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Heterogeneous Effects of High School Peers on Educational Outcomes

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Silvia Mendolia, Alfredo R. Paloyo, and Ian Walker[1]

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Abstract

We investigate the relationship between peers' abilities and educational outcomes at the end of high school using data from the rich Longitudinal Study of Young People in England (LSYPE) matched to the National Pupil Database of children in state schools in England. In particular, we focus on the effect of peers' abilities, measured through achievements in Key Stage 3 (Age 14), on high powered test scores at Ages 16 and 18, and on the probability of attending university. Our identification strategy is based on a measure of the peers of peers' ability. In particular, for each individual, we look at her high school peers and select their primary school peers who do not attend the same high school and who did not attend the same primary school as the individual. We then use peers-of-peers ability, measured using Age 11 test scores as an instrument for high school average peer ability, measured using Age 14 test scores. We also use quantile regression to explore the effect of peers' ability on different parts of the distributions of the outcomes. Our results show that average of peers' abilities has a moderate positive effect on test scores at Ages 16 and 18, and that being in a school with a large proportion of low-quality peers can have a significantly detrimental effect on individual achievements. Furthermore, peers' ability seems to have a stronger effect on students at the bottom of the grade distribution, especially at Age 16.

JEL Classification: I20, J24

Keywords: Peer effects; instrumental variables; test scores

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1 Silvia Mendolia, University of Wollongong; Alfredo R. Paloyo, University of Wollongong and RWI; Ian Walker, Lancaster University Management School. *– We are grateful to the Department for Education Longitudinal Team, especially Tim Thair, for providing the LSYPE data and their assistance in understanding it. The authors are solely responsible for the views expressed here. The data are available from the Centre for Longitudinal Studies, at https://www.ioe.ac.uk/research/54617.html, and the authors' code is available from the corresponding author. We are grateful for comments from seminar participants at Lancaster, Melbourne, Sydney, and SFI Copenhagen.* *– All correspondence to: Dr Silvia Mendolia, School of Accounting, Economics and Finance, University of Wollongong, Wollongong NSW 2522, Australia, e-mail: smendoli@uow.edu.au*

1. Introduction

The analysis of peer effects in education has received increasing attention among economists and applied social scientists in recent years (see, e.g., the recent review by Sacerdote, 2011). A number of studies (Angrist and Lang, 2004; Lavy et al., 2012; Gibbons and Telhaj, 2015, among others) typically find modest but statistically significant peer effects in test scores. In addition, there is some evidence that heterogeneous peer effects exist. In particular, Burke and Sass (2013) and Ding and Lehrer (2007) find that high-ability students benefit from other high-ability students while Imberman et al. (2012) find that good peers have positive effects which are greatest for low-achieving students.

The aim of this paper is to investigate the relationship between peer ability and individual attainment levels in high-stakes educational tests at the end of compulsory schooling at Age 16 and at the end of high school at Age 18 using a rich and recent dataset of English teenagers. Estimating the size of peer effects is important because they imply that educational interventions may have multiplier effects (Glaeser, Sacerdote, and Scheinkman 2003), i.e., that the impact of an educational intervention may self-propagate within a group of students. Furthermore, we devote a substantial focus to the potential heterogeneity in the effect of peer ability because this has efficiency implications for the mixing of pupils in a school or in a classroom. An ideal student mix may raise the average scholastic attainment of a group in ways which other educational interventions may not be able to achieve.

Our study contributes to the existing literature on peer effects in education in three main ways. First, we provide evidence based on a recent dataset of English teenagers, and we focus our attention on high-stakes educational outcomes at the end of high school. The existing literature based on British data mostly analyse the impact of peers on junior high school achievement at Age 14 (Lavy et al., 2012; Gibbons and Telhaj, 2015). Second, we investigate the existence of heterogeneous peer effects across the grade distribution.

We contribute further to the literature by estimating peer effects using a novel identification strategy to overcome the reflection problem and mitigate selection bias. Based on the outcomes of the “peers of one’s peers”, we use information on the primary school peers of an individual’s high school peers who satisfy two conditions: first, they must have attended a *different* primary school from the student of interest; and, second, they *must not be in the same high school* as the student of interest. This information is used as an instrument for an individual’s average peer ability in high school. The idea is that some of the peers of any specific high school student will have had primary school peers who have never been directly exposed to the student in question because they went to a different primary and high school. Therefore, these peers could never have had a direct effect on the student’s outcomes, although we explore the possibility of indirect effects. While peers of peers have been used in previous research we believe ours is the first study that adopts the strategy of excluding peers of peers that are not one’s own peers, now or in the past.

