Article:

TOMINEY, EMMA orcid.org/0000-0002-0287-3935, Cattan, Sarah and Salvanes, Kjell (Accepted: 2025) First Generation Elite: The Role of School Social Networks. American Economic Review. ISSN: 0002-8282 (In Press)

First generation elite: the role of school social networks

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September 19, 2025

Abstract

High school students from non-elite backgrounds are less likely to have peers with elite educated parents than their elite counterparts in Norway. We show this difference in social capital is a key driver of the high intergenerational persistence in elite education. We identify a positive elite peer effect on enrolment in elite programmes and on labour market earnings, then disentangle underlying mechanisms. Exploiting a lottery in the assessment system, a causal mediation analysis shows the overall positive peer effect reflects a positive effect on application behaviour (conditional on GPA), which dominates a negative effect on student GPA. We consider implications for income mobility finding that encouraging further mixing between elite and non-elite students in high school could improve mobility across the whole distribution.

Keywords: Peers, Elite university, Subject choice, Social mobility; Social capital; Teacher bias
JEL codes: I24, J24, J62

Acknowledgements: We have received useful comments from many including seminar audiences at the Yale University, Princeton University, University of Chicago, Columbia University, University of Oxford, University of Turin, University of California San Diego, University of California Los Angeles, CEPEO Institute of Education UCL, University of Copenhagen, University of Sheffield participants at the NORFACE IFS workshop, York Workshop for Labour and Family Economics, LSE and Sapienza workshop on Opportunity and Mobility, Erasmus University Rotterdam, SOFIE, University of Bergen workshop on Health, Human Capital and Social Insurance, University of Essex, Royal Holloway University of London. All remaining errors are our own. The authors gratefully knowledge financial support from from the Research Council of Norway through project no. 262675, and project no. 275274, the ESRC-funded Centre for the Microeconomic Analysis of Public Policy (ES/T014334/1), the Rockwool Foundation, and the European Research Council for grants agreement no. 819752 - DEVORHBIOSHIP - ERC-2018COG and ERC-2014-CoG-646917-ROMIA.

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1 Introduction

Recent research documents very high levels of socioeconomic segregation in elite graduate and post-graduate degrees. In the US, pupils from the top quintile of the parental income distribution have been found to be around 23 times more likely to attend an elite ('Ivy Plus') college than pupils from the bottom quintile (Chetty et al., 2020a). In Chile and the UK, graduates from fee-paying private high schools are over-represented in elite university programmes by factors of 16 and 7 respectively (Barrios-Fernandez et al., 2022; Britton et al., 2021).

In Norway, the setting of this study, elite education is also highly selective and associated with top paying jobs. Elite programmes have a high school GPA cut-off around 40% higher than other degree programmes and only admit 3 to 4% of each birth cohort. Even compared to non-elite graduate students, elite graduates are disproportionately present at the top of the income distribution at age 28-40, with many of them in leadership positions in the private and public sectors (Bütikofer et al., 2021; Kirkebøen, 2010).

Like in these other countries, elite programmes in Norway have an over-representation of students from high socio-economic backgrounds: 7 students come from the top 20% richest families for every student from the bottom 20%. Yet, many of the factors thought to be driving the socioeconomic segregation of students in elite degrees in the US, Chile and even the UK are unlikely to be at play in Norway and most European countries. There are no university tuition fees. There are no expensive private feeder high schools (Zimmerman, 2019; Barrios-Fernandez et al., 2022; Britton et al., 2021; Michelman et al., 2022). And there are no legacy enrolment policies (Chetty et al., 2020b). Instead, a centralised admission system allocates students to degrees based on their degree preference and their high school GPA. Comparable admission systems and no tuition fees are not only the standard in Nordic countries but also the preferred model in most European countries.

Why then are there still so few first generation elites in Norway? This paper argues that social capital is a key part of the answer. The component of social capital we focus on is the degree of exposure to peers from elite-educated families in high school ('elite peers' henceforth). We document that children from non-elite backgrounds are much less likely to have elite peers than children from elite backgrounds. We ask whether this lack of exposure causally hinders students from non-elite backgrounds to become first generation elite and, if so, what mechanisms drive this impact. These notions are tightly linked to the idea of economic connectedness in friendship networks, which Chetty et al. (2022) find to be positively correlated with upward mobility.[1]

A key innovation of the paper is to ask *why* being exposed to elite peers influences higher education outcomes and whether this matters in the labour market. As mentioned above, for a student to be admitted to an elite degree, they need to have a high enough GPA *and* they need to express a preference for that program. Elite peers can potentially influence both margins through a number of mechanisms.

First, elite peers can influence GPA through at least two mechanisms. On the one hand, elite peers can have spillovers on the effort and subsequent learning of other students. These spillovers could arise, for example, if elite peers, who are likely to be high achieving and highly motivated, help their classmates learn more effectively and/or impart their aspirations for higher education onto them. On the other hand, in a system where GPA is partly based on teacher assessments like it is in Norway, the presence of elite peers could distort teacher's assessment behaviour. If teachers 'mark on a curve', a higher proportion of elite students will create downward pressure on the rank of other students since elite students are likely to be highly ranked. And if teachers are prone to implicit bias, a higher proportion of elite peers may also trigger further distortion in the way that teachers assess elite students relative to non-elite students of similar ability.[2] A priori, it is not clear whether elite peers would have a positive or negative effect on overall GPA. In this paper, we identify the effect of elite peers on overall GPA and exploit that GPA is based on scores to *both* blindly assessed and teacher assessed exams to disentangle these potentially counter-acting mechanisms from each other.

In addition to influencing high school GPA, elite peers could affect students' probability to enrol in an elite degree through a second margin - by influencing their university application decisions conditional on their GPA. Interactions with elite peers – and possibly with their parents – might change students' information set about the content of and returns to these programmes and/or their beliefs about which programmes are a good match for them (Lundberg 2020; Porter and Serra 2020; Michelman et al. 2022; Mani and Riley 2019). Especially for high-SES students, it may

[1]Another explanation is ability differences, but we remove this as a possibility by controlling flexibly for student ability.

[2]See Campbell (2015) and Doyle et al. (2023) for evidence of a teacher bias against lower income students, Duflo et al. (2008) for evidence that teacher behaviour adjusts to student ability composition and Papageorge et al. (2020) for evidence that teacher expectations are important for college completion.

also change students' preferences for elite programmes by changing the probability that they enrol in a degree also attended by high school peers. In turn, this might encourage students who have a GPA high enough for an elite degree to actually apply for such a programme and/or affect the set of programmes to which they apply in a way that increases their chances of admission and enrolment. In this paper, we identify the causal impact of elite peers on elite degree enrolment conditional on GPA – i.e. via this second margin – by exploiting a unique feature of the Norwegian institutional context whereby a lottery assigns students to taking certain subjects as blindly assessed exams. We show evidence to support that this lottery provides a credible source of exogenous variation in GPA.

The paper is divided into four parts, each yielding a key finding. All the analysis is based on administrative register data tracking nine cohorts of students who finished middle school between 2002 and 2012 through their education and, for those who reach 30 or more by the last year of observation (2021), into the labour market. We link these individuals to their parents to identify their socio-economic backgrounds. Using school identifiers, we link them to their high school peers and peers' parents to create our measure of social capital - the proportion of peers' parents who have an elite education in the student's high school cohort.

The first part of the paper asks what effect elite peers have on the probability to enrol in an elite degree for students from different socio-economic backgrounds. To identify this effect, we exploit within school, between cohort variation in peer composition across nine cohorts of high school students. This approach has been extensively used since it was initially proposed by Hoxby (2000),[3] and we perform an extensive set of robustness checks to probe its validity in our context. Among other tests, we adopt the approach proposed by Borusyak and Hull (2023) and we show that including only the "expected" exposure to elite peers within a school in lieu of the school and cohort fixed effects and middle school GPA is sufficient to identify the effect of exposure to elite peers.

Our first finding is that exposure to elite peers increases enrolment of the average student in an elite degree. However, this effect is three times larger for students with at least one elite educated parent (high SES) than it is for students with low educated parents (low SES).[4] Evidence points

[3]Among others, see Angrist and Lang (2004); Lavy et al. (2011); Black et al. (2013); Carrell et al. (2018); Cools et al. (2019).

[4]We explore the sensitivity of these results to different definitions of elite and SES. A similar SES gradient emerges

towards exposure to high status adults (rather than high ability peers) as an important channel for the elite peer effect. Combined with the fact that high SES students are on average twice as likely to be exposed to elite peers than low SES students are, these estimates imply that the socioeconomic gradient in exposure to elite peers in high school explains 12% of the gap in elite degree enrolment between these two groups. In other words, the segregation of students into high schools by socioeconomic status is a significant driver of the intergenerational persistence in elite education in Norway.

The second part of the paper starts delving into the mechanisms of this effect and asks what effect elite peers have on high school GPA. Using a similar identification strategy as above (this time with GPA as the outcome), we estimate the effect of elite peers on overall high school GPA and on each of its components. This unique feature of the Norwegian context helps us tease out whether elite peers have a different effect on blindly assessed exam scores (which provide the cleanest measure of underlying effort or knowledge) and on teacher assessed exam scores.

Our second finding is that exposure to elite peers is detrimental for overall GPA (and hence for chances to be admitted in an elite degree through that channel), and particularly so for low SES students. However, elite peers significantly *improve* students' scores on blindly assessed exams, which suggests that elite peers do have positive spillovers on the effort and knowledge of other students. What drives the negative effect of elite peers on GPA is a large negative effect of elite peers on teacher assessed exam scores. This negative effect is partially explained by elite peers lowering the rank of other students. But, even within student cohort rank, the downgrade is larger for the low SES students.

The third part of the paper aims to identify the effect that elite peers have on students' probability to enrol in an elite degree *over and beyond* their effect on GPA. This is challenging because GPA is endogenous with respect to individual elite degree enrolment. To estimate elite peer effects conditional on GPA, we therefore need to instrument GPA. We exploit exogenous variation in GPA resulting from a lottery inherent in the Norwegian examination system whereby schools randomise the subjects on which students are blind externally-assessed in their third year.[5]

when SES is defined by parent income and when elite is defined by peers' parents' income or occupational prestige.

[5]We show that student assignment to externally-assessed maths exams is both balanced on a number of students' observable characteristics and a strong determinant of GPA, making it a plausibly valid and relevant instrument for GPA.

Our third finding is that elite peers have a positive effect on the probability of enrolling in an elite degree conditional on GPA. We use these results to decompose the overall effect of elite peers on elite degree enrolment into i) an *indirect* effect of elite peers, working through their effect on GPA, and ii) a *direct* effect (conditional on GPA). This is a causal mediation analysis in the sense that it takes into account that the mediator, here high school GPA, is endogenous (Celli 2021; Huber 2019). We find that the positive direct effect of elite peers on students' application behaviour conditional on GPA dominates any negative indirect effect through GPA (driven by the teacher downgrade).

The fourth part of the paper turns to the labour market implications of the elite peer effects we have uncovered. We provide causal evidence on the effect of elite peers on earnings using the subset of cohorts for whom we can observe earnings from age 30 and discuss the implications of this evidence for intergenerational mobility.[6]

Our fourth finding is that exposure to elite educated families raises earnings in the early 30s. Importantly and opposed to the findings for the US and Chile (Zimmerman, 2019; Barrios-Fernandez et al., 2022), we find that the high average earnings premium to enrolling in an elite degree is very similar for the low and high SES students. To quantify the impact that elite peers have on the earnings of students across the parental income distribution, we estimate how the intergenerational 'rank-rank' coefficient (from a regression of parents' percentile rank on their child's rank at age 30-32) varies with the degree of exposure to elite peers. We find that exposure to elite peers in high school raises mobility at the bottom of the parental income distribution, but also exacerbates intergenerational persistence at the top. A direct implication of this finding is that a policy that encourages further mixing between elite and non-elite students in high school could improve mobility across the whole distribution. We illustrate this point by way of a series of simulations which reassign low SES students in schools with low exposure to elite peers, into schools with a high exposure - and vice versa for the high SES students.

Our paper speaks to three strands of literature. First, it contributes to the intergenerational mobility literature (for example, see Corak et al. 2014 and Adermon et al. 2021). Specifically our paper relates to a small but growing literature on the role of social capital in driving mobility

[6] Earnings measured in the early 30s are a good predictor of lifetime earnings (Bhuller et al. 2017) and income rank reduces a potential measurement error bias relating to the age income is measured (Nybom and Stuhler 2017). We use the rank of mean earnings for ages around 30 for the students.

(Chetty et al., 2022, 2020b; Barrios-Fernandez et al., 2022). We provide causal evidence that the segregation of children from elite families at the high school level is a driver of the persistence in elite education and in income, especially at the top of the distribution. Whilst previous studies are based on data from the US or Chile, these countries can to some extent be considered outliers in terms of their high level of income inequality and low intergenerational mobility as indicated by the Gatsby curve (Corak, 2013). The Norwegian context is more comparable to other European countries and opportune to study the role of social networks in driving inequality, since other drivers, such as credit constraints and legacy university admission systems, are less likely to be salient, if at all.

Second the paper relates to the large literature on the effect of peer characteristics on educational and economic outcomes.[7] It is most closely linked to three specific strands of this literature. Bertoni et al. (2020) and Cools et al. (2019) focus similarly on the effects of peers with high parental education and their heterogeneity (by socioeconomic background and by gender, respectively). Dahl et al. (2021) and Altmejd et al. (2021) identify sibling peer effects in the field of high school and college major respectively. Finally Abdulkadiroğlu et al. (2014) and Barrow et al. (2020) explore the individual test score effect of "just getting in" to elite high schools in the US, a treatment which increases exposure to peers from higher in the socio-economic distribution. Consistent with these papers, once we condition on the mean ability of peers we find a negative effect on elite enrolment from exposure to high ability peers, suggesting that it is high-status peers, rather than high-achieving peers that are key inputs for the prospective first-generation elites. Our paper exploits unique features of the institutional context to provide a rich description of the mechanisms underlying the elite peer effect on elite degree enrolment and to quantify the relative contribution of these peer effects working through GPA and over and beyond GPA.

Finally, our analysis of elite peer effects on blind and non-blind assessments speaks to the literature on the impact of teacher discretion on academic achievement and long-term outcomes. Several papers in the literature contrast these two types of assessments to provide evidence of teacher stereotypes (Lavy, 2008; Lavy and Sand, 2018; Burgess and Greaves, 2013), while other papers directly elicit teacher bias using Implicit Bias tests (Carlana, 2019; Alesina et al., 2018). To the extent we measure student ability well, our results are consistent with teachers downgrading

[7] See Sacerdote (2011) and Epple and Romano (2011) for review articles on the effect of school peers on academic achievement.

similarly able students on the basis of their SES status and show that such behaviour can have profound consequences for social mobility. Our results also suggest a clear policy implication not only for Norway but also for other systems, including the US, where university admission is partly based on teachers discretionary evaluations of performance: increasing the weight that blindly assessed exams has in GPA can increase the chances that high-ability low SES students become first generation elite.

2 The Norwegian Education System

High school Norwegian education has been compulsory until the age of 15-16 since 1959; all students must now complete seven years of primary school followed by three years of middle school (Black et al., 2005a).[8] After completing these 10 years of education, students decide whether to continue their education in high school or to drop out to join the labour force. Those who continue onto high school choose between an academic track and a vocational track. The academic track, which we focus on in this paper, lasts 3 years and is geared towards preparing students to attend higher education.

The assignment mechanism of students to high schools varies across counties and cohorts. In some counties (including all rural counties), schools have catchment areas and geographical distance determines student high school allocation.[9] Other counties have a free high school choice system where intake is centralised and based on middle school GPA. During our period of analysis, which focuses on cohorts graduating from middle school between 2002 and 2010 (and start high school up to 2012), eight out of nineteen counties had free school choice. Because these areas tend to be the most densely populated areas, the majority of high school students in our sample had free school choice.[10]

Higher education Higher education institutions include universities (in Bergen, Oslo, Trondheim and Tromsø) and university colleges. Since the early 2000s, Norwegian universities offer

[8] The seven years of primary school includes a year of preschool education, which was made mandatory in 1996.

[9] A small number of private colleges instead require tuition fees for students - only one in our sample.

[10] Some counties have changed their assignment systems over recent years. For example, the two largest cities in Norway - Oslo and Bergen - have varied their intake systems over recent years (Bütikofer et al., 2020; Dalla-Zuanna et al., 2020). Oslo moved from a local catchment to school choice admissions based system between 2006-2009 but reverted back from 2010; whilst Bergen moved to school choice admissions from 2006 onward. We test and reject that our results are sensitive to the type of admissions system.

three-year bachelor degrees and five-year combined bachelor-master degrees. 98% of university students attend a public institution, and even private institutions are funded and regulated by the Ministry of Education and Research. There are no tuition fees for attending a public higher education in Norway, and most students are eligible for financial support (part loan/part grant) from the Norwegian State Educational Loan Fund (NSELF).[11]

To pursue a higher education, students must apply for a combination of a field of study at a specific institution (e.g. law at the University of Oslo). Since the late 1990s, admission to public higher education institutions has been centralised and is based on student ranking for programmes and high school GPA, conditional on students having completed the requisite high school modules (e.g. maths at high school is required for a maths degree). Every year, the deadline for applying to programmes is mid-April, which is when students first submit their ranking of up to fifteen programmes to a central organisation - the Norwegian Universities and Colleges Admission Service.[12] Students can adjust their ranking until July. Then offers are made sequentially where the order is determined by the students' application score derived from the student's high school GPA.

Elite degrees Whereas 'elite' higher education refers to highly competitive, private institutions with high tuition fees such as Ivy League colleges in the US (e.g. Chetty et al. 2020b) and 'Russell Group' universities in the UK (Britton et al., 2021), in Norway 'elite education' refers to a set of specific degrees at specific institutions that are both highly selective and associated with the best earnings outcomes. Specifically, elite degrees are five-year masters degrees in a select set of subjects at specific universities, and we follow Bütikofer et al. (2018) in defining elite programs as degrees at the master level (or above) in Economics from the Norwegian School of Economics, Engineering at the Norwegian University of Science and Technology, Engineering School in Trondheim or Norwegian University of Science and Technology and in Economics, Law or Medicine from the University of Oslo, Bergen, Trondheim and Tromsø. Not only are these elite programmes associated with high earnings, but a majority of future leaders in the private and public sectors are recruited from these institutions (Kirkebøen, 2010; Bütikofer et al., 2021). The elite educated are positioned high in the

[11]The NSELF is a national body founded in 1947 with the task to provide student aid in the form of direct transfers or scholarships and to issue loans under conditions specified by the Norwegian state. Since the 1980s financial aid is not dependent on the student's own means or that of their parents.

[12]The Norwegian Universities and Colleges Admission Service handles the admission process to all universities and to most university colleges, and therefore to all elite degrees we consider in this paper.

income distribution, compared to individuals with no degree, with an undergraduate degree and even a non-elite graduate degree (see Appendix Figure A1).

Similarly to the US or the UK, access to elite degrees is highly competitive: only a very small proportion - around 3% per birth cohort - attend these elite degree programmes. Important differences with other contexts are that there are no tuition fees for these degrees and no easier access for legacy students - because a centralised admission system allocates students based only on high school GPA (given the student's ranking of programmes). As we show in the next section however, despite these equalising features of the higher education system in Norway, there is a very strong socioeconomic gradient in the likelihood to pursue a higher education and an even stronger one in the likelihood to pursue an elite degree. This is true even conditional on previous ability, measured through national exams taken prior to high school. Our paper aims to better understand the role that high school social networks play in driving these inequalities.

High school GPA High school GPA is a combination of grades on three types of exams: i) teacher (internal) assessments, ii) grades on externally (blindly) assessed exams, and iii) grades on oral exams assessed by both the student's teacher and an external examiner. In each of the three years of high school, students receive a teacher assessment on all subjects. In addition, they must take several mandatory exams in May or June of each academic year. In their first year, 20 percent of students are chosen randomly to sit for a final exam in one course. In their second year, all students sit a final exam in one course, either oral or written and the subject of these exams is chosen at random at the county level of each school.

In their third year, all students take four exams: one written exam in Norwegian language, two written exams in two other subjects and a final oral exam in one other subject. It is the responsibility of the county to allocate a student to a topic for the written examination, with the exception of mandatory exams (Norwegian in the third year). As described in detail in Andersen and Lokken (2020), there are several administrative procedures in place to avoid any non-random selection of students for particular courses or type of exams, and in fact there are no incentives to do so. We make use of this lottery later in the paper (Section 7). Like Andersen and Lokken (2020), we find strong support for the random assignment of exam subject within school and programme of study in our sample.

3 Data and descriptive statistics

Our data comes from Norwegian register and administrative data that have been linked by Statistics Norway. We select our sample to include all students finishing middle school and entering the academic track of high school between 2002 and 2010. The linked data allows us to follow these students from middle school through to high school, onto university (if they ever enrol) and the labour market. The data links students' educational records to a rich set of information on their parents, including parental education, occupation and income. It also contains school identifiers, which allows us to identify students' peers.[13]

Table 1 provides summary statistics for the individuals in our analytical sample in the first column, and in the low and high SES sample (as defined below) in the second and third columns. Our sample has close to 178,000 students studying in 556 high schools spread throughout Norway.

