenwald et al., 1998). I followed Carlana (2019) to design a Gender-Scientific implicit association test to elicit the extent to which students automatically associate Scientific disciplines with men and Humanistic disciplines with women. Subjects are presented with two sets of stimuli. The first set of stimuli are female and male names. Given the multicultural environment, in order to be neutral with respect to language differences and use names that could be identified by every student as clearly referring to male or female, I followed the approached used in the Gender-Science IAT designed by Project Implicit [47]. I used as female and male names words such as Man, Son, Father, Boy, Uncle, Grandpa, Husband, Male, Mother, Wife, Aunt, Woman, Girl, Female, Grandma, Daughter. The second set are words related to Scientific disciplines (e.g., Math, Physics, Engineering, etc.) and Humanistic disciplines (e.g. Literature, History, Humanities, etc.). The IAT is composed of seven rounds. Round 1 and 2 are practice rounds of only female and male names and only Humanistic and Scientific disciplines respectively. In the following five rounds, one word at a time (either a female or male name, or a word associated with Humanistic or Scientific in a random fashion) appears on the screen and individuals are instructed to categorize it to the left or the right according to different labels displayed on the top of the screen. In "hypothesis-inconsistent" ("hypothesis-consistent") rounds individuals categorize to one side of the screen - Humanistic Male (Humanistic Female) and to the opposite side of the screen - Scientific Female (Scientific Male). The order of the two types of rounds was randomized at the individual level. The blocks used to calculate the IAT score (d-score) are rounds 3, 4, 6, and 7. The number of words that need to be categorized is 20 in blocks 3 and 6, and 40 in blocks 4 and 7, as in the standard IAT 7-blocks (Greenwald et al. 2003). The measure of implicit association between gender and Scientific is given by the standardized mean difference score in four types of rounds. The intuition is that people with a greater implicit association of Scientific with men and Humanistic with women take longer to correctly categorize names in the "hypothesis-inconsistent pairings". Thus, the higher and more positive the d-score the stronger is the association between the two concepts. The order of the four types of blocks was randomized at the individual level. The IAT was incorporated in Qualtrics using the ad-hoc approach designed by Carpenter et al. (2021)[48].

The third section of the survey consisted in questions regarding explicit associations. Following Delfino (2020) and Carlana (2019), I asked questions concerning their beliefs regarding the distribution of men and women and the performance of women compared to men in different fields.

[47] Organization of researchers founded by Dr. Tony Greenwald (University of Washington), Dr. Mahzarin Banaji (Harvard University), and Dr. Brian Nosek (University of Virginia). implicit.harvard.edu

[48] An explanation of the approach can be found at this link: https://iatgen.wordpress.com/

Finally, the last section of the survey contained questions regarding demographic information and the students' social network.