In many countries, sorting of pupils between schools on the basis of family socioeconomic status and other characteristics exists. Peer effects in this context may amplify existing disparities between groups of students, with high-achieving students benefiting from each other while low-ability students impair each other’s learning. Differentiation may further occur within and between schools through streaming or tracking. Those who support segregation by ability within schools suggest that teaching might be more efficient if it is tailored to homogeneous ability groups (see Galindo-Rueda and Vignoles (2005) for a thoughtful discussion on this issue). However, concerns have been raised about these practices as they might lead to increased inequality of opportunities, especially for students who come from disadvantaged socioeconomic backgrounds and are thus likely to be in the bottom of the grade distribution (Bradley and Taylor 2008). Peer effects may then reinforce disadvantage.

The analysis of peer effects is important for reasons apart from the multiplier effect. First, it is a critical issue for educational policies related to the expansion of school choice. Choices related to peers’ composition may lead to some segmentation across schools based on students’ ability

(Epple and Romano, 2000). In Britain, like in many other countries, school choice depends mostly on place of residence, and then subsequently on parental choice and academic selection. The combination of these factors results in large variations in the pupil mix within schools (Atkinson et al., 2008). Second, educational policies might be needed to be tailored differently depending on the relevance of peer effects. These interventions can be more (or less) effective when targeting individuals or specific groups within a school. Lastly, if peer effects are heterogeneous, this can have implications on the importance of carefully mixing students across different ability groups, as average individual achievements can be influenced by the mix of peers and not just by their average achievement.

However, identifying the effect of peers' ability on individual achievements is particularly complicated from an empirical point of view for several reasons (Angrist, 2014). First, peer groups are not exogenous and they are, to a certain extent, self-selected. For example, children attending the same school are likely to have some common unobserved characteristics, perhaps related to the area in which they live and the socioeconomic background of their families. The correlation between these factors and both the educational outcomes and the nature of the peer group might lead to an overestimation of the effect of peers' ability because of positive selection bias.

Second, individuals affect their own peer group as much as the peer group affects them, so peers' achievements are not exogenous with respect to individual educational outcomes, especially when pupils have exposed to each other for some years. Students' learning is affected by direct contact and social interaction, and individual achievements are likely to be correlated with those of other students in the same class or school. This mechanism is known as the "reflection problem" (Manski, 1993).

We use data from a recent and rich dataset – the Longitudinal Study of Young People in England (LSYPE), which includes a variety of information on the child, the family, and the school. The existing literature in the UK mostly relies on the National Pupil Database (NPD), which has a very limited set of family background characteristics. Our results exploit the richness of LYSPE and suggest that peer ability has a moderate effect on test scores at age 16 and 18, but it does not significantly affect the likelihood of attending university. Furthermore, peer ability seems to have a stronger effect on students at the bottom of the grade distribution, especially at age 16. These findings are consistent with the existing evidence from nonexperimental studies on peer effects. We thus complement it by providing new results based on a new quasi-experimental identification strategy.

The rest of this paper is organised as follows. In Section 2, we provide a brief overview of the existing literature. We present the data and explain the peer-ability indicators and outcomes in Section 3. In Sections 4 and 5, we discuss the estimation methods and the results, respectively. Finally, we conclude in Section 6 with a discussion of policy implications.

2. Related literature

Researchers have been interested in the analysis of peer effects on a variety of outcomes, including health-risky behaviours (McVicar and Polanski, 2014; Trogdon et al., 2008), and on a number of academic and educational outcomes (Zimmerman, 2003; Hanushek et al., 2003; Carrell, 2009; Duflo et al., 2011; Lavy et al., 2012; Gibbons and Telhaj, 2015). However, estimating peer effects is complicated by what Manski (1993) refers to as the "reflection problem", which makes it difficult for an empirical researcher to disentangle the specific effect of peers' achievements on the individual.