Data on individual education attainment comes from the national education database, where six-digit educational codes contain highly detailed information on both the level and field. Throughout the paper, we distinguish between two groups of students, based on the education of their parents. The 'low SES' group includes students with at least one parent with no further education beyond compulsory education and no parent with an elite education. The 'high SES' group includes students with at least one parent with an elite education and no parent with compulsory education.[14]

Our main outcome variable Y_{isc} is an indicator for whether student i entering high school s in cohort c enrols into an elite degree within six years of completing middle school.[15] Elite degrees are defined as the set of 5-year bachelor/masters degree in law, medicine, and STEM obtained in the best institutions of the country (see full list of degrees in Section 2). Even though high school is only three years long, we define the outcome as enrolling into a degree within six years of completing middle school because it is very common in Norway to have one or two gap years between high school and university in order to travel, work or complete military service.[16]

[13] By far most students starting high school in Norway do this within the Norwegian school system. There is no tradition of attending high school in other countries. Some families will of course move to another country during high school, and we lose track of them in the data, but this is negligible.

[14] We discuss in Appendix Section A1 results for the intermediate SES group and when defining SES based on household income instead of parental education.

[15] We focus on enrolment in elite degrees as opposed to completion of an elite degree as our main outcome because our interest in this paper lies in how peers shape subject choice.

[16] 2% of the sample of students with a degree in STEM, law or medicine study for the degree abroad but, as it is not possible to link the institution, these students are excluded from our sample.

Whilst most students in the academic track attend a higher education institution, only one in ten pursue an elite degree, reflecting their high selectivity (Table 1). This represents 3% of the cohort graduating from middle school. Among students pursuing an elite degree, close to 70% complete a 5-year STEM or Economics/Business masters degree, while 20% complete a law masters degree and 10% complete a medical degree. The second and third columns of Table 1 compare the statistics for low and high SES groups. A SES gradient exists in attending university which is very pronounced when it comes to enrolling in an elite degree, with the probability of enrolling being five times as large for high SES students than for low SES ones. These patterns align with Bütikofer et al. (2021), whose findings suggest that, although Norway has one of the lowest intergenerational income elasticities in the world, intergenerational education persistence is high and comparable to other countries, including the US, with much lower levels of income mobility.

We define the student's peer group as all students entering the same high school in the same year.[17] On average students are exposed to 95 high school peers.[18] We construct our main treatment variable, P_{-isc}, as the proportion of parents who have an elite education in the student i's cohort c in high school s (excluding student i's own parents).[19] From Table 1, the proportion of elite peers in their school cohort is twice as high among high SES students than it is for low SES students.

In all regressions we control for a set of covariates relating to the individual student or their parent, which are all predetermined with respect to the student entering high school. Student covariates include an indicator for gender; whether they were born in Norway and their middle school GPA (standardised to have a mean of 0 and standard deviation of 1 within cohort of all middle school students). Covariates for the student's parents include indicators for whether the mother and the father's highest levels of education are compulsory education, high school degree, or university/post-graduate degree; a variable measuring whether the student has zero, one or two elite educated parents; and an indicator for whether the student's household is in the richest decile (based on the distribution across all cohorts in our sample of household income measured at the end of middle school and deflated to 2020 prices). Table 1 shows that high school students are disproportionately female (60%) and selected on family income, as 25% of their families have

[17] These are defined within the academic high school track.

[18] This varies between 30 and 159 at the 10th and 90th percentile.

[19] Note that we use the same grouping of elite education for students and parents since these elite groups have been stable over time in terms of being very competitive to enter and a basis for recruitment to top positions in the labour market, paying top salaries (see Strømme and Hansen 2017).

income in the top 10% of the income distribution. They are also selected on ability: the average middle school GPA in the sample is 0.67 standard deviations above the GPA of the average middle school student.

High school GPA is an average of grades on the three types of assessments taken by each student (teacher assessments, written and oral assessments) across the three years of high school. We standardise GPA within each cohort of high school students to have a mean of 0 and standard deviation of 1. As Table 1 show, high SES students perform better than low SES students.

To look at long-term earnings implications of our results (Section 8), we use data on labour market earnings (before taxes and transfers) for ages 30-32. While our full sample includes students born between 1986-1993, for this part of the analysis we use the cohorts born 1986-1991 for whom we can observe earnings at least from age 30. We smooth out the transitory component of income as much as possible by calculating, for each individual, the mean income across the available years.[20] To analyse the effect of exposure to elite peers on long run outcomes, we calculate the student's earnings percentile rank within each birth cohort.[21] Whilst percentile rank of students in the total sample is 58 on average, low SES students in our sample average at the 55th percentile, whilst high SES students at the 65th percentile. To estimate intergenerational mobility regressions, for each student, we calculate parents' percentile rank of income by taking the average of real household income when the child was aged 15-19, the ages when students make decisions about the pursuit of elite education (see Chetty et al. 2020a). The percentile rank of income is calculated across the population of parents.

4 Empirical strategy

4.1 Benchmark model

The main aim in this paper is to identify the reduced form effect of exposure to elite peers on students' educational outcomes and earnings. Our empirical strategy exploits exogenous variation in exposure to elite peers across cohort within school, that is the variation that comes from the randomness of being in one cohort as opposed to another cohort, among students going to the same

[20] Bhuller et al. (2017) suggest rank stability of earnings from age 30. Our last year of earnings data is measured in November 2021, so for those born in 1986 income data is available at the full age range of 30-32; whilst for those born in 1991 income is available at age 30. We deflate earnings to 2020 prices.

[21] We use data on the full birth cohort (and not only our sample members).

high school.[22] This strategy relies on the idea that there is some variation in adjacent cohorts' peer composition within a school that is idiosyncratic and beyond the easy management of parents and schools.

This strategy has been used in a large number of papers where school admission is based on distance to school (as was the case in Hoxby (2000) who pioneered this approach). In contrast, in Norway - similarly to many European countries - in most areas included in our dataset the high school admission system is competitive. That is, admission is centralised in a system where students rank schools and are then assigned based on their ranked-ordered list and middle school GPA. This means that, in oversubscribed schools, there is a minimum admission score or cut-off for enrolment, which varies from year to year depending on the year-to-year distribution of students' middle school GPA and application choices across cohorts within school.

Middle school GPA being the main determinant of admission, this feature of the context mechanically creates a correlation between the student's own middle school GPA and their peers' middle school GPA (and therefore their peers' parental education). This means that, in our context, within-school cross-cohort variation in elite peer exposure is arguably exogenous conditional on the student's middle school GPA. To be conservative, in our benchmark specification we control not only for middle school GPA, but also for a set of other individual student characteristics.

We estimate the following benchmark model by OLS:

$$Y_{ics} = \beta_1 P_{-ics} + \beta_2 M_{ics} + X'_{ics}\beta_3 + \alpha_s + \rho_c + \epsilon_{ics} \tag{1}$$

where Y_{ics} is an indicator for whether student i in cohort c and school s enrols in an elite degree within 6 years of graduating from middle school; P_{-ics} measures the proportion of cohort-school peers' parents who have an elite degree, excluding student i; M_{ics} is student i's middle school GPA; X_{ics} is a set of other individual student characteristics (gender, immigrant status, maternal and paternal education, the number of parents with elite education, and whether parental income is in the top decile of the distribution); α_s is a school indicator; ρ_c is a cohort effect; and ϵ_{ics} is an error

[22] Here we focus on idiosyncratic variation in cohort composition, as opposed to classroom composition, so we need not worry about schools and parents manipulating the assignment of students to classrooms.

term. Using this notation, identification of β_1 relies on the following assumption being true:

$$E(\epsilon_{ics}|\alpha_s, \rho_c, M_{ics}) = 0. \tag{2}$$

We cluster standard errors at the school level to account for unobserved correlation of error terms within schools and follow Hoxby (2000) in weighting regressions by school size to take account of the parent peer variables group averages, taken from groups of different sizes.[23]

Our empirical strategy is only valid insofar as we have enough identifying variation in the data and our identifying assumption is true. We comment on both of these aspects below.

Identifying variation The standard deviation of our treatment variable is 0.056 in the raw data and reduced by less than half to 0.027, once we remove school and cohort effects and falls only very slightly to 0.026 when additionally removing middle school GPA effects. This suggests that sufficient variation for identification remains. The magnitude of the residual variation of the identifying variable can be visualised a binscatter plot showing the co-variation between the school-cohort deviation on elite college enrolment versus the school-cohort deviation in peer quality. Specifically, the figure is a representation of the residual from a regression of our outcome of interest on cohort and school fixed effects (denoted R_y) and the residual from a regression of our treatment variable on cohort and school fixed effects (denoted R_t). Figure 1 plots a binscatter of R_y against R_t and a line showing the linear fit between the two. Panel (a) plots for the raw data to use as a benchmark to assess the variation once we have controlled for the school and cohort fixed effects (panel b). Panels (c) and (d) plot the residual estimates for the low and high SES samples respectively. The figures show much variation remains after controlling for the school and cohort fixed-effects and that the within-school variation in our treatment and outcome variables, R_t and R_y respectively, is non-zero.[24][25] We also show that this variation is year-to-year variation and not simply within-school trends by plotting time trends for randomly picked schools within each decile of average cohort intake (see Appendix Figure A3).

[23] Appendix Sections A2 and A3 specify a model including just essential controls (school, cohort fixed effects and middle school GPA, so without X_{ics}); and in which the peer effect enters nonlinearly, respectively.

[24] Appendix Figure A2 plots figures controlling additionally for middle school GPA.

[25] The figures in panel (e)-(h) of Figure 1 plot variation in high school GPA residuals along with the three components of the written examinations, teacher assessments and oral examinations, and show similar patterns. For the GPA figures the z-scores are plotted for comparability across the different measures.

Validity of design OLS estimates of equation (1) will be unbiased if $E(\epsilon_{ics}|\alpha_s, \rho_c, M_{ics}) = 0$. That is, conditional on the high-school the focal student attends and their middle school GPA, the composition of their peers - including the proportion of elite peers - is random. Borusyak and Hull (2023) provide a strategy for testing the likely validity of this identification assumption.

The method consists of simulating counterfactual peers within schools, by permuting individual birth cohorts with specific values of middle school GPA randomly and estimating the "expected" treatment (the expected proportion of elite peers within a school). Because middle school GPA is continuous and our sample is too small to permute individual birth cohorts with each value of middle school GPA in a school, we approximate this by permuting individual birth cohorts with specific *deciles* of middle school GPA within each school.

If our identification assumption is correct, regressing the elite degree enrolment on just two variables - the proportion of elite peers and the expected proportion of elite peers - will lead to a coefficient comparable to our benchmark specification. We compute the school average proportion of elite parents across 500 such permutations, which measures the "expected" treatment denoted $\tilde{P}_s$, and run the following regression:

$$Y_{ics} = \delta_1 P_{-ics} + \delta_2 \tilde{P}_s + u_{ics} \tag{3}$$

To be in line with our benchmark specification, we report the estimates of parameters in Equation 3, where we also control for the vector X_{ics} of individual controls (included in our benchmark to be most conservative). In Section A2 we additionally report both our benchmark and application of Borusyak and Hull (2023) in a specification which excludes controls X_{ics}.

4.2 Elite peers vs high-achieving peers

Our empirical strategy approximates an experiment whereby we shift students' exposure to elite peers. That is, we identify an overall reduced form effect of elite peers, as opposed to a structural effect of shifting exposure to peers with elite parental education, holding all other peer characteristics constant.

Peers with elite educated parents have a host of other correlated characteristics, and most obviously tend to be high-achieving (among other characteristics). In light of the academic peer effect literature, a natural question to ask is whether the reduced form effect that we identify captures the effect of being exposed to peers with elite social status, as opposed to the effect of being exposed to high-achieving students.

To shed light on this, we exploit the data that we have on peers' ability (measured by middle school GPA) and estimate, in a second specification, the effect of elite high school peers conditional on these peers' (leave-one-out) average middle school GPA, $\bar{M}_{-ics}$. That is:

$$Y_{ics} = \tilde{\beta}_1 P_{-ics} + \tilde{\beta}_2 M_{ics} + X'_{ics}\tilde{\beta}_3 + \tilde{\beta}_4 \bar{M}_{-ics} + \alpha_s + \rho_c + \epsilon_{ics} \tag{4}$$

The coefficients $\tilde{\beta}_1$ and $\tilde{\beta}_4$ are identified from the same variation as in the benchmark model, that is cross-cohort within-school variation in elite peer compositions. Naturally, because peers' elite parental education and ability are correlated with each other, identifying $\tilde{\beta}_1$ from $\tilde{\beta}_4$ is only possible insofar as there is meaningful variation in one peer characteristic after controlling for the other.

5 Elite peer effects on elite degree enrolment

5.1 Benchmark results

The estimates of Equation 1 for the full sample are reported in column (1) of Table 2. Across all students (panel A), exposure to elite peers significantly increases average students' enrolment in elite education. A one standard deviation (SD) increase in the proportion of elite educated parents in a school-cohort leads to a 2.6 percentage point (ppts) increase in the likelihood that students in this school-cohort enrol in an elite degree. Panels B and C in column (1) of Table 2 report the estimates of β_1 in the benchmark model in the samples of low SES and high SES students and show that the effect of elite peers in one's high school cohort is statistically significant for both but three times larger for high SES students than it is for low SES students (4 ppts vs 1.3 ppts). A test of the null hypothesis that the effects for low and high SES students are equal is rejected with a p-value of 0.00. These estimated peer effects are economically significant, comparing to around one third of the size of the gender differences in enrolment (see Appendix Table A1 for the full set of results).[26]

[26]The estimate for the middle education category lies in between the reported estimate for low and high SES samples; whilst defining SES by family income instead of by education similarly leads to a SES gradient in the peer

Combined with the summary statistics presented in Table 1, our results imply that low SES students face a double disadvantage: not only are they exposed to a smaller share of elite peers in their school cohort than high SES children are on average, but being exposed to elite peers is also less beneficial to their future educational outcomes than it is for high SES children. To measure the contribution of these two sources of disadvantage to the SES gap in elite education enrolment, we perform an Kitagawa–Blinder–Oaxaca decomposition of the gap in elite education enrolment between low and high SES students. We re-estimate the benchmark model estimated on the sample pooling the low and high SES subsamples and use the estimates of the model to compute the SES gap in elite degree enrolment that is attributable to the average SES gap in each explanatory variable and to the SES gap in the coefficients associated with these variables. We find that the SES gap in average exposure to elite peers in high school explains 1.5 ppts or 7.2% of the SES gap in elite degree enrolment, while the SES gap in the *effect* of such exposure explains another 1 ppt or 4.8% of the SES gap in elite degree enrolment. In total therefore 2.5 ppts or 12% of the SES gap in elite enrolment stems from exposure to elite peers in high school. See Appendix Table A2. This is non-negligible relative to other variables included in the model; for example, the SES gap in ability (as measured by middle school GPA) explains 5 ppts or 24% of the SES gap in elite degree enrolment.

5.2 Elite peers vs. high-achieving peers

As discussed in Section 4, peers with elite educated parents also tend to be high-achieving (as shown in Table 1).[27] To explore the possibility that the elite peer effect that we find is driven by peers' academic skills rather than their "social pedigree", column (2) of Table 2 augments our benchmark model with the (leave-one-out) average middle school GPA of peers within the same high school cohort.

Conditional on peer academic achievement, the elite peer effect is higher for the total sample as well as low and high SES students, increasing to 4.3, 2.3 and 6 ppts respectively. The increase in the coefficient is due to the negative effect on enrolment of exposure to high ability peers, which reduces enrolment by 5.8, 2.8 and 10.5ppts respectively for the full, low and high SES student

effect. See Appendix Section A1.

[27] See de Gendre and Salamanca (2020); Feld and Zoelitz (2017); Lavy et al. (2011); Tincani (2017) for heterogenous peer ability effects.

samples respectively. This is consistent with Abdulkadiroğlu et al. (2014) and Barrow et al. (2020), who find that exposure to high achievement peers has a negligible or even negative effect on grades for students, partially explained by a reduction in the relative achievement for the students who "just get into" very selective high schools in the US. This means that high-status peers, as opposed to high-achieving peers, positively influence the prospects of high school students.

5.3 Validity of identification strategy and specification tests

We provide evidence of the validity of our identification strategy by performing several tests. Column (3) of Table 2 reports the estimates of the specification implied by the Borusyak and Hull (2023) approach described in Section 4. That is, the results represent a regression of the outcome on our treatment variable, controlling for the expected treatment in lieu of the school, cohort fixed effects and middle school GPA. The method yields strikingly similar estimates to those in our benchmark specification in column (1).[28] Column (3) reports also the coefficient on the expected treatment. As expected, it is positive since it reflects the correlation between the proportion of elite parents in a school and elite enrolment.

A set of additional robustness checks test whether our benchmark estimates are likely to be biased by correlation between trends in unobservable determinants of outcomes and elite peer composition, summarised in detail in Appendix Section A3. These confirm that our results do not change when controlling for school-specific linear trends; controlling more flexibly for interacted cohort and year fixed effects whilst pooling data for low and high SES students; dropping observations whose identifying variation does not look random and augmenting the benchmark with teacher traits to proxy for time-varying school quality. We run two placebo analyses. The first confirms that exposure to elite peers during high school is not correlated with pre-determined variables of student birth outcomes, middle school subject choice or mother and father income in the middle school period. A second placebo check shows that the elite peer composition in the period before (lead) and after (lag) the true high school cohort does not change student elite enrolment decisions. The highly robust estimates of the elite peer effect together with the placebo analyses, provide evidence strongly supporting our identifying assumption within our benchmark model.

[28] Note that the sample has fallen slightly in column (2) which reflects some empty cells within school-middle school GPA bands. The benchmark estimates are very similar when run on the restricted sample. This result is included in Appendix Section A2 along with the benchmark and Borusyak and Hull (2023) method excluding controls X.

In specification tests, we show that our results are robust across sub-samples defined by student birth order; marital breakup; city of residence; school size; high school admission mechanism and high school majors and not likely confounded by measurement error. We test for, but find little evidence of the presence of non-linearities in the effect of peers across the level of exposure to elite peers. On the other hand, the effect of peers does vary across the distribution of student own ability. Whilst for low ability students, the likelihood to enroll into an elite degree programme is very low for both low and high SES students, the SES gradient materialises and increases with student ability. Compared to high SES students of the same ability, the low SES students with medium to high ability face the greatest disadvantage in terms of the benefits of being exposed to elite peers. See Appendix Section A3 for details.

5.4 Heterogeneity

5.5 Gender and immigration status heterogeneity

Figure 2 suggests that the effect of exposure to elite educated peers during high school on elite enrolment is larger for males than females (the coefficients are 3.9ppt compared to 1.8ppt in the full sample). Within gender, the SES gradient is still present and the peer effect is considerably larger for low SES males or females compared to high SES males or females. Cools et al. (2019) find that the effect of school peers is heterogeneous depending on the gender of the peer themselves - where female students were negatively affected by the presence of "high achieving boys" within their class. In our setting, the effect of exposure to elite peers is similar if the peer has the same or opposite gender (with a p-value of 0.785 and 0.738 for low and high SES students).

We analyse heterogeneity in the effect of elite peer exposure across the student's second generation immigration status, measured with an indicator for their mother or father being born outside of Norway. 21% and 23% of low and high SES students have at least one parent born outside of Norway, respectively. The estimated peer effect is very similar when comparing second generation immigrant students with students whose parents were born in Norway.[29]

[29]See Appendix Figure A11. The p-value for equality of coefficients 0.739 and 0.464 for high and low SES students respectively.

5.6 Definitions of elite

Parents who graduated from an elite university programme are elite in a way that represents a mix of knowledge and human capital, as well social standing (Barrios-Fernandez et al., 2022). They may have high levels of income and consumption and/or hold prestigious occupations, and this could be what influences high school students to pursue an elite education. As expected, the regressions which change the peer variable to represent these difference concepts of elite - prestigious peers (those with an elite occupation) and wealthy peers (with an elite level of education) are important for student enrolment, suggesting that having elite education is reflecting eliteness measured across different dimensions (see Appendix Section A4.).

6 Elite peer effects on students' academic performance

Having established the presence of a significant elite peer effect on elite degree enrolment and a socioeconomic gradient in this effect, we turn to analysing the mechanisms underlying this effect. We start by analysing the effect of elite peers on high school GPA, a central determinant of higher education enrolment decisions in Norway.

We estimate the elite peer effects on overall GPA by using the same identification strategy as above and estimating Equation 1, this time with high school GPA as the dependent variable. The estimates of these models are reported in columns 1 and 2 in panel A of Table 3 and show that an increase in the proportion of elite peers in a student's school cohort has a negative and statistically significant effect on overall GPA, with a strong socio-economic gradient. Specifically, exposure to elite peers has a significantly detrimental effect on the GPA of low SES students, reducing their grade by 17.1% SD, and a smaller detrimental effect on the GPA of high SES students of 4.6% SD.[30] This is partially explained by the peer academic achievement and, once we condition on the average ability of the high school peers in columns 3 and 4, the negative effect on overall GPA falls to 5.3% of a standard deviation for low SES students, and becomes small and statistically insignificant for high SES students.