Manski (1993) distinguishes between the three non-exclusive channels through which individuals may have characteristics and outcomes similar to their peer group: via the endogenous effect, via exogenous effects (also called contextual effects), and via correlated effects. In our context, an endogenous effect arises if the individual's achievement varies with the average achievement of the peer (or reference) group; an exogenous effect arises if the individual's achievement varies with the observable socioeconomic characteristics of the peer group; and correlated effects arise if the individual has similar achievements as her peers because they are subject to similar shocks. For policy purposes, there is a tendency to emphasise the estimation of the endogenous effect as this generates the social multiplier which allows an intervention's effects to self-propagate within a group (Angrist, 2014)

Researchers have applied several different techniques to overcome these empirical problems: including random assignment (e.g., Carrell et al., 2009, and Duflo et al., 2011); exploiting within-school random variation (e.g., Lavy and Schlosser, 2011; accounting for school and pupil fixed effects (e.g., Lavy et al., 2012, and Gibbons and Telhaj, 2015, among others); using instrumental variables (e.g., Goux and Maurin, 2007), and the network of "friends of friends" (as in Moriarty et al., 2012). Most studies find relatively small effects, and the evidence about the heterogeneity of peer effects is both thin and mixed. For example, Imberman et al. (2012) find that good peers have positive effects which are greatest for low-achieving students, and Lavy et al. (2012) find that low-achieving students are most adversely affected by an increase in the share of bad peers. In contrast, Burke and Sass (2013) for the US, and Ding and Lehrer (2007) for China, show that high achievers benefit most from increases in peer quality. For Kenya, Duflo et al. (2011) report positive peer-ability effects on achievement growth, especially for high achievers.

A number of studies have analysed the impact of peers' ability on outcomes in higher education, such as college grades and graduation, exploiting the random allocation in college accommodation in the US (Sacerdote, 2001; Zimmerman, 2003; Foster, 2006; Winston and Zimmerman 2004; Stinebrickner and Stinebrickner, 2006; Carrell et al., 2009). For example, famously, Sacerdote (2001) uses the random allocation of students in dormitories at Dartmouth College to show that peers have an effect on students' grades. Similarly, Carrell et al. (2009) uses the random assignment of students at the United States Air Force Academy to show substantial nonlinear peer effects, finding that these effects are higher at the bottom of the grade distribution.

More relevant to our purposes are those studies that analyse the effect of peers' ability on educational achievements in school. Some studies have looked at primary school children and have exploited several different strategies to analyse the impact of peers in early ages (e.g., Hoxby, 2000; Hanushek et al., 2003; Angrist and Lang, 2004; Lefgre, 2004; Ammermueller and Pischke, 2006;

Vigdor and Nexhyba, 2007; Goux and Maurin, 2007). Hanushek et al. (2003) use data from the Texas Assessment of Academic Skills, and control for fixed school, individual, and school-by-grade effects to show that peers' achievements have a positive effect on individual grades, and that this effect is constant across quartiles of the grade distribution. Similarly, Lefgren (2004) uses data from Chicago public schools and examine peer effects using school tracking policies. The author shows that peer effects are quite small but generally positive and significant. Angrist and Lang (2004) analyse the results of the METCO program in Boston, which sends black disadvantaged students to public schools in high-socioeconomic-status areas, and they indicate that there is limited evidence of statistically significant effects.

A distinct strand of the literature examines peer effects in middle and secondary schools. These studies mostly show small but significant peer effects (e.g., Kang, 2007; Lavy et al., 2007; Schindler Rangvid, 2008; Calvo-Armengol et al., 2009). In the UK, Bradley and Taylor (2008) estimate peer effects using information on pupils changing schools in the last two years of their compulsory education. They show that peer effects exist and are stronger for low-ability students and non-white children. However, pupils who change school may be systematically different from those who do not change, especially when the reasons for the change can be related to school achievements. In addition, Atkinson et al. (2008) use a panel of schoolchildren from the southwest of England to look at the effect of the introduction of teachers' performance related pay in England, and show significant and non-trivial peer effects conditioning for school and teacher fixed effects.

The studies that are closest to ours are Lavy et al. (2012), and Gibbons and Telhaj (2015). Both papers exploit the change in peers from primary to high school and use the National Pupil Database (NPD) to analyse the effect of peer ability measured at the end of primary school through Key Stage 2 examinations (at Age 11) and on achievements at the beginning of high school, measured through Key Stage 3 exams (at Age 14). Lavy et al. (2012) use within-pupil and cross-subject regressions, and exploit the variation in achievements by subject to show negative effects arising from bad peers but little effect of the average peer quality of the good peers. Gibbons and Telhaj

(2015) exploit year-to-year changes in secondary school peer group, and account for fixed effects for both primary and high school attended. Their work shows small and significant peer effects as well as complementarities between peers with different ability levels.

Our strategy to overcome the reflection problem and mitigate the impact of selection bias is based on the outcomes of the peers of one's peers. These peers went to a different primary and high school. Therefore, these peers could never have had a direct effect on the student's outcomes in the sense of being in the same classroom or, indeed, the same school. We demonstrate a strong first-stage relationship between a student's average peer ability and the peers-of-peers ability, and we use the latter as an instrument for the former to estimate the causal impacts of average peer ability on individual scholastic outcomes.

3. Data

3.1 Institutional background

Education in England is organised in Key Stages (KS). Children enter primary school at 4–5 years old, and move to Key Stage 1 (at Age 6–7). Key Stage 2 starts at Age 7–8, and lasts until Age 10–11 (Year 6) when children leave primary education and enter secondary school. At this point, Key Stage 3 starts (Age 11–14), followed by Key Stage 4 (Age 14–16). At the end of Key Stage 4, students take the General Certificate of Secondary Education (GCSE) which coincides with the end of compulsory schooling.

Local Educational Authorities (LEA) are responsible for organizing their admission policies for primary and secondary schools. Government schools cannot select students on the basis of their ability, even if some studies have suggested that schools find ways to select students on the basis of parental characteristics that might be correlated with ability (West and Hind 2003). Our sample includes over 640 high schools and over 82 percent of them are government comprehensive schools while voluntary-aided and -controlled schools (usually those schools with a religious denomination) account for 15 percent.

Parents are free to choose any school they prefer, but when schools have a number of applicants which is higher than the available places, they allocate places according to some published criteria. Usually, looked-after children and children with special needs have priority, followed by children who have siblings in the same school, and then children living in the area with proximity as the tie-breaker.

In secondary schools, students are grouped with different peers for different subjects, so they do not have a unique “class” for all subjects. Furthermore, students are sometimes taught in groups of similar ability (determined after an initial observation period) for some subjects – although not all schools “set” by ability, and that this varies by subject, with a higher prevalence of ability setting for Mathematics and Science and a lower incidence for English (Kutnick et al., 2006). Some GCSE examinations are organised in “tiers” and different students sit a different test depending on their ability group, so that the maximum grade that they can achieve depends on their allocated tier.

3.2 Dataset

The LSYPE dataset is managed by the UK Department of Education and covers a wide range of topics, including family relationships, attitudes toward school, family and labour market, and some more sensitive or challenging issues, such as risky health behaviours, personal relationships, etc. Young people included in LSYPE were selected to be representative of all young people in England but, at the same time, the survey oversampled specific groups (and, in particular, young people from a low socioeconomic background). The survey started when these adolescents were in Year 9 in 2004 at the age of 14. The records of LSYPE children can be linked to the NPD, a pupil-level administrative database of all English pupils including detailed information on pupil test scores and achievements, as well as school characteristics. We use this data to collect information about LSYPE children’s results in test scores at Ages 11, 14, and 16, which is the minimum school-leaving age for this cohort. This occurs at the end of a stage of the national curriculum known as KS4, and culminates in the GCSEs exams.

In the first wave of LSYPE, around 15,000 young people were interviewed across more than 700 high schools. On average, data were collected for 27 students in each school. In the first four waves, parents or guardians were also interviewed. Our final sample includes 9,213 observations of children with non-missing information on test scores at ages 11, 14 and 16, peers' test scores, and other essential information on the child's family background. The selected observations were not significantly different from the original data in terms of their observable characteristics.

3.3 Outcomes

We are interested in analysing the effect of peers' ability on academic outcomes at the end of high school and on the chances that a young person will take further studies after compulsory education. Table 1 provides the descriptive statistics for our outcome variables. We analyse peer effects on attainment in GCSE tests at Age 16. At the end of KS4 (from 13 to 16 years old), pupils generally take the national public GCSEs in most subjects studied (often in as many as ten subjects). GCSE grades range from A* to G. Our dependent variables include the number of subjects with "pass" grades (A*–C) in GCSE exams (Figure 1 shows the distribution), and a binary variable equal to 1 if the child has five GCSE passes including Mathematics and English, which is usually required for students following an academic track for progression beyond Age 16 into senior high school. Table 1 shows that more than half of the adolescents in the sample achieved five or more GCSE exams with a grade between A* and C, and 42% take A-level exams. Of those who stay in education after age 16, 35% attend university and, within this subsample, 20% attend an institution that is part of the Russell Group of institutions that is regarded as being elite.[1]