As explained in Section 2, overall GPA is a weighted average of blindly assessed written exams, teacher-assessed internal grades, and oral exams assessed jointly by the student's teacher and an

[30]The coefficient (standard error) in the total sample is -0.118 (0.013).

external examiner. To explain why elite peers have a negative effect on high school GPA and a particularly negative one for low SES students, we re-estimate the model this time with each GPA component as the dependent variable (Panel B of Table 3). First, we find that exposure to elite peers in high school *increases* grades on externally-assessed written exams for both high and low SES students. Among all components of high school GPA, externally-assessed written exams can be considered as the cleanest measure of learning or knowledge. As a result, we interpret this positive effect of elite peers on externally assessed exam scores as reflecting positive spillovers of elite peers on the learning or effort and motivation put into learning by other students in the class. The fact that all students seem to benefit from their elite peers, regardless of their ability or socio-economic background, is also reassuring in suggesting that low and high SES students do interact with each other.

In contrast, exposure to elite peers *decreases* the grades of low SES students on exams assessed by teachers either fully (internal grades) or partly (oral exams). The negative effect on teacher assessment is four times as large for low SES students than it is for high SES students, reported in columns (1) and (2). Again, part of this negative teacher assessment effect stems from the ability of the high school peers. Controlling for the mean middle school GPA among high school peers in columns 3 and 4, the teacher assessment downgrade is present just for the low SES students. For oral exams, the elite peer effect is insignificant for high SES while it is negative and statistically significant for low SES students.[31] The p-values confirm the SES gradients are significant for overall GPA and teacher assessments but not the written exam.

The SES gradient in the negative effect of elite peers on exams where teachers have some discretion over students' grade is consistent with teachers marking on a curve, i.e. that they assess student's achievement relative to others.[32] If this were the case, because elite students tend to be high achieving, an increase in elite peers in the cohort would create downward pressure on the rank of other students. This downward pressure would be more strongly felt among lower ranked students than among higher ranked students, thus creating a more negative effect of elite peers on

[31]The peer effect on GPA outcomes for the middle SES households tends to sit in between estimates for low and high SES households, suggesting a linear SES gradient, although the confidence intervals often overlap across samples. The exception is for the written assessment where the exposure to elite peers has the same coefficient across household SES. See Appendix Figure A4.

[32]In Norway, teachers are not officially supposed to mark to a curve, but may nonetheless grade students relative to others.

teachers assessments of low SES students than on those of high SES students.[33]

To corroborate this conjecture, we present in Figure 3 estimates of the elite peer effect on teacher assessments, this time allowing an interaction between the peer effect and the student's ability rank within the cohort, where the rank is calculated using the middle school GPA, ranked across all students within the same high school cohort. The figure clearly shows that the negative effect of the exposure to elite peers on the teacher assessment is driven by lower ranked students within the cohort, in line with the idea that the presence of elite peers in the cohort have a mechanical negative effect on the rank of other students.

However, this 'rank effect' does not fully explain why the effect of elite peers on GPA is *more negative* for low SES students than it is for high SES students. Indeed, as is clear from Figure 3, the negative effect of elite peers on teacher assessments is always larger for low SES students than it is for high SES, conditional on their middle school GPA rank. These patterns might be explained by several reasons including 1) the existence of a systematic teacher bias against low-SES students, where this bias responds to cohort composition and gets exacerbated by the presence of more elite peers; 2) if high SES students have a higher latent academic achievement and will achieve better grades at high school even conditional on their middle school GPA, then even conditional on the rank we may expect such patterns; 3) the socio-emotional skills of the low SES students may react to the proportion of elite peers in their cohort, leading to a downgrade in the teacher assessment. All of these potential mechanisms are consistent with the reduction in the teacher bias in columns (2) and (3) once the mean ability of peers is included additionally as a control.[34]

7 Elite peer effects on elite degree enrolment conditional on GPA : results from a causal mediation analysis

The paper so far has established that elite peers have a positive effect on the probability that students enrol in an elite degree (Section 5), but a negative effect on their high school GPA (Sec-

[33]In analysis which replaced the dependent variable with the students' rank of middle school GPA calculated among their high school peers, the effect of increasing exposure to elite peers was to lower the students' own rank. See Appendix Table A9. Therefore, even though the written exam score marked nationally increases with elite peer exposure, their rank within the classroom falls.

[34]The robustness and sensitivity analyses carried out for the benchmark estimation are repeated on the GPA outcomes, showing that the benchmark estimates are robust to the validity tests. See Appendix Table A10, Appendix Figure A12 and panels c)-f) of Appendix Figure A7.

tion 6). This implies that, conditional on GPA, elite peers must have a positive effect on students' likelihood to apply to elite degrees.[35] Such positive effect could derive from elite peers or their parents by acting as role models and/or providing information about these educational routes and their returns. Especially for high-SES students, it could also derive from elite peers changing the preferences of other students for elite degrees by changing the probability that they enrol in the same degree as high school friends.

7.1 IV strategy to estimate the direct effect of elite peers

In this section, we use a causal decomposition method to quantify the direct effect of elite peers on the probability of enrolling in an elite degree conditional on GPA from the indirect effect of elite peers working through GPA. To estimate the direct effect of elite peers, we need to estimate the following model, which corresponds to our benchmark model augmented to include high school GPA as an explanatory variable:

$$Y_{ics} = \gamma_1 P_{-ics} + \gamma_2 GPA_{ics} + \gamma_3 M_{ics} + X'_{ics}\gamma_4 + \alpha_s + \rho_c + \epsilon_{ics} \tag{5}$$

where GPA_{ics} refers to high school GPA of student i in cohort c and school s.

In the model above, GPA_{ics} is likely endogenous because it is likely to be correlated with unobserved individual determinants of elite degree enrolment. As a result, an OLS estimation of Equation 5 would fail to recover γ_2 in an unbiased way. And because P_{-ics} and GPA_{ics} are correlated, it would also fail to recover γ_1 in an unbiased way. To overcome this issue, we need to instrument high school GPA with a variable that is strongly predictive of GPA (relevance), but that only affects the probability of enrolling in an elite degree through its impact on GPA. This exercise can be seen as a causal mediation analysis with endogenous mediators discussed in Celli (2021) and Huber (2019).[36]

To instrument high school GPA, we propose to exploit a unique feature of the Norwegian high

[35] We do not directly observe application behaviour and so are not in a position to comment on whether elite peers have an effect on the probably that students apply for an elite degree versus on the probability that they make better strategic decisions and end up being more likely to be accepted into an elite degree. We leave this interesting question to future work.

[36] There are a few examples of mediation analysis taking account of the endogeneity of mediators through an instrumental variables strategy in the economics literature. For example, see Aklin and Bayer (2017), Attanasio et al. (2020) and Nicoletti et al. (2023).

school system and provide some justification for our instrument below. Specifically, we exploit a lottery which randomly allocates students to take externally assessed examinations in a specific subject in the final, third year of high school. We define our instrument as an indicator that takes the value 1 if student i was randomized into taking math as an externally assessed subject in the third year of high school, and 0 otherwise.

We focus on the randomisation into taking math (as opposed to another subject) because it is likely to have the strongest first stage in our context. Indeed, whilst one could argue that the marking of maths subjects are less subjective than other subjects, mathematics has been shown to be prone to strong teacher bias, which are therefore more strongly circumvented in blindly assessed exams (Copur-Gencturk et al., 2020).[37] Interestingly, in our context and in line with this, we find that the negative effect of elite peers on teacher assessments is particularly strong for maths.[38] Being randomly assigned into a written maths exam therefore is likely to raise GPA most strongly. And as we see below, the first stage F-statistic is high particularly for low SES students.

To operationalise this IV mediation strategy, we estimate Equation 5 jointly with the following first stage equation:

$$GPA_{ics} = \delta_1 P_{-ics} + Z^{'}_{ics}\delta_2 + M^{'}_{ics}\delta_3 + X^{'}_{ics}\delta_4 + \alpha_s + \rho_c + \epsilon_{ics} \tag{6}$$

where Z_{ics} denotes the instrumental variable and the notation for other terms is as before. The direct effect of exposure to elite peers on student enrolment is the conditional effect given by coefficient γ_1. The indirect effect of exposure to elite peers through the channel of high school GPA is the product of δ_1 from equation 6 and γ_2 from 5 (i.e. the product of the effect of elite peers on high school grades and the effect of high school grades on elite enrolment).

The instrument - being assigned to a written math exam - must satisfy the rank condition and affect elite degree enrolment decisions only through its effect on high school GPA. This condition could be violated if the probability of being assigned a written exam is higher for certain schools, or programmes of study for example. However, we include school and programme of study fixed effects

[37] Copur-Gencturk et al. (2020) show that teachers assessment of maths performance for two students providing a similar answer are linked to their SES, gender and ethnicity.

[38] When repeating the analysis in Table 3 but replacing the dependent variable with the teacher assessment in maths, English or Norwegian, the negative downgrade is of greatest magnitude for maths. For low SES students the coefficient (standard error) is -0.034(0.006), -0.018(0.005) and -0.013(0.004) and for high SES students is -0.009(0.009), -0.006(0.006) and -0.005(0.005) for maths, English and Norwegian respectively.

in the regression to account for the fact that randomisation is done within school and programme of study. Indeed, a balance test which regressed the instrumental variable on the set of covariates included in the benchmark specification, augmented by indicators for programme of study in high school (groupings of majors into social science, humanities, science and general) shows very little significance of student characteristics in predicting the lottery assignment to take a maths exam, validating the exclusion restriction. See Appendix Table A11.

The additional assumption invoked when using an IV mediation strategy beyond typical IV assumptions, explained in Huber (2019) is that the estimated effect of GPA on elite enrolment, γ_2 from Equation 5, is homogeneous and therefore not estimated across a different set of compliers compared to the average effect that would be estimated within the population. We provide evidence in support of this homogenous treatment effect assumption, as the the coefficient γ_2 estimated for the total sample is very similar to that estimated across many sub-groups, defined by defining in more detail the parents' education, the household earnings and an indicator for the ability of the father being low or high, across the low and high SES samples (an exception is estimate for low ability fathers in the high SES sample - because the sample size is very small). See Appendix Figure A13.

7.2 IV and mediation analysis results

Panel A of Table 4 reports the first stage estimates of δ_1 and δ_2 from Equation 6, separately for the low and high SES samples. These estimates confirm that the instrument is relevant for the low SES student sample where the F-statistic on the instrumental variable is 77. The F-stat for the high SES sample is lower at 5.6, which is intuitive since high SES students perform very highly anyway and there was a lower downgrade in teacher assessments for these students. For this reason we now focus on reporting the results for low SES students.

Panel B of Table 4 contrasts the OLS estimates of the overall effect (i.e. unconditional on GPA) of elite peers on elite degree enrolment in columns 1 and 3[39], with the IV estimates of the direct effect of elite peers (parameter γ_1 of Equation 5) in columns 2 and 4. Columns 2 and 4 in Panel B of Table 4 also report the estimates of γ_2 of Equation 5, the effect of GPA on the probability of

[39] Note that the OLS estimates are slightly different from those presented in Table 2 because we now also control for high school programme indicators (as in the first stage equation).

enrolling in an elite degree.

As expected, high school GPA has a strong positive and statistically significant effect on the probability of enrolling in an elite degree. The coefficient on the elite peers in the IV specification is 0.026 and statistically significant in the low SES sample, which means that an increase in exposure to elite peers by one SD encourages low SES students to raise their enrolment in elite degrees by 2.6 percentage points (conditional on GPA).

The final rows of Table 4 decompose the total peer effect on student enrolment to an elite degree from Table 2 into the direct effect γ_1 from Equation 5 and the indirect effect $(\delta_1 * \gamma_2)$ working through GPA. Interestingly the direct effect of exposure to elite peers is large enough to cancel out the negative effect coming from grades. The direct effect of elite peers could reflect the effect of elite peers on students' information set (about programmes, their returns and/or their probability to be admitted) and/or through their preferences for such degrees, though our current strategy and data do not allow us to be more precise on the nature of these underlying mechanisms. The analysis suggests that increasing the weight in blind written maths examinations for low SES students in overall GPA could raise enrolment of these students in elite degree programmes.

8 How does exposure to elite peers shape intergenerational income mobility?

We conclude our analysis by considering the extent to which the elite peer effect on elite degree enrolment (and the social gradient in this effect) we have uncovered in this paper translates onto earnings and inequalities therein. If that is the case, policies aimed at reducing socioeconomic segregation in high school could be a potential lever to reduce the intergenerational persistence of earnings.

The key parameter that will determine the answer to these questions is the return to an elite degree and the gap in returns between low and high SES students. While elite degrees have been shown to have high labour market returns in other contexts, this evidence is, to our knowledge, missing for Norway. Moreover, it is not a given that the returns would be positive for low SES students - a requirement for any policy aimed at increasing the number of first generation elites to have an impact in the labour markets for this group.[40]

[40] Zimmerman (2019) shows that the returns to business focused elite degrees in Chile are close to zero for males not from private high schools which are the types of high schools that charge high tuition and serve upper-income

In this final section, we tackle three questions: is the earnings premium to an elite degree positive across SES backgrounds? Does exposure to elite peers in high school raise the longer-run outcome of earnings age 30-32? Does exposure to elite peers exacerbate or mitigate the link between child and parents' earnings? To answer these questions, we use data on the earnings of the six oldest cohorts in our data (born between 1986-1991). For these cohorts it is possible to measure income for some ages between 30 and 32 years old, which has been shown to be the age at which earnings rank becomes relatively stable and predictive of earnings rank at older ages (Bhuller et al., 2017).

Earnings premium to enrolling in an elite degree We estimate a Mincer style regression of earnings on an indicator for whether the student enrolled in a degree and an indicator for enrolling in an elite degree (with the category of no degree omitted) on the full set of controls we included in Equation 1, as well as school and cohort fixed effects. We estimate this specification for low and high SES students separately, as the earnings premium could be different between the two. The results of this specification are reported in panel A of Table 5 where the dependent variable is the (within cohort) percentile rank of earnings age 30-32 in columns 1) and 2) and an indicator for earning in the richest decile in columns 3) and 4). We find evidence of a very high average earnings premium to enrolling in an elite degree, which is only slightly smaller for low than high SES students. Remarkably, the similar coefficients for low and high SES students are found also when considering earnings in the top 1%, 10%, 25% and 50% of the earnings distribution (see Appendix Table A12).[41] Although the evidence presented here is not necessarily causal, it does suggest that the returns to becoming first generation elite are likely to be positive so that increasing the probability that low SES students enrol in an elite degree could increase social mobility.

Effect of elite peers on earnings Having established a positive earnings premium to enrolling in an elite degree across SES backgrounds, we tackle question two and estimate the effect of being

households and hence that are rarely attended by low SES students, and for females. On the contrary the returns are similar or even higher for low compared to high SES students on elite medical school programmes. Michelman et al. (2022) attributes the different returns across the programmes as a requirement to schmooze when moving from business programmes and into the labour market, which is not required for other programmes, such as medicine. Hastings et al. (2013) on the other hand finds large positive returns for highly selective degrees across SES.

[41] Allowing a different coefficient for studying for different elite programmes of law, STEM and medicine, hitting the top earnings percentile is more likely when studying law for high SES, but when studying medicine for low SES students - consistent with high returns to high SES in programmes requiring higher levels of schmoozing, in Zimmerman (2019). For outcomes earnings percentile or richest decile the earnings premium from different elite degrees are similar across low and high SES students. See Appendix Table A13 for these results.

exposed to elite peers during high school on adult earnings by re-estimating our benchmark (Equation 1), with the percentile rank (columns 1-2) and earnings in the top decile (columns 3-4) as outcomes in panel B of Table 5.[42] We see in columns (1) and (2) of Table 5 that being exposed to elite peers in high school increases the percentile rank but this effect is lower for low SES students than it is for high SES students (1.09 percentiles compared to 2.5 with the p-value for equality at 0.013). It also increases the probability of being in the richest decile at age 30-32 but only for high SES students (2.2 ppts and again the p-value suggests the two estimates are significantly different). This is true also in Panel C, which includes the additional control of the peer mean ability. These results show again a negative coefficient on the ability of the high school peers and a slightly increased estimate of the effect of exposure to elite peers during high school.

We also show results more broadly across the earnings distribution which suggest that for both low and high SES students, there is no statistically significant effect of exposure to elite peers on entering the top earnings percentile, but an increased chance of earning in the top decile (for high SES students), top quartile and the top half of the income distribution. For all earnings measures the SES gradient exists such that the high SES students enjoy a greater peer effect. See Appendix Table A12.[43]

These estimates of the impact of elite peers on earnings percentiles are 3 to 4 times larger than what we would expect if elite peers *only* affected earnings through educational achievement (assuming that our estimates of the earnings returns to an elite degree are causal).[44] This suggests that the social capital built in high school could have quite profound implications for labour market outcomes, which work well beyond the impact it has on educational achievement per se. There are a number of mechanisms through which elite peers in high school could affect earnings over and beyond its impact on enrolment in elite degrees. For example, the connections made in high school could have an effect on the type of occupations that students choose and the firms they work at.

[42] This is important given that Dahl et al. (2021) find that increasing integration of different genders in military training drives short-run but not longer-run outcomes such as attitudes, field of study or occupation.

[43] Our results of the earnings effects of peers are robust to the set validity tests conducted for the benchmark. See Appendix Table A14 and Appendix Figure A14.

[44] To compute these numbers, we first estimate the impact of enrolling in an elite degree on earnings percentiles without controlling for enrolling in a higher education degree. If elite peers only affected earnings by increasing the probability of enrolling in an elite degree, we would expect an effect size of elite peers on earnings percentiles of 0.013 $\times$ 18.480 = 0.240 for low-SES students and 0.040 $\times$ 17.062 = 0.682 for high-SES students. This is about one third of the overall effect of elite peers on earnings percentile that we estimate in the data. These figures are reported in Appendix Table A15.

Understanding these mechanisms is beyond the scope of the paper but we note that these findings are an interesting avenue for future research.

Implications for intergenerational income mobility We have shown so far that elite peers increase the educational attainment and earnings of low SES students, but they have a stronger effect on the outcomes of high SES students. This means that while exposure to elite peers could increase the number of first generation elites and thus increase mobility at the bottom of the parental income distribution, it could also exacerbate the lack of mobility at the top of the parental income distribution. To verify this hypothesis empirically, we estimate the extent to which the degree of intergenerational income persistence across the parental income distribution varies with the child's exposure to elite peers in high school, allowing non-linearity in the rank-rank coefficient across the parental income distribution and across the level of exposure to elite peers in high school:

$$r^c_{ics} = \delta_{11} r^p_{ics} + \delta_{12}(r^p_{ics})^2 + \delta_{21} r^p_{ics} \times P^{high}_{-ics} + \delta_{22}(r^p_{ics})^2 \times P^{high}_{-ics} + \beta_3 M_{ics} + X'_{ics}\beta_4 + \alpha_s + \rho_c + \epsilon_{ics} \quad (7)$$

where r^c_{ics} is the child's rank in the children's earnings distribution at age 30-32, r^p_{ics} is the parents' rank in the parents' earnings distribution when the child was 15-19, and P^{high}_{-ics} is an indicator taking the value 1 if child i had a level of exposure to elite peers during high school that was higher than the mean (c. 6%) and 0 otherwise.[45]

Figure 4 shows the predicted value of child's earnings rank, as a function of the parent's rank and the level of exposure to elite peers. For any value of the parent percentile rank, the child's percentile rank is higher in the high exposure group with above average proportion of elite peers than in the low exposure treatment. Importantly, as the additional uplift is highest at the bottom and the top of the parent income distribution, whilst exposure to elite peers lifts mobility at the bottom of the parental income distribution, it also increases persistence at the top of the income distribution.[46]

The curve labelled "Total Effect" plots the predicted value of the child's earning rank, given the level of exposure at each parent percentile. More specifically, at every percentile along the

[45] This follows a similar strategy of Pekkarinen et al. 2009, used for example in Bütikofer and Salvanes 2020 and Kaila et al. 2021.

[46] Note that this pattern of increased mobility for the low SES families is repeated if we instead estimated Equation 7 with a cubic specification for the heterogeneity.

distribution of parent income, we take an average of the fitted value for the low exposure and the high exposure estimate weighted by the proportion of parents with high exposure to elite peers. Because elite peer exposure is lower for children with low earnings parents than for children with high earnings parents, the total effect is lower for the former and higher for the latter. Segregation of children from elite educated parents in high school could therefore be a factor explaining why intergenerational persistence in earnings is particularly high at the top of the distribution in Norway (Pekkarinen et al., 2017) and in other contexts (Chetty et al., 2014).[47]

Given these results, our estimates suggest that reducing exposure to elite peers for high SES students and increasing exposure for low SES students would raise intergenerational mobility.[48] To illustrate this point, we use our estimates to conduct several simulations through which low and high SES students are re-assigned across high schools in a way that reduces the level of socioeconomic segregation more or less strongly. These simple simulations do not intend to mimic the effect of particular interventions (e.g bussing, affirmative action or quotas), which policy makers could and have used to reduce socio-economic segregation. Rather, the objectives is to calculate the net consequence for mobility of a change in segregation, abstracting from general equilibrium effects.