[1] The Russell Group consists of the following 24 institutions: Birmingham, Bristol, Cambridge, Cardiff, Durham, Edinburgh, Exeter, Glasgow, Imperial College, King's College, Leeds, Liverpool, LSE, Manchester, Newcastle, Nottingham, Oxford, Queen Mary College, Queen's Belfast, Sheffield, Southampton, UCL, Warwick, and York.

Figure 1 Distribution of Number of GCSE's with Grade A-C*

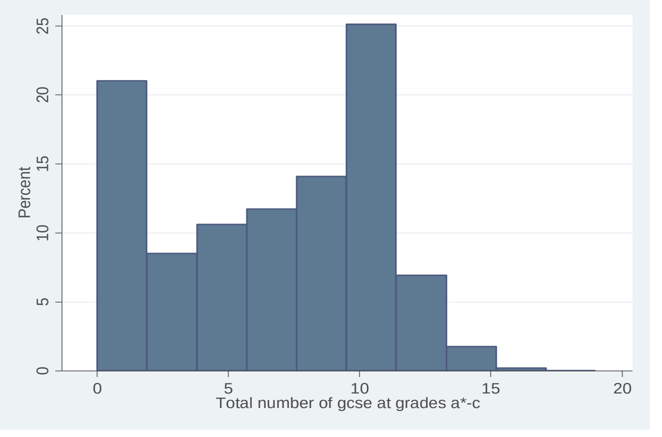


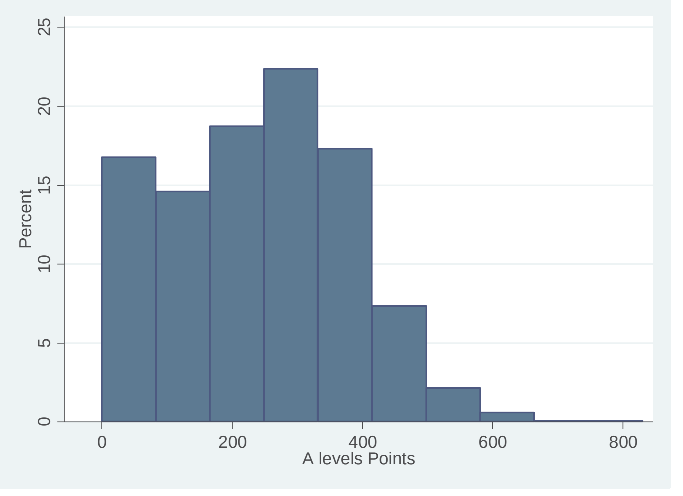
Table 1 Descriptive Statistics of Outcome Variables

Educational Outcomes	Mean (Std. Dev.)
Has 5 or more GCSE with A*–C incl. English and Maths	52.16%
Number of GCSEs with A*–C	6.44 (4.17)
Has A levels	42.02%
A-levels points | Has A levels	247.98 (132.77)
Has A level in Maths	9%
A-level points in Maths | A level in Maths	112.5 (52.74)
Has A level in Science	12%
A-level points in Science | A level in Science	132.894 (70.21)
Attending university	29.6%
Attending a Russell Group university | conditional on attending university	23%

Note.—A-level points are counted as 100 for Grade A, 80 for B, 60 for C, 40 for D, and 20 for E.

Figure 2 shows the distribution of A-level scores. We also explore the impact of the proportion of low achieving peers, on the students' performance in Mathematics and Science at A levels. As noted in Mendolia and Walker (2014), the determinants of performance in a particular subject (rather than overall school performance) are very hard to disentangle. It is particularly interesting to analyse peer effects in performance in these subjects, as the UK ranking of 15-year-old pupils in Mathematics and Science in the OECD's PISA tests has been constantly falling from 2000 to 2009. Furthermore, the UK has one of the lowest shares of 15-year olds intending to pursue a STEM career among the OECD countries and particularly lags behind in women's aspirations to study a STEM subject and engage in a STEM career (OECD, 2012).

Figure 2 Distribution of Number of A-Level Scores



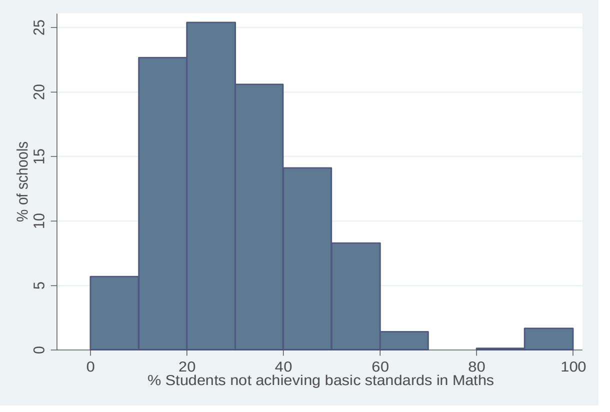
Finally, we analyse the effect of peers' ability on the probability of being enrolled at university at Age 19–20 and on chances to attend a Russell Group institution.

3.4 Peers' ability

We analyse the effect of peers' ability on individual educational outcomes at the end of high school. Peers' ability is measured through average achievements in KS3 tests (taken at Age 14) for children who attended the same high school of each LSYPE child.

Furthermore, we follow the literature on peer effects in education (e.g., Lavy et al., 2012) and investigate the effect of low-achieving peers in high school, in order to analyse whether a large fraction of "bad peers" is significantly detrimental for students' learning. To do so, we use the information on the percentage of students not achieving basic standards (called Level 5) in KS3 Mathematics. Figure 4 presents the distribution of this variable. Over 50% of schools in the estimation sample have a percentage of students not achieving basic standards in Maths below 30% and, as expected, there are very few schools where more than 50% of students are in this category.

Figure 4 *Distribution of Percentage of Students Not Achieving Basic Standard Mathematics*



As we have already discussed, peers' ability is endogenous as people from the same peer group share common unobserved characteristics and because individuals might affect their peer group inasmuch as their peer group affects them. Therefore, we rely on a novel identification strategy based on the peers of peers. In practice, for each LSYPE child, we look at her high school peers, and then we select her primary school peers who did not attend the same primary school as she did and do not currently attend the same high school. These individuals are likely to have affected the peers (through attendance of the same primary school) but have likely never met the student of interest. Therefore, these peers of peers cannot have had a direct effect on the student's achievements.

Our analysis is limited to children who are in LSYPE, and, consequently, we do not have a complete overview of all students in a particular primary or high school and our estimates could potentially be affected by measurement error for this reason. However, the LSYPE sample was designed to be representative of various subgroups of the students' population in England, and using students in LSYPE allows us to access to all the available information on their families and backgrounds (which are not included in NPD). Peers-of-peers ability is measured through achievements in KS2 tests taken at the end of primary school at Age 11.

Our sample is composed of over 9,200 individuals, who come from 640 high schools and 4,126 primary schools. On average, LSYPE children have a high school peer group of 15 students (in LSYPE) who come from many different primary schools (from two to 23 primary schools). The vast majority of high schools (around 80%) draw their students from a group of 8 to 14 primary schools. Therefore, the size of the peers-of-peers group varies from one to 97 children, and table 3 shows that over 70 percent of LSYPE children having a peers-of-peers group of three or more students (see Table 2).

Table 2 Peer of Peers Group Size

Number of Peers	Percent of LSYPE Children
1 peer of peers	10
2 peers of peers	18
3–4 peers of peers	10
5–7 peers of peers	10
8–10 peers of peers	12
11–15 peers of peers	12
15+ peers of peers	28

3.5 Other independent variables

We estimate three versions of our model, progressively increasing the number of covariates. The independent variables included in the model should not be affected by peers' ability. In the first specification of the model, we control for a basic set of individual and family characteristics, including child's gender and achievement in the KS2 test (Age 11), maternal education and marital status, and employment status of both parents (Wave 4 – Age 17). In the second specification, we add the Index of Multiple Deprivation (IMD) score, which is a measure derived from income, employment, health and disability, education, housing, crime, and living environment. Lastly, in the final specification of the model, we control for individual ethnic background and for some school characteristics, such as government region, number of students, religious denomination, and the gender mix of the school.