In a nutshell, for all simulations, intergenerational mobility rises once the exposure to elite peers is re-balanced across low and high SES students.After the simulation, the intercept from the rank-rank regression is higher suggesting a higher earnings rank for very low SES students, and the gradient of the relationship between parent and child percentile rank is flatter. It is worth noting that the increased mobility from equalising the exposure to elite peers may come with an efficiency cost, as Table 5 suggests a consequence may be a reduced percentile rank or top ten percent share in the income distribution (holding the absolute value of earnings at each rank fixed). See Appendix Section A5 for the full description of the simulation exercise along with results.

[47]The high mobility suggested for low SES families defined by parents' income percentile in Figure 4 and relatively low mobility for low SES students defined by parents' education in Table 5 is consistent with Bjorklund and Salvanes (2011) and Landersø and Heckman (2017) who find much higher intergenerational persistence in education compared to income, in Norway and Denmark respectively.

[48]Of course this is in the absence of general equilibrium effects which may see parents changing their behaviour in response, such as in Agostinelli et al. (2020).

9 Conclusion

Socioeconomic inequalities in elite education are high, even in Scandinavian countries where income inequality is notoriously low. The main contribution of this paper is to show that social interactions in high school play a key role in driving inequalities in education and earnings outcomes within and across generations.

First, we show that Norway's high school admission system creates high levels of segregation of children of elite educated parents into the same high schools. Moreover, we show that being exposed to elite peers in high school has a stronger positive effect on the probability of enrolling in an elite degree and on the earnings of high SES student than on those of low SES students. Together, our findings suggest that this segregation is responsible for reducing mobility at the bottom of the socioeconomic distribution while exacerbating persistence at the top. Interestingly, the elite peer effect on educational attainment that we find is of similar order of magnitude as the effect of peers with 'rare' characteristics found in other papers, such as peers with a parent with graduate education (Cools et al. 2019) and peers with a history of domestic violence (Carrell et al. 2018).[49]

The findings presented in this paper are important in the context of the intergenerational mobility literature. They provide causal evidence that social capital and in particular the level of economic connectedness among high school peers is a mechanism behind the intergenerational persistence (or lack thereof) of education and income. Moreover, they support the idea that social capital is a key reason why intergenerational income persistence is so high at the top of the distribution in Norway. While our findings are for the Norwegian context, they may also be relevant to explain similar patterns in other countries, such as the US (Chetty et al., 2014).

The second contribution of our paper is to explain the mechanisms through which elite peers affect children's educational outcomes. Our findings are threefold. First, exposure to elite peers

[49] Cools et al. (2019) show that a 1 standard deviation increase in the proportion of male peers who have at least one parent with post-college education lowers the probability of females completing a 4-year bachelors degree by 2.2ppts - a 6% decrease from a mean of 35%. In comparison our estimates suggest a 1 standard deviation increase in the proportion of elite peers raises elite enrolment by 2.6ppts on average. Carrell et al. (2018) study the effect of exposure to "disruptive peers", defined as peers who have been exposed to domestic violence. The authors find that exposure to at least one disruptive peer reduces college enrolment by 1ppt (1.4%). This parameter is comparable in size to the effect of exposure to "any elite", which we find raises enrolment by 1ppt in the total sample, 0.8 ppt in the low SES sample and 5.1 ppts in the high SES sample.

raises the test score in written and blind marked high school examinations suggesting increased learning or effort of students. This peer effect is of equal size for low and high SES students, which reassuringly suggests that the students from different backgrounds interact with students from elite families. Second, through a teacher assessment downgrade, elite peer exposure penalises the GPA of low SES students much more than for high SES students. We argue that this pattern reflects the fact that elite peers push the rank of other students down the distribution of teacher grades. Conditional on rank however, the teacher assessment downgrade remains stronger for low SES than high SES students. Third, a causal mediation analysis is used to illustrate that, conditional on GPA, students' exposure to elite peers increases their likelihood to apply to an elite degree. Because this positive peer effect dominates any negative peer effect through teacher grades, we find the overall effect of elite peers to be positive.

Overall, our findings suggest that considering peer interactions is very important for policy-makers interested in improving the life chances of low SES students as well as intergenerational mobility. A direct implication of our findings is that policies increasing the social mixing of students from different parental education backgrounds could be beneficial to improve social mobility across the parental income distribution. Our estimates suggest that increasing the reliance of university admission systems on standardised, blindly assessed tests could improve the educational and economic chances of low SES students by increasing the benefits that low SES students have from being exposed to elite peers.

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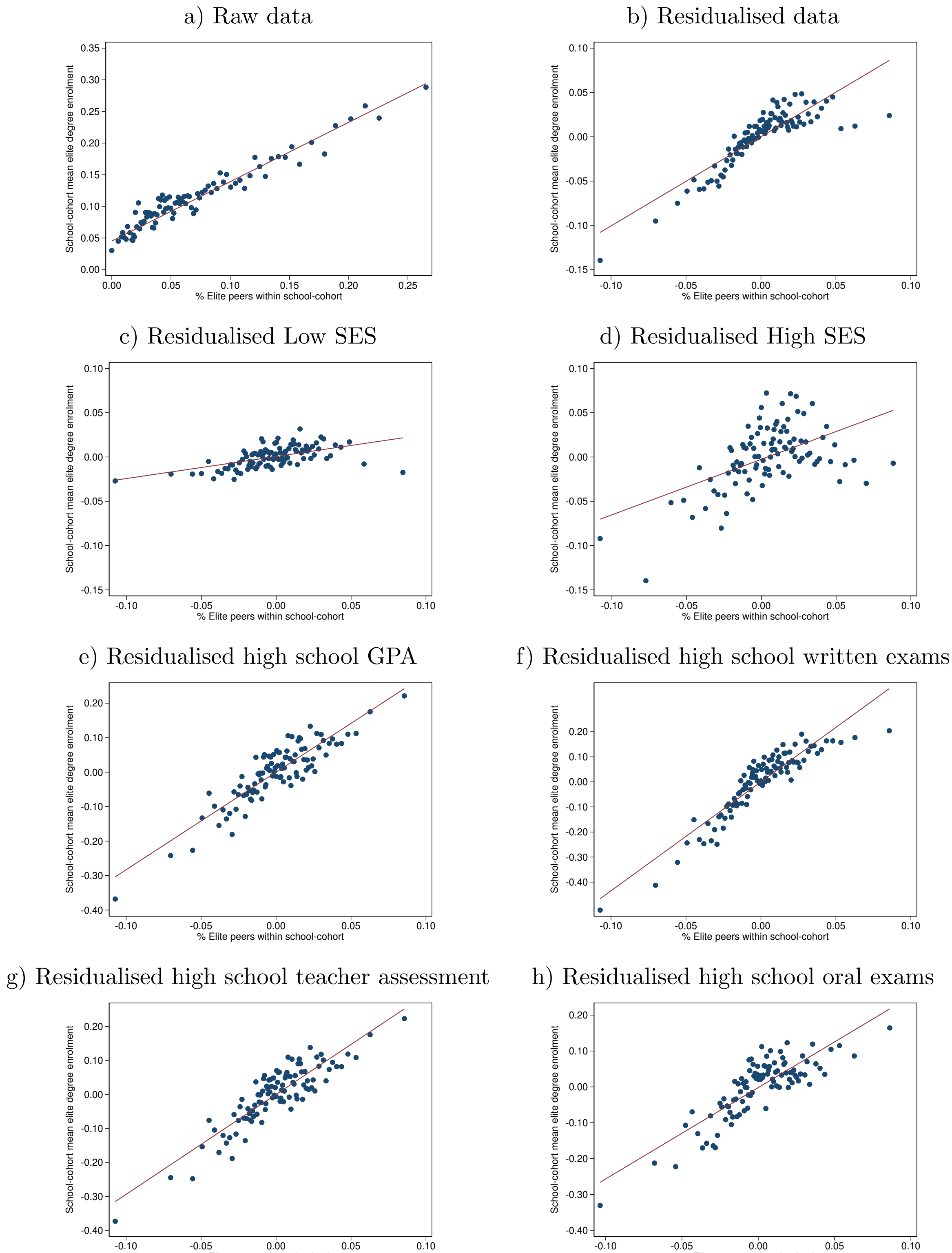
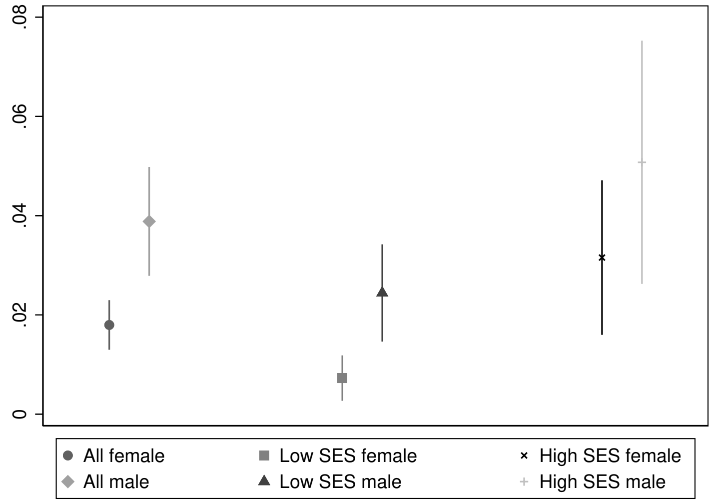
Figure 1: Plotting school-cohort variation in elite peers against elite enrolment and high school test scores



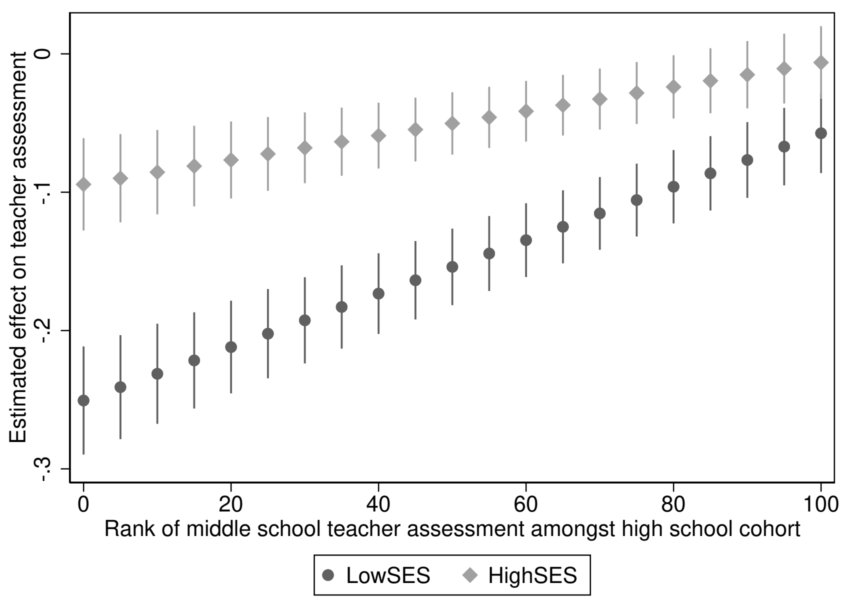
A residual (R_y) is predicted from a regression of elite degree enrolment on cohort and school fixed effects. A residual (R_t) is predicted from a regression of exposure to elite peers on cohort and school fixed effects. Binscatter figures in panel a) plot the variance in the raw data of elite degree enrolment and elite peer exposure and panels b)-d) plot R_y against R_t and the linear fit for the full, low and high SES samples. Panels e)-g) plot residual binscatter plots for z-scores of the high school GPA residuals.

Figure 2: Estimated peer effect coefficients in gender heterogeneity analysis



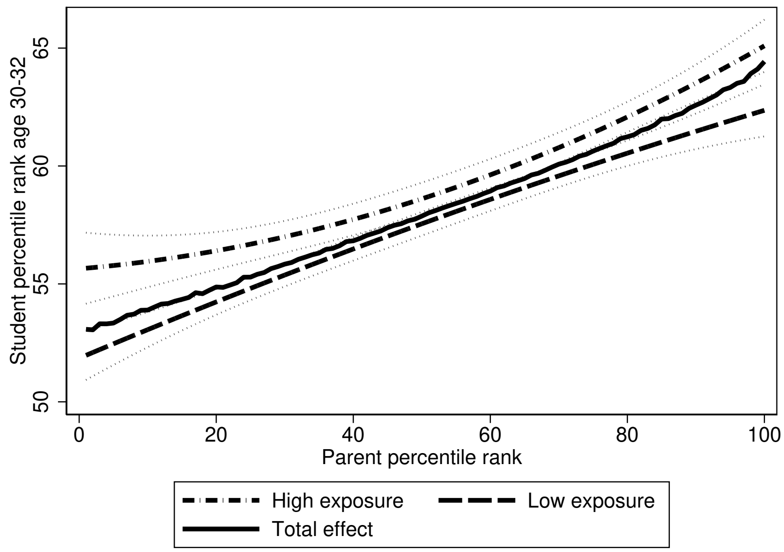
Notes: The figure plots the coefficient estimates from Equation 1 allowing for heterogeneity in the effect of the proportion of elite educated peers in high school across female and male students.

Figure 3: Marginal effect of exposure to elite social networks on high school teacher assessment across student middle school teacher assessment rank



Notes: This graph plots the marginal effect of an increase in P_{-ics} on the probability of enrolling in an elite degree as a function of the rank of the student's middle school teacher assessment amongst the high school cohort. Estimated on the benchmark specification including the rank of middle school GPA and an interaction between the rank and the proportion of parents from an elite educated background. The marginal effect in the low SES (high SES) sample is plotted as a dark grey circles (light grey diamonds).

Figure 4: Intergenerational mobility: estimating the percentile rank-rank correlation across exposure to elite peers



Notes: This graph plots the fitted values from an intergenerational mobility rank-rank regression allowing for the interaction between exposure to elite peers and the parent percentile rank to be quadratic. High (low) exposure is defined as above (below) mean proportion of elite peers in the high school cohort. The line "Total Effect" plots the predicted outcome as a weighted average across low and high exposure to elite peers, at each parent percentile rank.

Table 1: Summary statistics of the sample

	Full sample	Low SES sample	High SES sample
	Mean (sd)	Mean (sd)	Mean (sd)
Enrolls in higher education	0.904	0.861	0.956
Enrolls in elite degree	0.102	0.053	0.260
% of parent peers with elite degree	0.061	0.047	0.100
	(0.056)	(0.047)	(0.068)
Covariates			
Female	0.601	0.651	0.527
Born in Norway	0.873	0.836	0.852
Middle school GPA (std)	0.676	0.496	0.921
	(0.634)	(0.639)	(0.591)
Mother's highest education level			
Compulsory education	0.516	0.932	0.161
High school degree	0.126	0.068	0.144
University degree	0.358	0.000	0.695
Father's highest education level			
Compulsory education	0.578	0.916	0.073
High school degree	0.139	0.084	0.042
University degree	0.282	0.000	0.885
% of own parents with an elite degree	0.066	0.000	0.580
	(0.194)	()	(0.183)
Family income in the top decile	0.214	0.123	0.485
	(0.309)	(0.244)	(0.352)
Mechanisms			
High school GPA (std)	0.013	-0.252	0.494
	(0.999)	(0.951)	(1.000)
Long-run outcomes			
Student in top decile of earnings 30-32	0.141	0.104	0.230
Student percentile rank 30-32	58.494	55.181	64.667
	(26.728)	(25.926)	(28.068)
Number of pupils	177,219	58,328	20,018

Notes: The table presents means (standard deviations) of the main analysis variables on a sample of students ending middle school between 2002-2010. Elite degree status defined as enrolment into Economics/Business, Engineering, Law of Medicine at a top institution (see Section 3). Elite occupation takes the value 1 for STEM occupations, lawyers or doctors. High school (middle school) GPA is standardized within cohort to have mean 0 and standard deviation 1. Low SES sample defined as the group of students who have at least one parent with the compulsory level of education, but no parent with an elite education. High SES sample defined as the group of students who have at least one parent with an elite degree, but no parent with a compulsory level of education. Long-run outcomes are measured for the oldest 6 cohorts where sample size is 73,868; 25,188; 8,290 for the total sample; low SES and high SES respectively.

Table 2: Effect of elite peers on the probability of enrolling in an elite degree

	(1) Benchmark	(2) Elite and academic peers	(3) Expected treatment	(4) Quadratic
A - All students				
Proportion of parents w/elite degree	0.026***	0.043***	0.020***	0.024***
	(0.003)	(0.003)	(0.001)	(0.003)
Peer mean middle school GPA		-0.058***		
		(0.004)		
"Expected" treatment			0.103***	
			(0.005)	
Proportion of parents w/elite degree sq.				0.001
				(0.002)
Number of pupils	177,219	177,219	165,910	177,219
Number of schools	556	556		556
B - Low SES students sample				
Proportion of parents w/elite degree	0.013***	0.023***	0.016***	0.014***
	(0.003)	(0.003)	(0.002)	(0.003)
Peer mean middle school GPA		-0.028***		
		(0.003)		
"Expected" treatment			0.097***	
			(0.009)	
Proportion of parents w/elite degree sq.				-0.001
				(0.001)
Number of pupils	*58,610*	*58,610*	*53,604*	*58,610*
Number of schools	*524*	*524*		*524*
C - High SES students sample				
Proportion of parents w/elite degree	0.040***	0.060***	0.033***	0.058***
	(0.008)	(0.009)	(0.003)	(0.010)
Peer mean middle school GPA		-0.105***		
		(0.017)		
"Expected" treatment			0.076***	
			(0.011)	
Proportion of parents w/elite degree sq.				-0.008**
				(0.004)
Number of pupils	*20,018*	*20,018*	*19,516*	*20,018*
Number of schools	*459*	*459*		*459*

Notes: Column (1) reports OLS estimates of a regression of an indicator for whether the student is enrolled in an elite degree within 6 years of starting high school on the proportion of parents with elite degree in the student's school's cohort, student's gender, middle school GPA, an indicator for whether the student was born in Norway, mother and father's highest education level, the number of student's own parents who have an elite education, and an indicator for student's family income in the top decile of the income distribution. Regressions include cohort and school fixed effects. Column (2) includes the additional regressor of the mean middle school GPA among high school cohort. Column (3) reports the coefficient from application of Borusyak and Hull (2023) which controls only for the "expected treatment" and individual controls (see Section 4 for details and Section A2) and column (4) augments the specification in column (1) with a quadratic in exposure to elite peers. Panel A reports the coefficients estimated in the full sample, panels B and C report the coefficients estimated in the low SES and high SES samples, respectively. See Table 1 for definitions of low and high SES students samples. Regressions are weighted by school size to take account of the parent peer variables group averages, taken from groups of different sizes. Standard errors clustered at the school level. *** p<0.01, ** p<0.05, * p<0.1

Table 3: Elite peer effect on overall GPA and its components

	(1)	(2)	(3)	(4)
	Benchmark		Controlling for peer ability	
	Low SES	High SES	Low SES	High SES
A - Dep var: overall GPA				
Proportion parents w/elite degree (std)	-0.171***	-0.046***	-0.053***	-0.006
	(0.016)	(0.012)	(0.013)	(0.012)
p-value low=high	*[0.000]*		*[0.000]*	
Peer mean middle school GPA			-0.318***	-0.202***
			(0.015)	(0.030)
p-value low=high			*[0.000]*	
Number of observations	*58,610*	*20,018*	58,610	20,018
B - Dep var: components of GPA				
Externally assessed written exam grades	0.030**	0.030*	0.062***	0.048***
	(0.012)	(0.016)	(0.012)	(0.016)
p-value low=high	*[0.983]*		*[0.361]*	
Peer mean middle school GPA			-0.087***	-0.091***
			(0.014)	(0.031)
p-value low=high			*[0.893]*	
Number of observations	*58,610*	*20,018*	*58,610*	*20,018*
Teacher-assessed internal grades	-0.162***	-0.040***	-0.041***	0.004
	(0.016)	(0.012)	(0.013)	(0.012)
p-value low=high	*[0.000]*		*[0.000]*	
Peer mean middle school GPA			-0.331***	-0.228***
			(0.014)	(0.028)
p-value low=high			*[0.000]*	
Number of observations	*58,610*	*20,018*	*58,610*	*20,018*
Semi-externally assessed oral exam grades	-0.064***	-0.012	-0.028**	0.003
	(0.011)	(0.014)	(0.012)	(0.015)
p-value low=high	*[0.002]*		*[0.082]*	
Peer mean middle school GPA			-0.096***	-0.076**
			(0.015)	(0.037)
p-value low=high			*[0.651]*	
Number of pupils	*49,414*	*17,189*	*49,414*	*17,189*