4 Estimation

We begin our analysis by estimating a linear-in-means model of peer effects:

$$Y_{ihp} = \alpha + \bar{A}_{ih}\beta + \mathbf{X}_i'\boldsymbol{\gamma} + \epsilon_i, \tag{1}$$

where Y_{ihp} represents a particular academic outcome for individual i who has attended primary school p and is now attending high school h. We define i's high school peers as those currently attending high school h but have attended a variety of primary schools apart from school p. The variable $\bar{A}_{ih}$ is the average ability (measured by KS3 score) for LSYPE children attending high school h excluding the individual (the "leave-one-out" mean), and $\mathbf{X}_i$ is a vector of child and family characteristics. We lower the likely upper bound provided by OLS estimation through the inclusion of a very detailed set of independent variables in $\mathbf{X}_i$ (see Section 3.4).

The parameter of interest is β, which captures the relationship between average peer ability $\bar{A}_{ih}$ and individual achievements Y_{ihp} at the end of junior high school and beyond: that is, GCSE results, A-level results, and the probability of going to university. This represents the endogenous effect in the terminology of Manski (1993) and, if significant, generates the social multiplier effect. The vector of coefficients γ captures the exogenous or contextual effects.

To account for the endogeneity of average peer ability in Equation (1), we use instrumental-variable estimation, with peers-of-peers ability in primary school (measured through their achievements at KS2 level at Age 11) as an instrument for the average high school peer ability (measured through KS3 results at Age 14). Our first-stage equation is

$$\bar{A}_{ih} = \delta + \bar{K}_{zt}\rho + \mathbf{X}_i'\boldsymbol{\pi} + \nu_j, \tag{2}$$

where the average high school peer ability $\bar{A}_{ih}$ depends on the peers-of-peers average performance $\bar{K}_{zt}$ in primary school (KS2 score) of those who attended primary schools z and currently attending high school t, where $t \neq h$. The underlying assumption is that the ability of the high school students' peers-of-peers in primary school did not affect the high schools' student achievements directly except through its impact on the student's current peers in high school.

One natural concern in the estimation of this model is that selection of secondary schools on the basis of unobservables could be driving the main findings. Parents choose the school for their children (or at least the area where they live) and, thus, individuals who attend the same high school are likely to have some common background characteristics. However, our instrument relies on peers of peers who do not attend the same high school as the individual and did not attend the same primary school. Around 80% of high schools in the estimation sample have more than eight primary school feeders, as shown in Section 3, and therefore peers of peers (who now attend a different high school) are likely to have come from an area with different socioeconomic characteristics. However, there is no reason to believe that these differences are systematic and peers of peers are a selected group (for example, they all attend a better or worst school than LSYPE students) because of the specific nature of the data and of the considerable number of primary and high schools in the data.

As noted in Gibbons et al. (2013), most households can choose between more than one school from their area of residence and on average, students in the same cohort living in the same neighbourhood attend just one of a handful of different local secondary schools. Further, a typical English secondary school is attended by pupils living in more than 60 Output Areas, the smallest proxy for neighbourhood (Gibbons et al., 2013).

Furthermore, previous literature has shown that neighbourhood composition has a very limited effect on test scores once one controls for family socioeconomic characteristics (Gibbons et al., 2013), and we believe that our rich data allow us to take into consideration a wide set of these factors.

In the model estimation explained so far, we have assumed that peer effects are homogeneous in the sense that the relationship between peers' ability and individual achievements is the same for each student. However, peer effects are likely to be heterogeneous and vary according to the individual ability of students. For example, peer ability might have stronger effects on weak students than on strong students or vice versa; or the presence of a group of weak students might have different effects on weak students than on strong ones (see, e.g., Kong 2007).

We use quantile regression to examine the potential heterogeneous effects of peer ability at different points of the achievement distributions. We estimate the effect of the average peer ability for students at different quantiles of the GCSE and A-level score distributions. In order to deal with the endogeneity of peer ability in high school, we use IV quantile regression (Chernozhukov et al., 2010; Chernozhukov et al., 2015; Lee, 2007) which has been used in a similar context in Kong (2007). The analysis is performed using the Stata routine cqiv with the uncensored option (Chernozhukov et al., 2011). A parametric version of the estimator proposed by Lee (2007) is used in the estimation. In particular, following Lee (2007), the following model is estimated:

$$Q_{Y_{i\,h\,p}|A,X}(\tau|A,X) = \alpha + \bar{A}_{ih}\beta(\tau) + \mathbf{X}_i'\boldsymbol{\gamma}(\boldsymbol{\tau}) + \epsilon_i, \tag{3}$$

and the first step linear quantile regression is modelled as

$$Q_{\bar{A}_{ih}|Z}(\beta|z) = \delta + \bar{K}_{zt}\rho + \mathbf{X}_i'\boldsymbol{\pi} + \nu_j, \tag{4}$$

where $\beta(\tau)$and $\boldsymbol{\gamma}(\boldsymbol{\tau})$ can be estimated by a τ^{th} quantile regression of Y on $\bar{A}$ and Z.