Notes: OLS estimates of the effect of the proportion of parents with an elite degree in the student's school cohort in the benchmark model where the dependent variable is now a measure of high school performance. See notes to Table 2 for detailed list of controls. The measures of academic performance are: overall high school GPA (block 1), average performance on externally assessed written exams across all three years of high school (block 2), average performance on teacher assessed grades across all three years of high school (block 3), and average performance on oral exams marked by an external examiner and the student's teachers across all three years of high school (block 4). All measures of performance are standardized to have mean 0 and standard deviation 1 within cohort. Columns (1) and (3) and columns (2) and (4) report the coefficients estimated in the low SES and high SES samples respectively, see Table 1 for definitions. Columns (3) and (4) include the estimates from a specification which controls additionally for the peer mean ability amongst the high school cohorts. Standard errors clustered at the school level. *** p<0.01, ** p<0.05, * p<0.1

Table 4: IV estimates and decomposition of the total effect of elite peers on elite degree enrolment

	(1) Low SES OLS	(2) Low SES IV	(3) High SES OLS	(4) High SES IV
A - First stage outcome: high school GPA				
Proportion of parents with elite degree (std)		-0.039***		-0.010
		(0.007)		(0.010)
Student took written math exam (IV)		0.095***		0.043**
		(0.011)		(0.018)
F statistic		*77.471*		*5.57*
B - Second stage outcome: erolment to elite degree				
Proportion of parents with elite degree (std)	0.011***	0.026***	0.032***	0.049***
	(0.004)	(0.004)	(0.009)	(0.019)
Overall high school GPA		0.385***		1.771**
		(0.053)		(0.714)
C - Decomposition				
Direct effect		0.026		0.049
Indirect effect		-0.015		-0.018
Total effect		0.011		0.031
Number of pupils	*58,586*	*58,586*	*19,968*	*19,968*
Number of schools	*500*	*500*	*409*	*409*

Notes: Sample of students ending middle school and entering high school between 2002-2010. Columns (1) and (3) report OLS estimation of a regression where the dependent variable is indicator for being enrolled in an elite degree within 6 years of finishing middle school. Columns (2) and (4) report two-stage least squares estimation, where the IV for high school GPA is lottery to take written exam in maths in year 3 of high school. Results in Panel A report the first stage regression estimates where the dependent variable is high school GPA. Results in Panel B report the second stage, i.e. a regression of an indicator for being enrolled in an elite degree within 6 years of finishing middle school. Model controls are the same as Table 2 including school, cohort and additionally high school program fixed effects. Regressions are weighted by school size to take account of the parent peer variables group averages, taken from groups of different sizes. Columns (1) and (2) report results for the low SES sample, columns (3) and (4) for the high SES sample - see Table 1 for definitions. Standard errors clustered at the school level. *** p<0.01, ** p<0.05, * p<0.1

Table 5: Long-term implications for earnings

	(1)	(2)	(3)	(4)
	Dep var: Earnings percentile		Dep var: Richest decile	
	Low SES	High SES	Low SES	High SES
A - Mincer regressions	9.843***	12.930***	0.027***	0.105***
Student ever enrolled in degree	(0.434)	(1.423)	(0.005)	(0.022)
p-value low = high	*[0.029]*		*[0.000]*	
Student ever enrolled in elite degree	27.644***	30.326***	0.247***	0.322***
	(0.773)	(1.485)	(0.009)	(0.023)
p-value low = high	*[0.093]*		*[0.000]*	
B - Peer effect regressions				
Proportion parents w/elite degree (std)	1.090***	2.466***	0.004	0.022***
	(0.304)	(0.530)	(0.004)	(0.008)
p-value low = high	*[0.013]*		*[0.016]*	
C - Peer regressions: academic and elite				
Proportion parents w/elite degree (std)	1.060***	3.187***	0.008**	0.036***
	(0.336)	(0.572)	(0.004)	(0.009)
p-value low = high	*[0.108]*		*[0.001]*	
Peer mean middle school GPA	-0.047***	-4.380***	-0.011**	-0.089***
	(0.467)	(1.323)	(0.005)	(0.020)
p-value low = high	*[0.002]*		*[0.000]*	
Number of pupils	25,188	8,290	25,188	8,290
Number of schools	498	400	498	400

Notes: Panel A runs a Mincer-style regression of earnings on an indicator for degree and an elite degree. The omitted category is no degree. The regressions include a gender dummy and year of birth dummy variables as controls. The dependent variable in columns (1) and (2) is the earnings percentile at age 30-32 and in columns (3) and (4) is an indicator for being in the top decile of the earnings distribution. Panel B estimates the effect of exposure to elite peers in the benchmark specification (including all controls and fixed effects) but with the dependent variable changed to be the earnings percentile of the student (columns 1-2) and an indicator for being in the top decile of the earnings distribution (columns 3-4). Panel C reports estimates of the benchmark specification of elite peer exposure on earnings including additionally the mean peer ability across high school cohort. The low SES sample in columns (1) and (3) is defined as the group of students who have at least one parent with no more than the compulsory level of education, but no parent with an elite education. The high SES sample in columns (2) and (4) is defined as the group of students who have at least one parent with an elite education, but no parent with a compulsory level of education. Sample of birth cohorts 1986-1991. Income is deflated to 2020. For the cohorts 1986-1989 income is measured ages 30-32; whilst for cohorts 1990 and 1991 is measured at 30-31 and 30 respectively (see Section 3). Standard errors clustered at the school level. *** p<0.01, ** p<0.05, * p<0.1

Online Appendix

A1 Robustness to alternative definitions SES

Our definition of household SES based on parental education is motivated by an interest in understanding why intergenerational persistence in education is so high. We now test the robustness of our findings to alternative definitions of SES based on parental education as well as on family income.

Figure A4 shows that the effect of elite peers for the intermediate SES group (comprising of children who are neither in the low nor the high SES groups) lies in between the effect we estimate for the low SES and high SES samples. Accordingly, if we redefine the low SES group as those with no elite educated parents, we still find a SES gradient that is, as expected, flatter than in our benchmark estimation.[1] Moving to an income-based definition of SES, Figure A5 plots the effect of exposure to elite peers across students' family income percentile rank and shows again a SES gradient in the effect of elite peers. The gradient is flatter than the benchmark SES gradient, as shown by the two lines intersecting with the y-axis at the points representing the estimates from Table 2, however our benchmark estimates lie within the confidence intervals when SES is defined by income. Overall, these results provide reassurance that our findings are not driven by the specific definitions of SES that we focus on in our benchmark results.

A2 Borusyak and Hull (2023) method to control for the expected treatment

Our identification assumption is that, conditional on school, cohort fixed effects and middle school GPA, the exposure to elite educated peers is random. The idea of Borusyak and Hull (2023) would be to simulate counterfactual peer measures by permutting students within the same school and middle school GPA bands across cohorts. This would lead to a school level estimate of the "expected" treatment. If our identification assumptions are correct, regressing the elite enrolment only on the true exposure to elite peers, and this expected treatment will lead to a coefficient comparable to our benchmark.

In Section 5 we report estimates using this method which control also for the individual controls X. However to illustrate that we need to control just for the expected treatment (and not the controls X) we include Table A3. Panel A) reports the coefficient from the benchmark model but includes only the essential controls (the continuous measure of MGPA, school and cohort fixed effects) as regressors. That is, the coefficient on P_{-ics} in panel A corresponds to coefficient β_1 in the following regression

$$Y_{ics} = \beta_1 P_{-ics} + \beta_2 MGPA_i + \lambda_s + \alpha_c + \epsilon_{ics}. \tag{8}$$

Panel B reports the coefficient on P_{-ics} and $\tilde{P}_s$, where the latter is labelled "expected treatment" in a regression of the outcome on these variables:

$$Y_{ics} = \delta_1 P_{-ics} + \delta_2 \tilde{P}_s + u_{ics} \tag{9}$$

Finally, in Table 2 the specification in column (2) applying the Borusyak and Hull (2023) method results in a smaller sample owing to some empty cells across the schools within middle school GPA

[1] The coefficients (standard error) are 0.024 (0.003) and 0.040 (0.008) for the low and high SES samples respectively.

bands. Panel C of Table A3 repeats our benchmark specification on the smaller sample, to allow a full comparison and the estimates are almost unchanged.

A3 Additional validity and specification checks

A3.1 School-specific linear trends

First, we re-estimate our main model in equation (1) including school-specific linear trends in order to control for trends in students' characteristics and/or school characteristics which may not be captured by the controls included in the model.[2] As shown in column (2) of Table A4, the estimates of this specification are very similar to those from our benchmark specification (included in the first column of the table for easy comparison).

A3.2 Fully interacted school and cohort fixed effects

A limitation of this first test is that time trends in outcomes may not be captured by the linear term well. We therefore perform a second robustness check, which pools the data for low and high SES student and estimates the model including a full set of interactions between school and cohort fixed effects. In this model, it is possible to identify the difference in the elite peer effect between the low and high SES group. The results, presented in panel C, report a peer effect for high SES students of 0.05 and for low SES students as 0.019, displaying the same SES gradient as our benchmark specification.

A3.3 Drop if more than random

Our third test is in column (4) of Table A4 is based on an idea proposed by Hoxby (2000) and referred to as 'drop if more than random' in this paper. A sensitivity analysis drops the schools whose variation in treatment does not appear to be random. These schools are selected as follows. We first regress for each school the proportion of elite peers on a constant and a quadratic in years, estimating the school-specific time trends. Next the cohorts for each school are randomly reordered five times. If the reordering of cohorts results in the original ordering, the process is repeated until the new ordering does not reflect the true order. After each random reordering, the regression of the proportion of elite peers on a constant and a quadratic in years is repeated, thereby estimating the time trends that would occur if cohorts were randomly assigned within a school. Following Hoxby (2000), if the R^2 of the regression using the true cohorts is 1.05 times the smallest R^2 of the five regressions with false assignment of cohorts, then the school is flagged as having changes in the composition of elite peers as "more than random". The benchmark estimation is then repeated on the sample of schools which have not been flagged.

A3.4 Control for changing teacher quality

A main concern with our identification strategy is that elite parents select into schools of improving quality. A fourth check aims to control for observable changes in school quality measured by the characteristics of teachers teaching in school s to cohort c - including the proportion of female teachers, the proportion of teachers from a professional background, the proportion from a low skilled background and the average age of teachers (as a proxy of teacher experience). These estimates reported in column and (5) of Table A4, are very similar to the benchmark estimates.

[2] That is, we estimate the following model: $Y_{ics} = \beta_1 P_{-ics} + X'_{ics}\beta_2 + \alpha_{s_1} + \alpha_{s_2} c \times D_{is} + \rho_c + \epsilon_{ics}$ where c is a cohort (linear) trend and D_s is an indicator for whether the student is in school s.

A3.5 Placebo tests

The estimates of coefficients β_1 for the low and high SES samples (and of the difference between the two in the second check) in all these robustness checks are very similar to the benchmark estimates in Equation 1. This provides us with strong confidence that our identifying assumption holds in this context. Nevertheless, we also perform a series of placebo tests checking whether the within school variation in the proportion of elite educated parents is associated with changes in student birth outcomes, middle school subject choice and parents' income during middle school. We pick these outcomes because these student and parent characteristics cannot be causally affected by peers but are likely to be correlated with the unobserved characteristics of other students selecting in the same schools. Each row in Table A5 reports the coefficient on the elite peer variables in Equation 1 where the dependent variable is a birth outcome; a middle school subject choice or mother or father income during middle school. As expected, the exposure to elite peers during high school is unrelated to outcomes measured before high school. An exception is the variable for fathers' income during middle school for which elite exposure during middle school is statistically significant at the 5% level. To ensure that this variable does not invalidate our estimates, Table A6 runs the benchmark estimation controlling for fathers' income during middle school, showing that the point estimates are identical to our benchmark estimation.

A further placebo test adds measures of the elite peer composition in the period before (lead) and after (lag) the cohort entered high school. If our identification strategy is valid, adding additional measures of the proportion of students with elite educated parents in the cohorts before (leads) or cohorts after (lags) the students' cohort should have no direct effect on the decision to enrol in elite education. The placebo analysis is reported in Table A7. Figure A6 plots the estimates for the students' true exposure along with the coefficients and confidence intervals for two leads and lags in the peer exposure variable and confirms that these variables are not statistically significant predictors of elite degree enrolment.

A3.6 Sensitivity of results to sample selection - birth order

The effect of exposure to elite educated peers may be different for first born children compared to the total sample, if for example children of higher birth order are more influenced by their older sibling than their school peers and their parents (Black et al., 2005b). Column (2) of Table A8 shows that indeed the peer effect is slightly higher for first borns, although the new estimates are not statistically different to the benchmark estimates.

A3.7 Measurement error from marital breakup

The incidence of marital breakup may be different across household socioeconomic status and it is possible that the rates of divorce or separation vary across the SES status of schools. This would cause a problem in our estimation as the treatment could have more measurement error in the low SES sample because it is based on all biological parents. Therefore the difference in coefficients between low and high SES may be driven by attenuation bias. We confirm that this is not a problem in Column (3) of Table A8 which restricts the sample to households who have not experienced divorce or separation by the year the student finishes middle school.

A3.8 Credit constraints - city of residence

The lack of tuition fees and wide availability of student grants and loans means that differential access to credit between low and high SES families is unlikely to be driving the SES gap in elite degree enrolment in the data. Nevertheless, it may be the case that for students attending high schools outside cities where elite degrees are offered, there are additional costs associated with moving to and finding accommodation in these cities. If low SES students do not have as many acquaintances or relatives in these cities as high SES students do, then this type of credit constraints may be one mechanism behind the SES gap in elite degree enrolment that the covariates included in the model do not control for.

To tease out the extent to which this is plausible, we re-estimate the model excluding students attending high school in Oslo. Oslo is the largest municipality in Norway, containing elite universities and a high exposure to elite educated families, and it is where this sort of mechanism is more likely to be at play. Column (4) of Table A8 show that the results are robust to this exclusion. These results also show that our benchmark results are not driven by students within Oslo naturally attending their local elite universities.

A3.9 Small schools

Our identification strategy may not be valid for areas with particularly small schools, where students may move together from a shared middle school to a shared high school. Column (5) of Table A8 suggests that our benchmark estimates are robust to dropping schools in the bottom decile of school size (where there are 31 or fewer students per cohort).

A3.10 High school admissions mechanism

Counties across Norway differed in their admissions procedure for high school between a local catchment area and, more commonly competition based upon middle school GPA. Our benchmark analysis was repeated separately by the procedure for admissions to high schools but the results are almost identical in the two samples. For the full sample, the coefficient on treatment of the proportion of parents with an elite degree is 0.027 (standard error 0.004) and 0.026 (standard error 0.005) for areas with local catchment and school choice admissions, respectively.

A3.11 High school major

High school students in Norway on the academic pathway specialize in specific majors from the second year, including sciences, economics, mathematics, social sciences, languages and humanities. Dahl et al. (2023) highlight relatively higher returns for engineering, natural sciences and economics compared to social sciences and humanities. It could be that elite students select into high school majors with relatively high returns, which explains the transition to elite degree programmes. To test whether our results are driven by major choice, we drop from the sample high school students specialising in the majors most associated with the highest returns found by Dahl et al. (2023), excluding sciences, economics and mathematics. The results, in column (6) of Table A8 are very similar to our benchmark specification.

A3.12 Measurement error

We consider whether, as Angrist (2014) points out, measurement error in parents' elite education may cause bias in our peer effect estimates and in particular inflate them (Feld and Zoelitz, 2017). To address if this is the case in our setting, we follow Carrell et al. (2018) and add measurement error to parents' elite education. Measurement error is added sequentially to the parents' elite education, at the rate of 1%, 5%, 10%, 25%, 50%, 75%, 90% and 100%. For each rate (e.g. 1%), a 1% sub-sample is chosen to be assigned error. Among the error sample, we randomly assign

2% of the sample to have both parents with an elite degree; 9% to have one parent with an elite degree and the remaining to have no parents with an elite degree, where these values represent the distribution in the benchmark sample. The new peer mean variables are calculated and the benchmark equation is re-estimated. Figure A7 shows that, similarly to Carrell et al. (2018), as more measurement error is added to the peer mean variable, our estimates attenuate towards zero, suggesting that our estimates are not likely confounded by measurement error.

A3.13 Nonlinearities

Our main model assumes linear elite peer effects, but one may argue that those could be non-linear and vary either with the degree of exposure to elite peers or with student ability.[3] First, panel d) of Figure A8 tests for peer effects at the extensive margin, measuring elite peer exposure by an indicator taking the value of 1 if the student has any elite peers, and 0 otherwise. The results suggest that exposure to any elite peers raises elite enrolment by 0.8ppts and 5.1ppts for low and high SES students respectively.

If elite peer effects were non-linear in exposure to elite peers, the social gradient in elite peer effects could merely reflect that low SES students have lower average exposure to peers than high SES students. Figure A9 plots the marginal effect of the proportion of elite families as implied by the estimates of a quadratic specification for each group, along with the densities of P_{-ics}. That is, we estimate: $Y_{isc} = \beta_{11} P_{-ics} + \beta_{12} P_{-ics} \times P_{-ics} + X_{ics}^{'} \beta_2 + \alpha_s + \rho_c + \epsilon_{ics}$. The estimates of the coefficients β_{11} and β_{12} are then used to compute these marginal effects and are reported in column (3) of Table 2. There is little evidence of non-linearity in the elite peer effect.[4]

To test whether the SES gradient in elite peer effects reflects a student ability gradient, we re-estimate the benchmark model allowing for the effect of elite peers on enrolment to vary with middle school GPA. Figure A10 plots predicted elite degree enrolment and shows, for low ability students, the likelihood to enrol into an elite degree programme is very low for both low and high SES students. The SES gradient materialises and increases with student ability. Compared to high SES students of the same ability, the low SES students with medium to high ability face the greatest disadvantage in terms of the benefits of being exposed to elite peers.

A4 Heterogeneity analysis: Definitions of elite

Elite educated parents of peers may have high levels of income and consumption and possibly to hold prestigious occupations and these could be why high school students are influenced to pursue an elite education themselves. To tease out whether our measure of elite peers (based on education) is appropriate to capture these various facets to elite, we estimate our benchmark model with two alternative definitions of elite peers.

The first is based on peers' family income and measures the proportion of elite peers as the proportion of peers' parents in the top 5% of the income distribution (of high school students' parents). This measure of family income is constructed by summing the income of mothers and fathers at the end of middle school and deflating to 2020 prices. It is calculated within the sample of academic high school students.Within our sample 19% of families are present in the top 5% of the income distribution, and there is a social gradient such that 17% of low SES and 24% of high SES families are defined as wealthy peers.

[3] See Feld and Zoelitz (2017), Lavy et al. (2011), Tincani (2017) for evidence of non-linearities in peer effects.

[4] The coefficient on the quadratic term for high SES is negative and statistically significant, but non-linearity kicks in at high levels of P_{-ics} where there is little support. Importantly, across the distribution of proportion of elite families, the peer effect is higher for high SES students.

The second measure of family eliteness is based on occupational prestige and defines the proportion of elite peers as the proportion of peers' parents working in an elite occupation, i.e. as a lawyer, doctor or in a STEM occupation (using the occupation classification into STEM from Deming and Noray (2018)). 1.7%, 1.4% and 2.3% of the total sample; low and high SES families respectively are defined as having occupational prestige.

Panels b) and c) of Figure A8 plot the coefficients and confidence intervals from regressions which change the peer variable to be prestigious peers (those with an elite occupation) and wealthy peers (with an elite level of income) respectively. As expected, these two dimensions of elite peer matter for student enrolment.

A5 Simulating the consequence for intergenerational mobility from reassigning low (high) SES students into schools with high (low) exposure to elite peers

We imagine the consequences for intergenerational mobility from a policy which aims to balance exposure to elite peers across high and low SES students. The idea for the simulation is as follows.

The simulations take a low SES student from a school with the lowest exposure to elite peers and moves them into a school with the highest exposure to elite peers whilst simultaneously taking a high SES student from the high exposure school and moving them to the low exposure school. Within each cohort, all schools were ranked by the proportion of parents with an elite degree. Starting with a school with the lowest exposure to elite peers (school a), a low SES student was randomly chosen from the set of low SES students to be reassigned into a school with the highest exposure to elite peers (school b). Simultaneously, a high SES student from school b was randomly selected from the set of high SES students to be reassigned into school a. The same procedure was repeated on the school with the second lowest exposure to elite peers (school c), where a low SES student, randomly picked from all low SES students within the school-cohort, was reassigned into a school with the second highest exposure to elite peers (school d) - and a high SES student was randomly chosen from the set of high SES students within school d from the same cohort, and moved into school c.

We varied the parameters of the simulation. Simulation 1 moved just one low and one high SES student, amongst schools from the bottom or top decile of the ranked exposure to elite peers, respectively. Simulation 2 chose the same set of schools with exposure to elite peers in the bottom or top decile but moved 5 low SES students and 5 high SES students from each school. Simulation 3 moved one low SES student from each school in the bottom half of the distribution of elite peer exposure and swapped with one high SES student from each school in the top half of the distribution (where again the low SES student in school a (c) is swapped with the high SES student in school b (d) etc.). Simulation 4 extended simulation 3 by moving 5 low SES students from each low exposure school and 5 high SES students from each high exposure school.

We repeat several simulations simply to show the sensitivity of our results to various reassignment strategies.

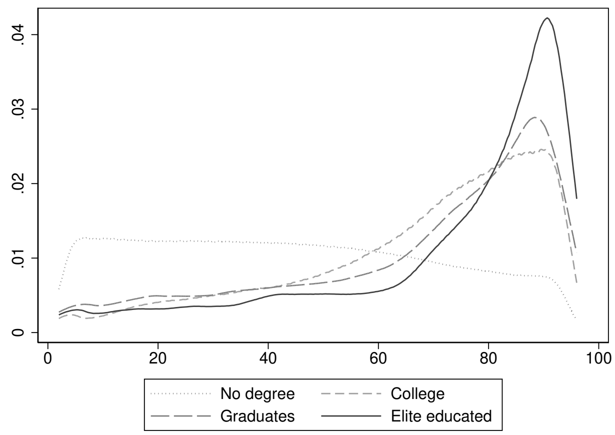
For each simulation, once the school re-allocations have taken place, we calculated the new mean exposure to parents with an elite degree within each school and cohort. Taking our estimates from Table 5 a new earnings percentile rank was calculated using the adjusted peer mean variable and assigning to any student who had been reassigned a school, the new school fixed effect. The parent percentile rank was then regressed on the new simulated earnings rank of the student to estimate the relationship between parent and student income under each of the four simulated reassignments.

This simulation does not aim to causally identify a change in intergenerational mobility, as this is not a general equilibrium model. Instead it is a useful exercise to understand whether intergenerational mobility increases or decreases from exposure to peers given the relatively higher effect of exposure to elite peers for the high SES students, compared to the low SES students.

Table A16 shows that for all simulations, intergenerational mobility increases once the exposure to elite peers is re-balanced across low and high SES students, as indicated by the higher intercept and the flatter slope coefficient. The increase in intergenerational mobility is shown graphically for the most extreme simulation we considered (moving 5 students from each school in Norway) in Figure A15. After the simulation, the intercept from the rank-rank regression is higher suggesting a higher earnings rank for very low SES students, and the gradient of the relationship between parent and child percentile rank is flatter.

A6 Appendix Figures

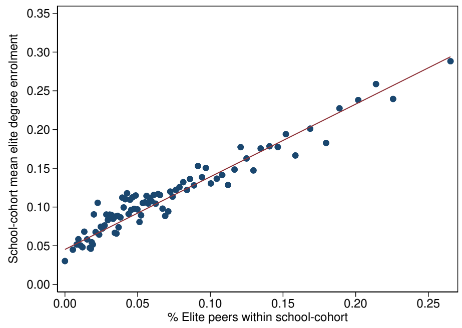
Figure A1: Density of earnings percentiles by education level



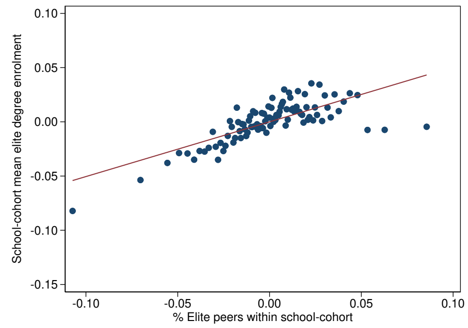
Notes: This graph plots the density of earnings percentiles across educational groups. Sample is the population of Norway aged 28-40 between 1993-2001. The percentile rank of earnings is calculated within each birth cohort.

Figure A2: Plotting school-cohort variation in elite peers against elite enrolment

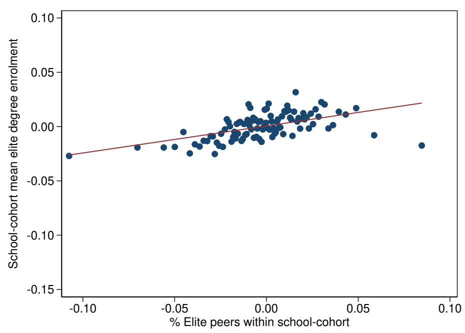
a) Raw data



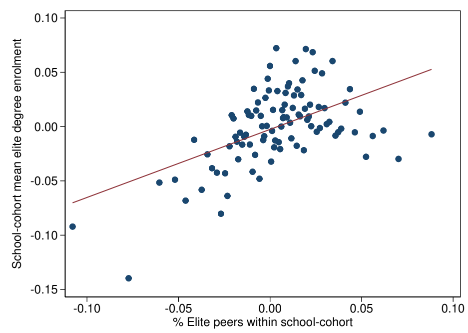
b) Residualised data



c) Residualised Low SES

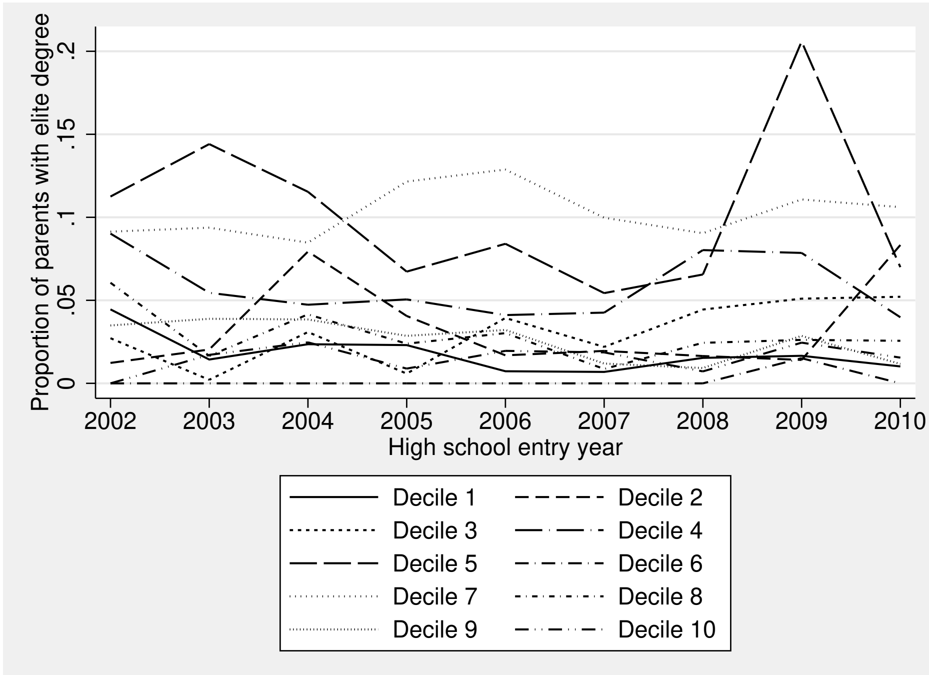


d) Residualised High SES



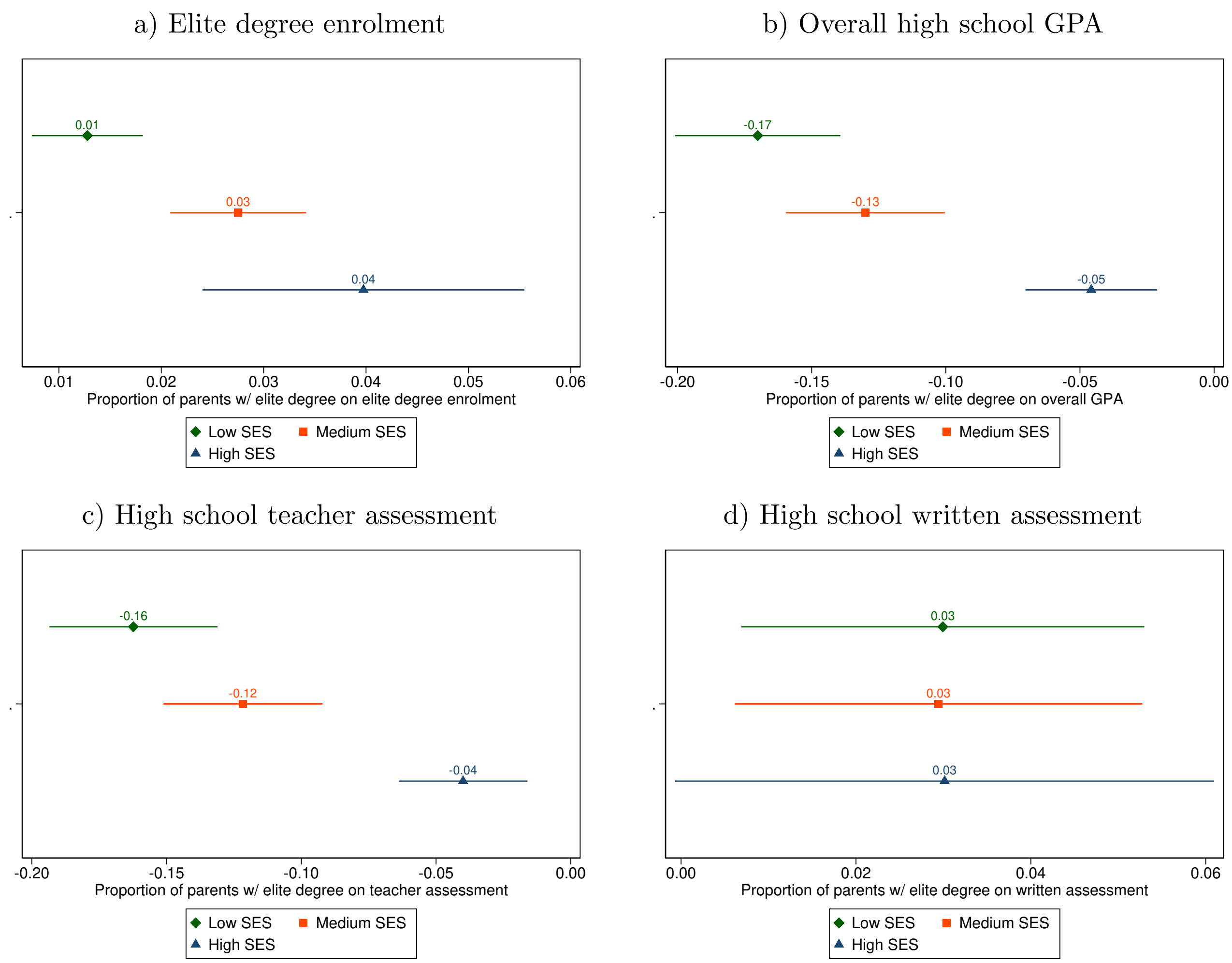
A residual (R_y) is predicted from a regression of elite degree enrolment on cohort and school fixed effects and middle school GPA. A residual (R_t) is predicted from a regression of exposure to elite peers on cohort and school fixed effects and middle school GPA. Bin scatter figures in panel a) plot the variance in the raw data of elite degree enrolment and elite peer exposure and panels b-d) plot R_y against R_t and the linear fit for the full, low and high SES samples.

Figure A3: Time series of exposure to elite peers for 10 schools



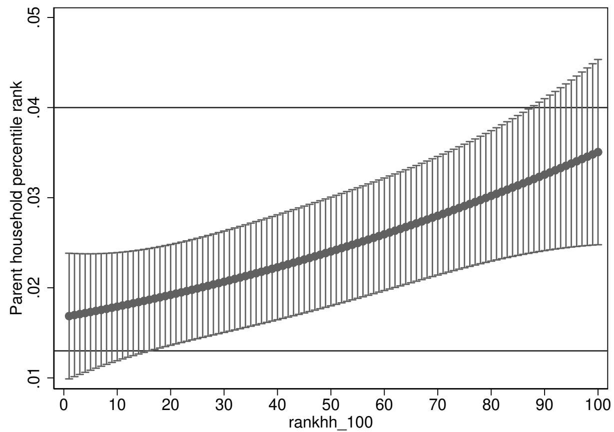
Notes: All schools were divided into deciles based on the average of their within cohort intake size across all years. One school was randomly chosen within each decile. The graph plots out the proportion of parents with an elite degree across the years for each of the ten randomly chosen schools.

Figure A4: Effect of exposure to elite peers on student outcomes by socioeconomic background



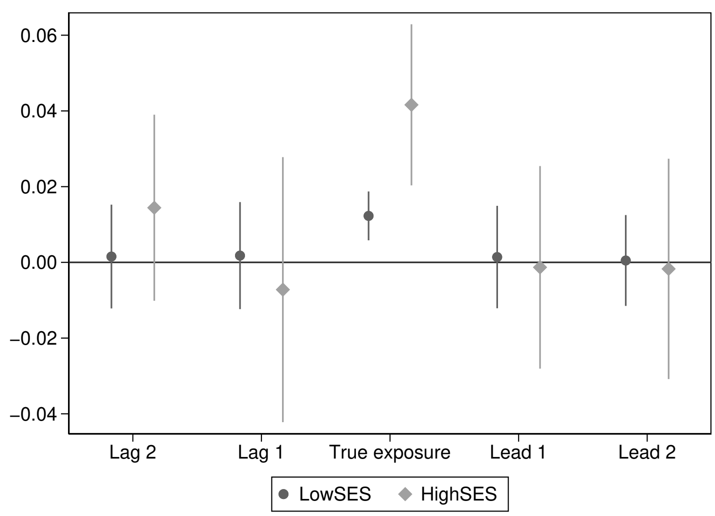
Notes: This graph plots the marginal effect of an increase in P_{-ics} on student outcomes: the probability of enrolling in an elite degree; overall high school GPA; high school teacher assessment and high school written exams. The coefficients are estimated from regression Equation 1. See notes to Table 2 for details of the specification. The low SES sample is defined as the group of students who have at least one parent with no more than the compulsory level of education, but no parent with an elite education. The high SES sample is defined as the group of students who have at least one parent with a post-secondary education, but no parent with a compulsory level of education. The medium SES sample defines households with the education in between - where no parent left school at the compulsory age and no parent has an elite education.

Figure A5: Redefining parent SES by household income percentile rank



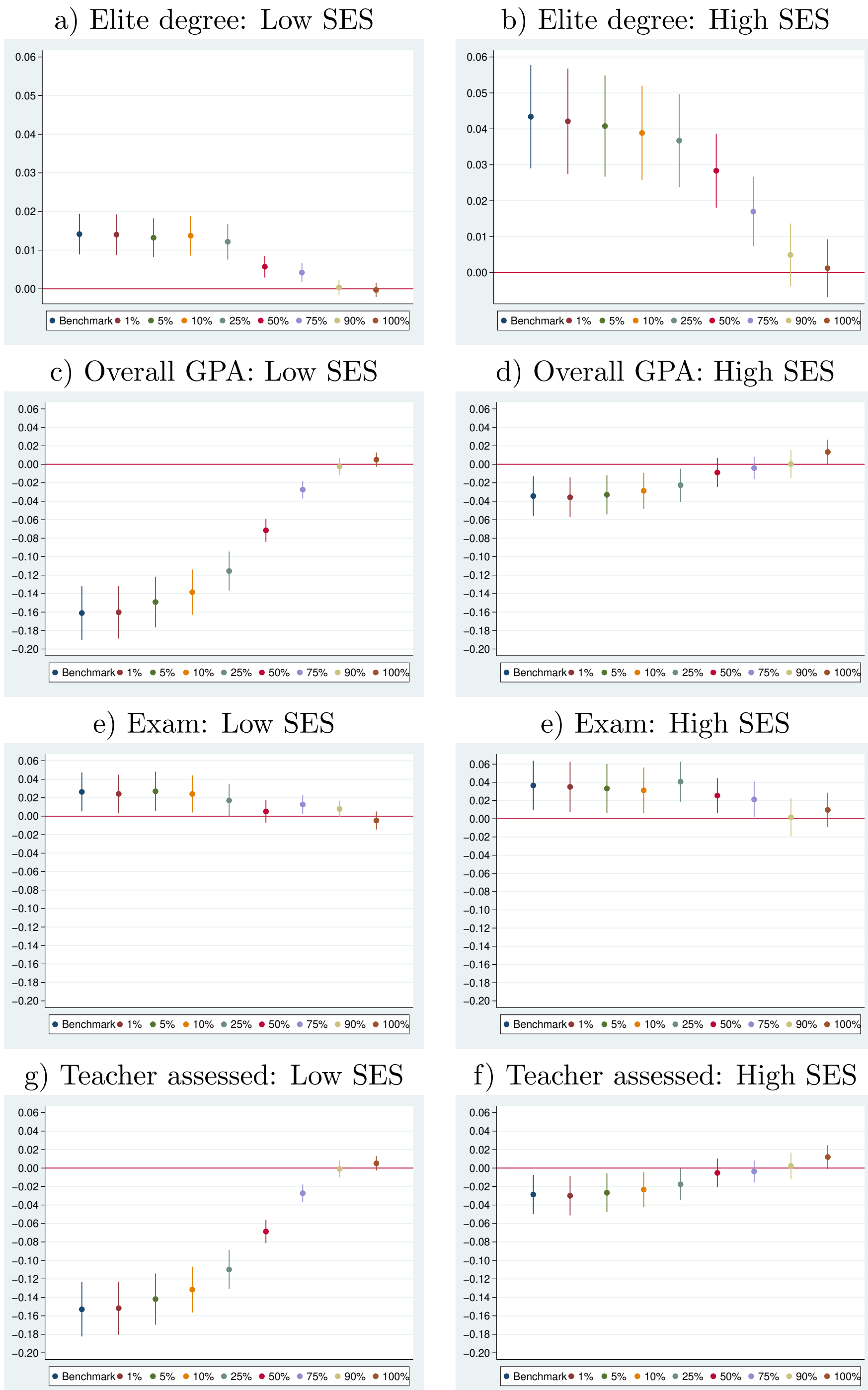
Notes: This graph plots the marginal effect (and 95% confidence intervals) of exposure to elite peers on elite degree enrolment, in the benchmark specification which is augmented by including an interaction between the peer variable P_{-i} and a quadratic in the parent household income percentile rank. The horizontal lines intersect at the y-axis at points representing the benchmark estimates of the effect of exposure to elite peers for low SES defined students (the lower line) and high SES students (the upper line) defined by parents' education.

Figure A6: Placebo: adding lead and lags of peer exposure to the benchmark regression



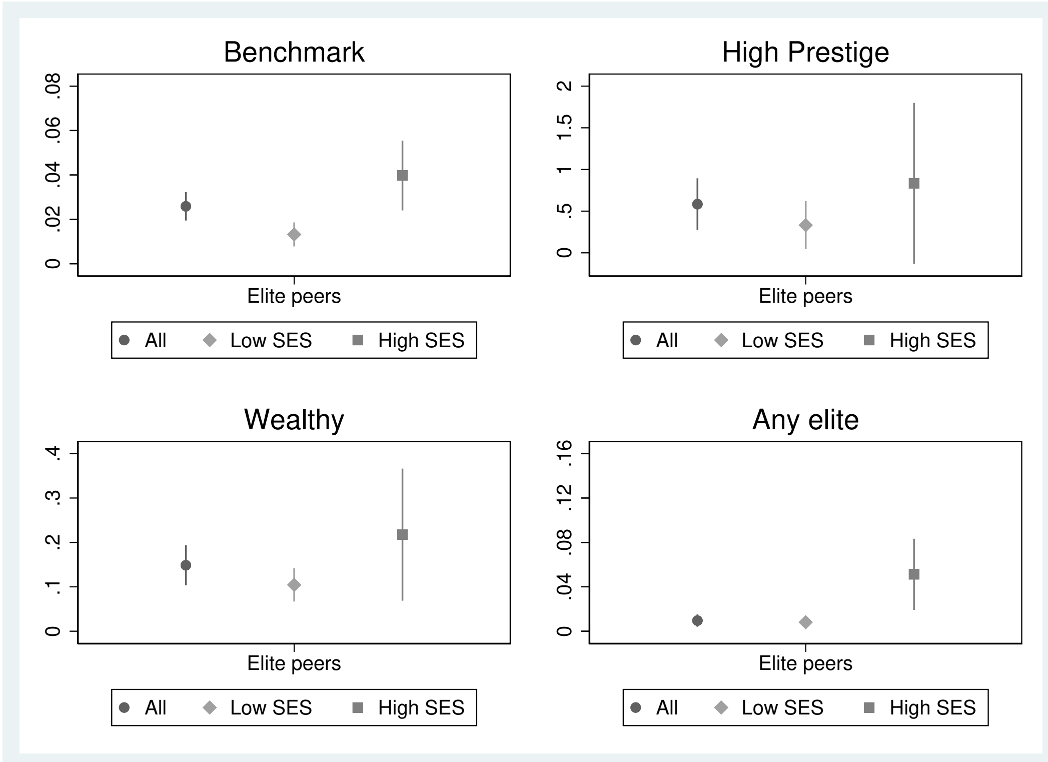
Notes: The figure plots the coefficients from columns (3) and (4) from Table A7. These regressions augment the benchmark regression by including additionally two leads and two lags in the peer exposure variable. Specifically for each student, a lead (lag) is measured as the proportion of parents with an elite degree calculated across the students entering high school in the year after (before) the student.

Figure A7: Measurement error



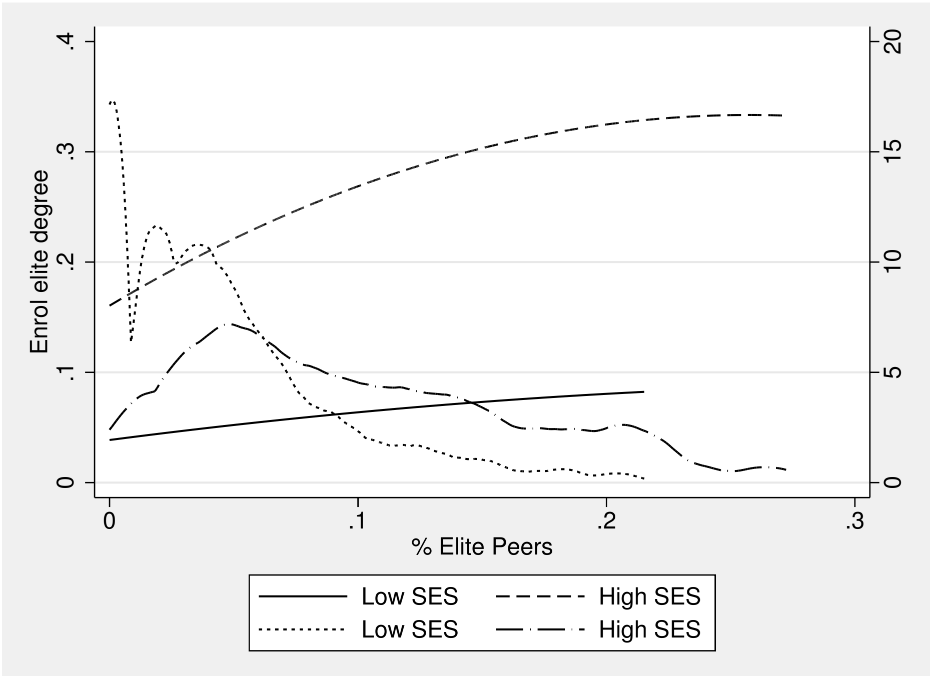
Notes: measurement error is sequentially added to the peer mean variable, at the rate of 1%, 5%, 10%, 25%, 50%, 75%, 90% and 100%. For each rate (e.g. 1%), a 1% sub-sample is chosen to be assigned error. Among the error sample, we randomly assign 2% of the sample to have both parents with an elite degree; 9% to have one parent with an elite degree and the remaining to have no parents with an elite degree, where these values represent the distribution in the benchmark sample. The new peer mean variables are calculated and the benchmark equation is re-estimated.

Figure A8: Estimated peer effect coefficients: types of Elite



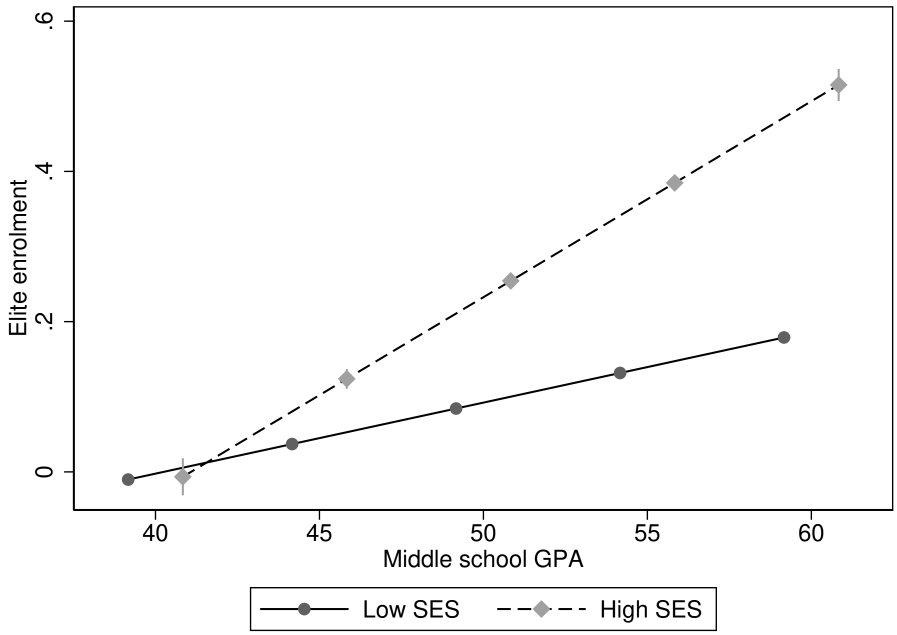
Notes: The figure plots the coefficients from analysis reporting the effect of the % of elite prestige peers in high school (panel b), the % of elite earning peers (panel c) and an indicator for being exposed to any elite educated peers (panel d). Each panel reports the coefficient on the elite peer variable across the total sample, low and high SES students.

Figure A9: Marginal effect of exposure to elite social networks implied from quadratic specification



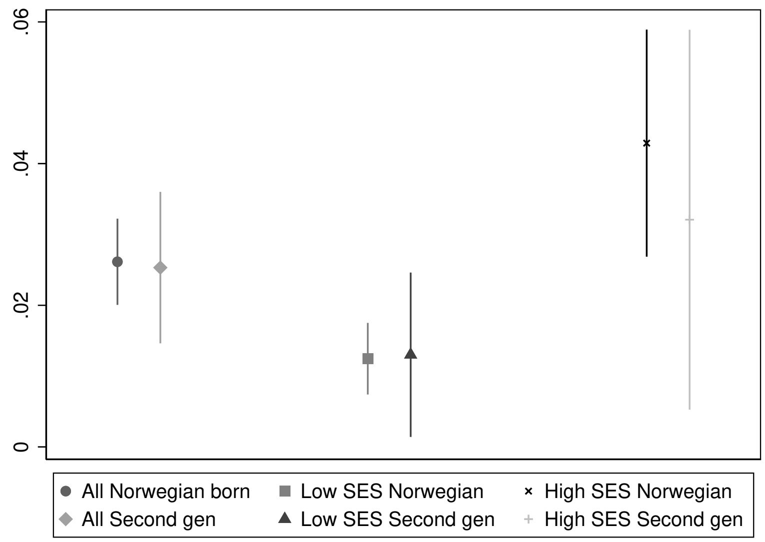
Notes: This graph plots the densities of P_{-ics} in the low SES (dotted line) and high SES samples (dot-dashed line). It also plots the marginal effect of an increase in P_{-ics} on the probability of enrolling in an elite degree as a function of P_{-ics} as implied by estimates of β_{11} and β_{12} in the equation of footnote 28. The marginal effect in the low SES (high SES) sample is plotted as a solid (dashed) line. The estimates of these coefficients are reported in Column (6) of Table A4.

Figure A10: Marginal effect of exposure to elite social networks: allowing for interaction between peer effect and middle school GPA



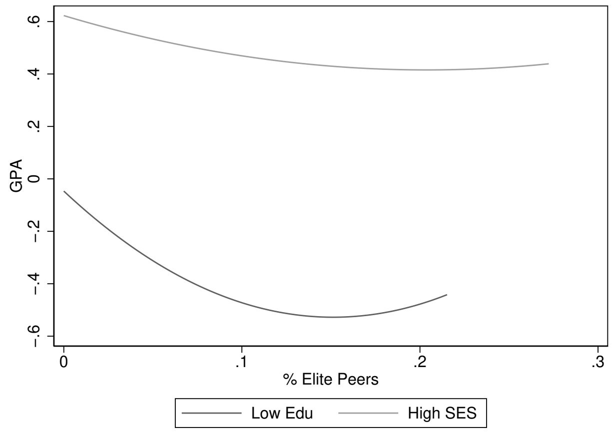
Notes: This graph plots the marginal effect of an increase in P_{-ics} on the probability of enrolling in an elite degree as a function of middle school GPA. The predictions are based on the benchmark specification regression model augmented additionally with the interaction between GPA and P_{-ics}. The marginal effect in the low SES (high SES) sample is plotted as a solid (dashed) line.

Figure A11: Estimated peer effect coefficients heterogeneity analysis by parents' immigration status



Notes: The figure plots the coefficient estimates from Equation 1 allowing for heterogeneity in the effect of the proportion of elite educated peers in high school across Norwegian born students and Second-generation immigrant students.

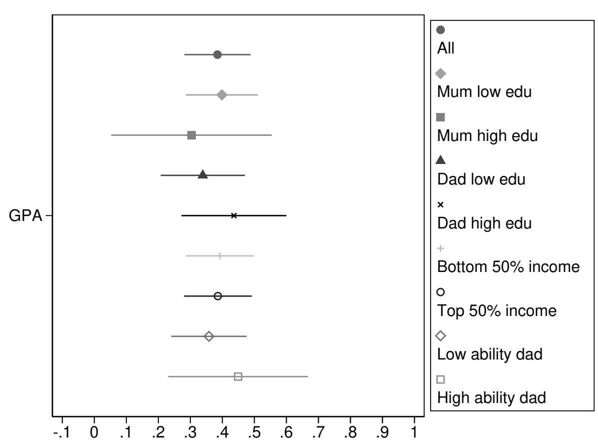
Figure A12: Marginal effect of exposure to elite social networks implied from quadratic specification on high school GPA



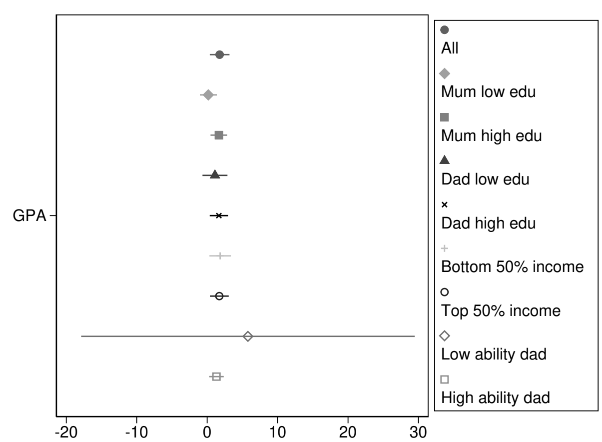
Notes: This graph plots the marginal effect of an increase in P_{-ics} on the GPA as a function of P_{-ics} as implied by estimates of β_{11} and β_{12} in the equation of footnote 28 but with the dependent variable replaced with the overall high school GPA. The marginal effect in the low SES (high SES) sample is plotted as a dark (lighter) line. The estimates of these coefficients are reported in Column (6) of Table A10.

Figure A13: Parameter heterogeneity in effect of GPA on elite enrolment

a) Low SES students

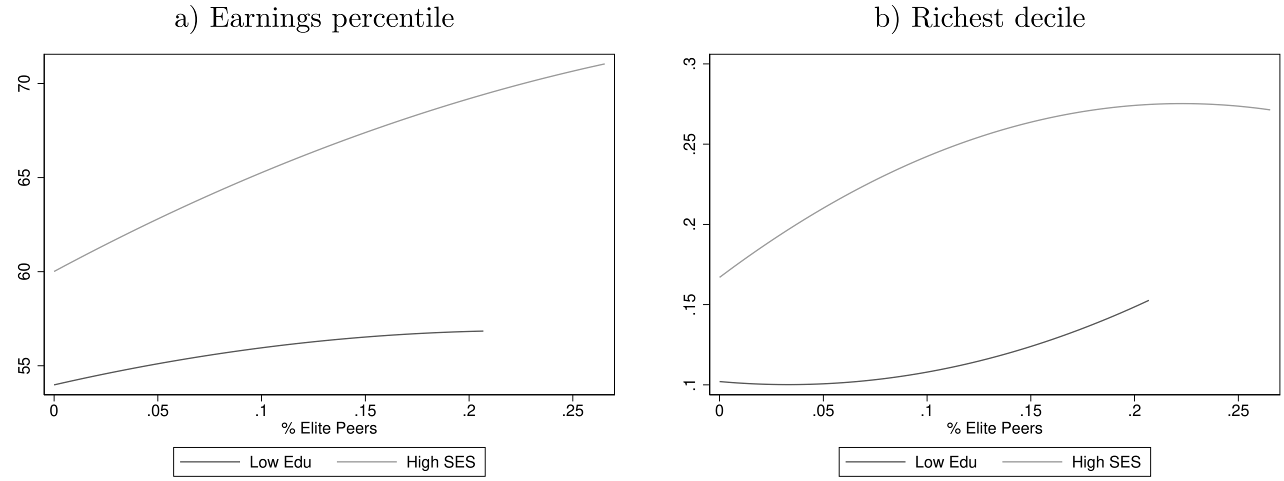


b) High SES students



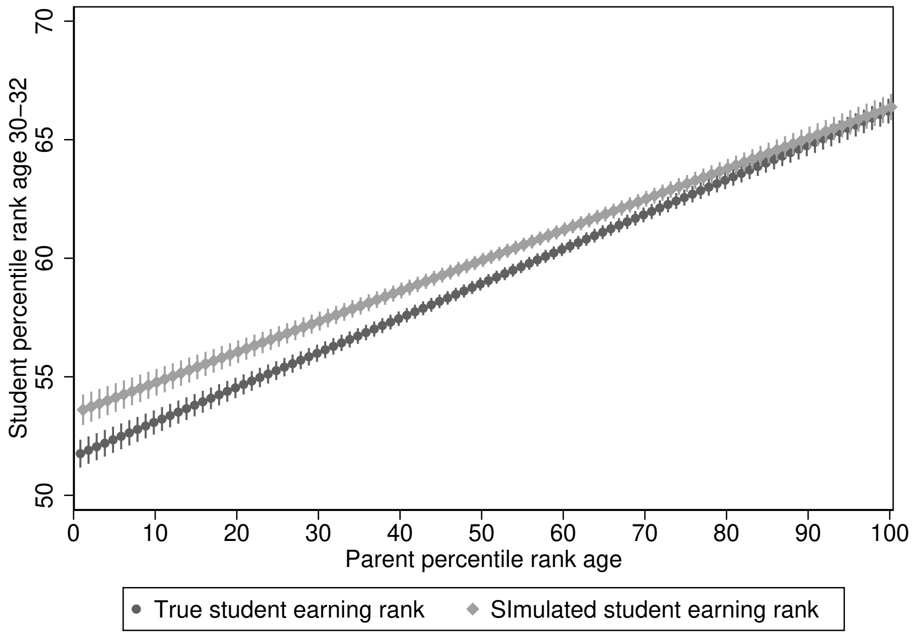
Notes: The figure plots the coefficients γ_2 from Equation 5, estimated for the total sample and across sub-groups defined by the mother or father having a low (less than degree) and high (degree +) education level, earning in the bottom or top half of the income distribution or having a low or high ability father (defined as having a father whose IQ test in the bottom or top half of the distribution), across the low and high SES samples.

Figure A14: Marginal effect of exposure to elite social networks on student earnings age 30-32 implied from quadratic specification



Notes: This graph plots the marginal effect of an increase in P_{-ics} on earnings as a function of P_{-ics} as implied by estimates of β_{11} and β_{12} in the equation of footnote 28 but with the dependent variable changed to the earnings percentile (Panel A) and an indicator for earning in the richest decile (Panel B). The marginal effect in the low SES (high SES) sample is plotted as a dark (lighter) line. The estimates of these coefficients are reported in Column (5) of Table A14.

Figure A15: The correlation between parent earnings rank percentile and student's (within-cohort) earnings rank percentile.



Notes: This graph plots the predicted relationship from a regression of parent earnings rank percentile (with parent earnings measured when the student is aged 15-19) on the student's earnings rank percentile (calculated within birth cohort) when aged 30-32. The bold symbols represent the relationship using the student's true earnings rank whilst the lighter symbols represent the relationship using the student's simulated earnings rank. The simulation, described in Section A5 is represented in column (5) of Table A16 which swaps 5 low SES students from each school in the bottom half of the distribution of exposure to elite peers with 5 high SES students from each school in the top half of the distribution to exposure to elite peers. We predict the new earnings percentile rank for each student using estimates from Table 5 given the student's new exposure to elite peers and (for those reassigned students) new school fixed effect.

A7 Appendix Tables

Table A1: Effect of exposure to elite families in high school on the probability of enrolling in an elite degree : Coefficients on control variables

	(1) All	(2) Low SES	(3) High SES
Proportion of parents with elite degree (std)	0.026***	0.013***	0.040***
	(0.003)	(0.003)	(0.008)
Student is a female	-0.073***	-0.053***	-0.125***
	(0.003)	(0.003)	(0.007)
Student is born in Norway	-0.011***	-0.032***	0.013
	(0.003)	(0.004)	(0.009)
Student's middle school GPA (std)	0.132***	0.086***	0.255***
	(0.004)	(0.003)	(0.007)
Proportion of student's own parent with an elite degree	0.182***		0.162***
	(0.007)		(0.021)
Student's parents are in top income decile	0.027***	0.004	0.042***
	(0.003)	(0.005)	(0.009)
Mother's highest education level (ref = compulsory level)			
High school	0.015***	0.007	0.032***
	(0.003)	(0.005)	(0.011)
University	0.006**		0.006
	(0.002)		(0.010)
Father's highest education level (ref = compulsory level)			
High school	0.018***	0.018***	0.008
	(0.002)	(0.004)	(0.018)
University	0.020***		0.022**
	(0.002)		(0.011)
Number of students	177,219	58,328	20,018
Number of schools	556	524	459

Table A2: Oaxaca Binder decomposition of the SES gap in elite degree enrolment

	SES gap in characteristics		**SES gap in coefficients**	
	Gap	Contribution	Gap	Contribution
Fraction of elite peers	-0.015***	7.2%	-0.010***	4.8%
	(0.002)		(0.003)	
Student's middle school GPA	-0.050***	24.2%	-0.140***	67.6%
	(0.001)		(0.005)	
Fraction of own elite parent	-0.116***	56.0%	0.022***	-10.6%
	(0.011)		(0.003)	
Mother's highest education level (ref = compulsory level)				
High school	-0.001***	-0.5%	-0.003**	1.4%
	(0.000)		(0.001)	
University	-0.013***	6.3%	0.007**	-3.4%
	(0.005)		(0.003)	
Father's highest education level (ref = compulsory level)				
High school	0.000***	0.0%	0.001	-0.5%
	(0.000)		(0.001)	
University	-0.038***	18.4%	0.020***	-9.7%
	(0.008)		(0.006)	

Notes: This table reports a selected set of results from the Oaxaca decomposition of the gap in elite degree enrolment between the high SES and low SES groups of students. Specifically, we estimate the equation 1 in the sample pooling both low and high SES children, denoted by $g = L, H$ respectively. See notes to Table 2 for description of the regression and controls. For each covariate X_{ig} included in the model, we construct two objects, reported in the first and second columns of the table respectively. The first, $\Delta(X)$, measures the gap in elite education enrolment between High and Low SES students explained by the gap in average characteristic X between the two groups. That is: $\Delta(X) = \beta_X^p(E^H(X_i) - E^L(X_i)$ where β_X^p is the coefficient associated with variable X in equation 1 estimated in the pooled sample and $E^g(X_i), g = H, L$ is the expected value of X in each sample. The second, $\Omega(X)$, measures the gap in elite education enrolment between High and Low SES students explained by the gap in the effect of characteristic X between the two groups. That is: $\Omega(X) = (\beta_X^H - \beta_X^L)E^p(X_i)$ where β_X^g is the coefficient associated with variable X in equation 1 estimated in the sample of students $g = H, L$. and $E^p(X_i)$ is the expected value of X in the pooled sample.

Table A3: Application of Borusyak and Hull (2023)

	(1) Total Sample	(2) Low SES	(3) High SES
A) Benchmark including essential controls			
% parents with elite education	0.034***	0.017***	0.040***
	(0.003)	(0.003)	(0.009)
N	177,219	58,328	20,018
B) Permute within schools and deciles of middle school GPA			
% parents with elite education	0.033***	0.020***	0.040***
	(0.001)	(0.002)	(0.003)
Expected treatment	0.137***	0.098***	0.083***
	(0.005)	(0.009)	(0.011)
N	165,910	53,604	19,516
C) Benchmark on the smaller permutted sample			
% parents with elite education	0.026***	0.011***	0.042***
	(0.003)	(0.003)	(0.008)
N	165,910	53,604	19,516

Notes: Panel A reports estimates of a regression of elite degree enrolment on peer elite exposure and essential controls of school, cohort fixed effects and middle school GPA as regressors. Panel B) reports the coefficient on the elite peer variable and "expected" treatment with no additional controls. Pancel C) reproduces the benchmark estimates in column (1) of Table 2 but on a smaller sample comparable to Panel B. Regressions are weighted by school size. Standard errors clustered at the school level. *** p<0.01, ** p<0.05, * p<0.1

Table A4: Validity of the empirical strategy

	(1) Benchmark	(2) School-specific linear trends	(3) School-cohort fixed effects interacted	(4) 'Drop if more than random'	(5) Including teacher traits
A - All students					
Proportion of parents with elite degree (std)	0.026***	0.027***		0.022***	0.030***
	(0.003)	(0.003)		(0.004)	(0.004)
Number of pupils	177,219	177,219		83,465	111,009
Number of schools	556	556		313	398
B - Low SES students sample					
Proportion of parents with elite degree (std)	0.013***	0.013***		0.010**	0.015***
	(0.003)	(0.003)		(0.004)	(0.004)
Number of pupils	*58,610*	*58,610*		*28,181*	*37,270*
Number of schools	*524*	*524*		*284*	*390*
C - High SES students sample					
Proportion of parents with elite degree (std)	0.040***	0.047***		0.038***	0.053***
	(0.008)	(0.008)		(0.013)	(0.009)
Number of pupils	*20,018*	*20,018*		*8,420*	*12,737*
Number of schools	*459*	*459*		*240*	*349*
D - Low and High SES students sample					
Proportion of parents with elite degree (std)			0.050***		
			(0.004)		
Indicator for low SES					
			(0.014)		
Proportion of parents with elite degree * low			-0.031***		
			(0.003)		
Number of pupils			*78,540*		

Notes: The full sample, low SES, high SES and pooled low and high SES samples in panels A, B, C and D. Column (1) is benchmark specification (equation 1 and Table 2). Column (2) controls for school-specific linear trends. Column (3) includes fully interacted fixed effects for the school and cohort estimated on pooled low and high SES samples. Column (4) is the benchmark estimated on subsample of schools where variation in elite peers evolves over time in a random way. Specifically, we drop schools where the R^2 from a school-level regression of the % of elite peers on a quadratic in year is 1.05 times the R^2 from five regressions where cohorts are randomly re-ordered for each. See subsection A3.3. Column (5) augments the benchmark with average traits of teachers within schools across cohorts: % of females, % from a professional or low skilled background and average age. Regressions are weighted by school size. Standard errors clustered at the school level. *** p<0.01, ** p<0.05, * p<0.1

Table A5: Placebo tests - Effect of elite peers on child birth outcomes

	(1) Estimate (p-value)	(2) No. students	(3) No. schools
Birth outcomes:			
Birth weight	-3.011	169,864	554
	(0.386)		
Low birth weight	-0.000	177,219	556
	(0.723)		
Gestation	-0.011	157,669	552
	(0.383)		
Height	-0.010	164,073	551
	(0.496)		
Head circumference	0.005	167,949	553
	(0.585)		
Congenital malformation	-0.000	170,133	554
	(0.999)		
Severe deformity	-0.001	170,133	554
	(0.340)		
Middle school subject choice:			
Maths	0.003	177,219	556
	(0.512)		
English	-0.000	177,219	556
	(0.954)		
Norwegian	-0.001	177,219	556
	(0.726)		
Other	0.001	177,219	556
	(0.243)		
Parent income during middle school:			
Mother income	-0.006	175,862	555
	(0.851)		
Father income	0.014**	173,666	556
	(0.032)		

Notes: OLS estimates of the benchmark model (equation 1) on the full sample and where the dependent variables are predetermined characteristics of the student (indicated in the first column). Standard errors clustered at the school level and p-values adjusted using stepwise multiple hypothesis testing procedure that controls for family wise error rate. *** p<0.01, ** p<0.05, * p<0.1

Table A6: Benchmark regression controlling for fathers' middle school income

	(1) Total sample	(2) Low SES	(3) High SES
Parents w/elite degree	0.026***	0.013***	0.040***
	(0.003)	(0.003)	(0.008)
Father's income	-0.001*	0.000	0.000
	(0.001)	(0.002)	(0.002)
Observations	173,666	58,610	20,018
Number of schools	556	524	459

Notes: OLS estimates of the benchmark model including additional varaiable of the father's income measured in middle school year. *** p<0.01, ** p<0.05, * p<0.1

Table A7: Placebo tests: lags and leads of exposure to elite peers

	(1) Total	(2) Low SES	(3) High SES	(4) Total	(5) Low SES	(6) High SES
% Parents with elite degree	0.027***	0.013***	0.042***	0.027***	0.012***	0.042***
	(0.004)	(0.003)	(0.009)	(0.004)	(0.003)	(0.011)
Elite exposure lag 1	-0.001	0.001	-0.012	-0.003	0.002	-0.007
	(0.004)	(0.005)	(0.012)	(0.005)	(0.007)	(0.018)
Elite exposure lead 1	-0.001	-0.002	-0.005	0.004	0.001	-0.001
	(0.005)	(0.005)	(0.012)	(0.006)	(0.007)	(0.014)
Elite exposure lag 2				0.009	0.002	0.014
				(0.005)	(0.007)	(0.012)
Elite exposure lead 2				-0.001	0.000	-0.002
				(0.006)	(0.006)	(0.015)
Observations	137,286	45,007	15,647	90,365	29,659	10,420
Number of schools		443	406	372	370	342

Notes: These regressions augment the benchmark regression by including additionally two leads and two lags in the peer exposure variable. Specifically for each student, a lead (lag) is measured as the proportion of parents with an elite degree calculated across the students entering high school in the year after (before) the student.

Table A8: Sensitivity analysis and interpretation

	(1) Benchmark	(2) First born children	(3) Two-parent families	(4) Exclude OSLO	(5) Exclude small schools	(6) Drop humanities general studies
A - All students						
Proportion of parents with elite degree (std)	0.026***	0.025***	0.026***	0.025***	0.026***	0.050***
	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.005)
Number of pupils	177,219	146,567	149,613	159,307	159,307	100,454
Number of schools	556	555	542	507	280	539
B - Low SES students sample						
Proportion of parents with elite degree (std)	0.013***	0.014***	0.013***	0.013***	0.013***	0.029***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)
Number of pupils	*58,610*	*51,270*	*49,025*	*52,938*	*50,882*	*35,208*
Number of schools	*524*	*524*	*518*	*482*	*280*	*513*
C - High SES students sample						
Proportion of parents with elite degree (std)	0.040***	0.041***	0.034***	0.040***	0.040***	0.065***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.011)
Number of pupils	*20,018*	*15,439*	*17,435*	*16,444*	*19,153*	*10,236*
Number of schools	*459*	*449*	*450*	*418*	*279*	*433*

Notes: OLS estimates of the coefficient on the variable measuring the proportion of elite educated parents in the student's youth cohort in different specifications in the full sample (Panel A), the low SES sample (Panel B) and in the high SES sample (Panel C). Column (1) refers to the benchmark specification from (equation 1) and also reported in Table 2. Column (2) refers to the benchmark specification estimated just for first born children. Column (3) drops the sample of divorced or separated households. Column (4) refers to the benchmark specification this time estimated on the subsample of schools outside of Oslo. Column (5) refers to the benchmark specification excluding schools in the bottom decile of the size distribution. Column (6) refers to the benchmark specification where we exclude high school students specialising in sciences, economics and mathematics. Standard errors clustered at the school level. *** p<0.01, ** p<0.05, * p<0.1

Table A9: Elite peer effect on GPA rank within the high school cohort

	(1) Full sample	(2) Low SES	(3) High SES
A - Overall GPA			
	-8.270***	-10.215***	-5.744***
	(0.433)	(0.543)	(0.463)
Number of observations	*177,219*	*58,610*	*20,018*
B - Components of GPA			
Externally assessed written exam grades	-6.140***	-7.152***	-4.670***
	(0.349)	(0.434)	(0.475)
Number of observations	*177,219*	*58,610*	*20,018*
Teacher-assessed internal grades	-8.272***	-10.141***	-5.757***
	(0.437)	(0.542)	(0.474)
Number of observations	*177,219*	*58,610*	*20,018*
Semi-externally assessed oral exam grades	-4.233***	-5.941***	-2.666***
	(0.347)	(0.460)	(0.530)
Number of observations	*149,488*	*49,414*	*17,189*

Notes: OLS estimates of the effect of the proportion of parents with an elite degree in the student's school's cohort in the benchmark model controlling for average peer ability where the dependent variable is now a measure of academic performance. See notes to Table 2 for detailed list of controls. The measures of academic performance are the student's rank within their high school cohort on the overall high school GPA (row 1), average rank on externally assessed written exams across all three years of high school (row 2), average rank on teacher assessed grades across all three years of high school (row 3), and average rank on oral exams marked by an external examiner and the student's teachers across all three years of high school (row 4). Column (1) reports the coefficient on the proportion of parents with an elite degree estimated in the full sample, column (2) and column (3) report the same coefficient estimated in the low SES and high SES samples, respectively. Standard errors clustered at the school level. *** p<0.01, ** p<0.05, * p<0.1

Table A10: Validity of the empirical strategy: dependent variable is high school GPA

	(1) Benchmark	(2) School-specific linear trends	(3) School-cohort fixed effects interacted	(4) 'Drop if more than random'	(5) Including teacher traits	(6) Quadratic specificaiton
A - Low SES students sample						
Proportion of parents with elite degree (std)	-0.171***	-0.178***		-0.339***	-0.174***	-0.215***
	(0.016)	(0.016)		(0.013)	(0.018)	(0.014)
Proportion of parents with elite degree squared						0.067***
						(0.009)
Number of pupils	*58,610*	*58,610*		*28,181*	37,270	*58,610*
Number of schools	*524*	*524*		*284*	*390*	*524*
B - High SES students sample						
Proportion of parents with elite degree (std)	-0.046***	-0.053***		-0.218***	-0.028***	-0.081***
	(0.012)	(0.014)		(0.035)	(0.013)	(0.019)
Proportion of parents with elite degree squared						0.016***
						(0.005)
Number of pupils	*20,018*	*20,018*		*8,420*	12,737	*20,018*
C - Low and High SES students sample						
Proportion of parents with elite degree (std)			-0.058***			
			(0.006)			
Indicator for low SES			0.052**			
			(0.024)			
Proportion of parents with elite degree * low			-0.146***			
			(0.008)			
Number of pupils			*78,540*			

Notes: OLS estimates effect of the proportion of elite educated parents in the student's youth cohort on high school GPA, in different specifications in the low SES sample (Panel A), in the high SES sample (Panel B) and pooled sample of low and high SES (Panel C). Column (1) is the benchmark specification (equation 1) and Table 2. Column (2) is benchmark specification controlling also for school-specific linear trends. Column (3) includes fully interacted fixed effects for the school and cohort; estimating on the pooled sample of low and high SES students. Column (4) the benchmark specification is estimated on the subsample of schools where variation in the elite peer variable evolves over time in a random way. Specifically, we drop the schools where the R^2 from a school-level regression of the proportion of elite educated peers on a quadratic in year is 1.05 times the R^2 from five regressions where cohorts are randomly re-ordered for each. See subsection A3.3. Column (5) the benchmark specification including additionally average traits of teachers within schools across cohorts: the proportion of females, the proportion of teachers from a professional or low skilled background and average age. The teacher background is defined by the occupation of their father. Column (6) refers to the benchmark specification augmented with a quadratic term in the elite peer variable. Regressions are weighted by school size. Standard errors clustered at the school level. *** p<0.01, ** p<0.05, * p<0.1

Table A11: Balance. Dependent variable is the Instrumental Variable.

	(1) Low SES	(2) High SES
Proportion of parents with elite degree (std)	-0.009	0.010*
	(0.006)	(0.006)
Student is female	0.001	0.006
	(0.004)	(0.004)
Student is born in Norway	-0.004	-0.001
	(0.005)	(0.007)
Mother years of schooling	-0.001	0.001
	(0.001)	(0.001)
Father years of schooling	-0.000	-0.001
	(0.001)	(0.001)
Middle school teacher assessments	-0.039	-0.064
	(0.063)	(0.101)
Middle school written assessments	-0.001	-0.003
	(0.006)	(0.009)
Middle school oral exams	-0.001	-0.003
	(0.005)	(0.008)
Middle school overall GPA	0.015	0.061
	(0.072)	(0.116)
Proportion of student's own parent with an elite degree	-0.013	0.012
	(0.036)	(0.013)
Student's parents are in top income decile	0.006	-0.018**
	(0.006)	(0.007)
Number of pupils	52,446	17,806
Number of schools	520	450

Notes: OLS estimates of a regression of the instrumental variable which is an indicator for a being assigned a maths examination through a lottery in year 3 of high school on the set of covariates reported and additionally school, cohort and programme fixed effects. The low SES sample in column (1) is defined as the group of students who have at least one parent with no more than the compulsory level of education, but no parent with an elite education. The high SES sample in column (2) is defined as the group of students who have at least one parent with a post-secondary education, but no parent with a compulsory level of education. Standard errors clustered at the school level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A12: Long-term implications for earnings

		(1) Low SES	(2) High SES		(3) Low SES	(4) High SES
	A - Mincer regressions			**B - Peer effect on earnings**		
Top 1%	Student has a degree	0.008***	0.041***	Parents w/	-0.002	0.007
		(0.002)	(0.013)	elite degree	(0.002)	(0.005)
	Student has elite degree	0.051***	0.075***			
		(0.005)	(0.013)			
Top 10%	Student has a degree	0.025***	0.082***	Parents w/	0.004	0.022***
		(0.005)	(0.024)	elite degree	(0.004)	(0.022)
	Student has elite degree	0.250***	0.284***			
		(0.010)	(0.025)			
Top 25%	Student has a degree	0.085***	0.151***	Parents w/	0.014**	0.034***
		(0.008)	(0.028)	elite degree	(0.006)	(0.011)
	Student has elite degree	0.420***	0.468***			
		(0.014)	(0.029)			
Top 50%	Student has a degree	0.198***	0.230***	Parents w/	0.017**	0.038***
		(0.009)	(0.026)	elite degree	(0.007)	(0.010)
	Student has elite degree	0.407***	0.424***			
		(0.016)	(0.027)			
Observations		20,454	6,765		20,454	6,765
No. schools		457	372		457	372

Notes: Panel A runs a Mincer-style regression of earnings on an indicator for degree and an elite degree. The omitted category is no degree. The regressions include a gender dummy and year of birth dummy variables as controls. Panel B estimates the effect of exposure to elite peers during high school on earnings. The earnings measure as dependent variable changes across rows, from an indicator for earning in the top percentile, top decile, top quartile and top half of the income distribution. The low SES sample is defined as the group of students who have at least one parent with no more than the compulsory level of education, but no parent with an elite education. The high SES sample is defined as the group of students who have at least one parent with an elite education, but no parent with a compulsory level of education. Sample of birth cohorts 1986-1988. Income is deflated to 2020. For the cohorts 1986; 1987 and 1988 income is measured ages 30-32; 30-31 and 30 respectively (see Section 3). Standard errors clustered at the school level. *** p<0.01, ** p<0.05, * p<0.1

Table A13: Mincer equation estimating correlation between elite degree programme and earnings

	(1)	(2)	(3)	(4)	(5)	(6)
	Low SES	High SES	Low SES	High SES	Low SES	High SES
	Earnings percentile		Richest decile		Richest percentile	
Student ever enrolled in degree	9.631***	8.581***	0.025***	0.069***	0.006***	0.032***
	(0.432)	(1.305)	(0.005)	(0.020)	(0.002)	(0.010)
Student enrolled in elite degree:						
STEM	26.056***	24.127***	0.236***	0.241***	0.034***	0.039***
	(0.928)	(1.409)	(0.011)	(0.021)	(0.005)	(0.011)
Law	25.479***	22.272***	0.131***	0.190***	0.035***	0.059***
	(1.325)	(1.781)	(0.016)	(0.027)	(0.007)	(0.014)
Medicine	40.883***	35.225***	0.662***	0.586***	0.231***	0.193***
	(2.278)	(1.879)	(0.027)	(0.028)	(0.012)	(0.015)
Observations	25,188	8,290	25,188	8,290	25,188	8,290

Notes: Mincer-style regressions of earnings percentile age 30-32 (columns (1) and (2)); an indicator for earning in the top decile (columns (3) and (4)) and an indicator for earning in the top percentile (columns (5) and (6)) on indicators for a degree, an elite STEM degree, an elite law degree and an elite medicine degree. The omitted category is no degree. The low SES sample in columns (1), (3) and (5) is defined as the group of students who have at least one parent with no more than the compulsory level of education, but no parent with an elite education. The high SES sample in columns (2), (4) and (6) is defined as the group of students who have at least one parent with a post-secondary education, but no parent with a compulsory level of education. Sample of birth cohorts 1986-1988. Income is deflated to 2020. For the cohorts 1986; 1987 and 1988 income is measured ages 30-32; 30-31 and 30 respectively (see Section 3). The regressions include a gender dummy and year of birth dummy variables as controls. Standard errors clustered at the school level. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A14: Validity of the empirical strategy: dependent variable is earnings in richest decile

	(1) Benchmark	(2) Including family fixed effect	(3) School-specific linear trends	(4) 'Drop if more than random'	(5) Quadratic specifi-caiton
A - Low SES students sample					
Proportion of parents with elite degree (std)	0.004	-0.003	0.004	0.005	0.001
	(0.004)	(0.036)	(0.005)	(0.007)	(0.005)
Proportion of parents with elite degree squared					0.004
					(0.003)
Number of pupils	*20454*	*20454*	*20454*	9,710	*20454*
Number of schools	*457*	*457*	*457*	236	*457*
B - High SES students sample					
Proportion of parents with elite degree (std)	0.022***	-0.045	0.036**	0.040**	0.039**
	(0.009)	(0.043)	(0.016)	(0.016)	(0.018)
Proportion of parents with elite degree squared					-0.005
					(0.006)
Number of pupils	*6765*	*6765*	*6765*	2,827	*6765*
	372	*372*	*372*	178	*372*

Notes: OLS estimates of the coefficient on the variable measuring the fraction of elite educated parents in the student's youth cohort in different specifications in the low SES sample (Panel A) and in the high SES sample (Panel B), on earning in the richest decile age 30-32. Column (1) refers to the benchmark specification (Equation 1) and reported in Table 5. Column (2) refers to the benchmark specification where we also control for school-specific linear trends. Column (3) refers to the benchmark specification this time estimated on the subsample of schools where variation in the elite peer variable evolves over time in a random way. Specifically, we drop the schools where the R^2 from a school-level regression of the proportion of elite educated peers on a quadratic in year is 1.05 times the R^2 from five regressions where cohorts are randomly re-ordered for each. See Section 4 for full details. Column (4) refers to the benchmark specification where we also control for a family fixed effect. Column (5) refers to the benchmark specification augmented with a quadratic term in the elite peer variable. Regressions are weighted by school size to take account of the parent peer variables group averages, taken from groups of different sizes. Standard errors clustered at the school level. Standard errors clustered at the school level. *** p<0.01, ** p<0.05, * p<0.1

Table A15: Mincer regression dropping dummy for having a degree

	(1) Low SES	(2) High SES	(3) Low SES	(4) High SES
Elite degree	18.480***	17.062***		
	(0.751)	(0.723)		
STEM			17.746***	14.404***
			(0.954)	(0.860)
Law			15.953***	15.486***
			(1.348)	(1.383)
Medicine			31.358***	26.154***
			(2.490)	(1.624)
Observations	20,454	6,765	20,454	6,765

Notes: Mincer-style regressions of earnings percentile age 30-32 on indicators for an elite degree (columns 1-2) and an elite STEM degree, an elite law degree and an elite medicine degree (columns 2-3). The omitted category is no elite degree. The low SES sample in columns (1), (3) is defined as the group of students who have at least one parent with no more than the compulsory level of education, but no parent with an elite education. The high SES sample in columns (2), (4) is defined as the group of students who have at least one parent with a post-secondary education, but no parent with a compulsory level of education. Sample of birth cohorts 1986-1988. Income is deflated to 2020. For the cohorts 1986; 1987 and 1988 income is measured ages 30-32; 30-31 and 30 respectively. The regressions include a gender dummy and year of birth dummy variables as controls. Standard errors clustered at the school level. *** p<0.01, ** p<0.05, * p<0.1

Table A16: Simulating a reassignment of low (high) SES students into schools with a high (low) level of elite peers

	(1) Benchmark	(2) Simulation 1	(3) Simulation 2	(4) Simulation 3	(5) Simulation 4
No. schools		Top and bottom decile		All schools	
No. children moved per school		1	5	1	5
Parent percentile rank	0.143***	0.139***	0.136***	0.139***	0.129***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Constant	53.090***	52.829***	53.032***	52.874***	53.474***
	(0.332)	(0.332)	(0.332)	(0.332)	(0.334)
Observations	30,849	30,849	30,849	30,849	30,849
R-squared	0.023	0.021	0.020	0.021	0.018

Notes: The table reports the coefficients from a regression of parent percentile rank in the earnings distribution (measured when the student was aged 15-19) on the student's (within birth cohort) percentile rank at age 30-32. See Section A5 for full details of the reassignment exercise. Column (1) reports the benchmark regression. Columns (2) and (4) report the coefficients after a simulation which reassigns one low SES student (one high SES student) from each school with the lowest (highest) exposure to elite peers into the schools with the highest (lowest) exposure, (Simulations 1 and 3) respectively. Columns (3) and (5) instead swap 5 low SES students from the low exposure school with 5 high SES students in the high exposure school (Simulations 2 and 4). In columns (2) and (3) low SES students are moved out of schools in the bottom decile of the distribution of exposure to elite peers and into schools in the top decile of the distribution; whilst the high SES students move from schools in the top to the bottom decile. In columns (4) and (5), one or five low SES students are moved out of all schools in the bottom half of the distribution of exposure to elite peers whilst one or five high SES students are moved out of all schools in the top half of the distribution. Exactly which students are chosen to be reassigned is explained in Section A5.