Furthermore, we follow Lavy et al. (2012) and estimate the effect of having low-ability peers in high school. To do so, we use the information on the percentage of students not achieving basic standard (called Level 5) in KS3 Mathematics which is available in the LSYPE dataset for each high school. In order to deal with the potential endogeneity of this variable, we apply the same strategy as in the previous model and instrument it with a variable indicating the percentage of students not achieving basic standards in KS2 Mathematics in peers-of-peers primary schools.

5 Results

Our main results are presented in Tables 3–16. We begin by presenting results from the least-squares estimation of the relationship between average peer ability and individual achievements in Table 3. When we progressively increase the set of control variables, including additional characteristics related to the socioeconomic status of the family and the area of residence, our main results are unchanged.[2] Model 2 includes the same variables as in Model 1, but also includes the Index of Multiple Deprivation score, which captures several dimensions of socioeconomic disadvantage such as income, education, housing, health, etc. It is important to show the stability of our

[2] We also tested our main results by including an additional indicator of economic disadvantage of the primary school attended (percentage of students eligible for free school meal). The substantive results were unaffected.

main results when controlling for this variable, as it is well-known that family socioeconomic status is a strong predictor of educational achievements later in life.

Table 3 presents results from Model 1 from OLS and IV estimations, including the basic set of individual and family characteristics. Unsurprisingly, OLS results are highly significant and suggest that improving peer ability has a positive effect on individual achievements at Age 16–17 (GCSE exams) and Age 17–18 (A-level exams); the sizes of the effect are nontrivial. A one standard deviation increase in peers' Key Stage 3 average score increases individual chances of having 5 or more GCSE with A*-C by 13 percentage points (the mean of this variable is 52%).

When we take into account the potential endogeneity of peer ability via IV estimation, most results have similar size and significance and confirm the OLS findings. Interestingly, we do not find any significant effect of peer ability on the chances to attend university and to get into an elite higher education institution when we use IV estimation – which might suggest that the more able students are relatively insensitive to their less-able peers. Our instrument relies on peers-of-peers test scores in primary school to estimate peer ability in high school, and it is possible that we do not see any significant effect on long-term outcomes because of the specific nature of the instrument and because the effect has faded over time. Results from first-stage regressions are reported in the Appendix (Tables 15–16). Table 3 reports the F statistics from the first stage and comfortably satisfy the rule of thumb for strong instruments.

Model 2 is more precise than Model 1, as it includes controls for the IMD score and it allows taking into consideration a broad indicator of family socioeconomic status and area of residence. As shown in Table 3, results from Model 2 corroborate the main findings from Model 1, especially in relation to the impact of peer quality on A-level results. A one-standard-deviation increase in the average KS3 of the peers of peers increases the probability of taking A-levels by about 8 percentage points and the average A-level score by about 56 A-level points in the IV estimation, which is equivalent to 40 percent of a s.d. These results are consistent in terms of size and significance when we use IV estimation and strongly support the idea that peer ability plays a substantial role in a student's decision to continue in education after GCSE and on her/his performance. Peers' average test scores also significantly affect chances of taking A level exams: a one-standard-deviation increase in the average peers' KS3 score increases the probability of taking A levels by almost 8 percentage points (the average of this variable is 42% in the estimation sample).

Table 4 presents results from the estimation of the effect of low-achieving peers. The results indicate that the effect of being in a school with a high proportion of peers who do not achieve basic achievement standards is sizeable and significantly negative on individual achievements. An extra 10 percent of peers not achieving basic standards in Maths decreases individual chances of taking A-levels by about 2 percent and decreases A-level scores by about 22 points (16 percent of an s.d.). These results are consistent with Lavy et al. (2012), who show that a 10-percent decrease in the proportion of "bad" peers at school is associated with an improvement of approximately 10–11 percent of an s.d. of the within-pupil KS3 distribution for students.

In general, the IV results confirm OLS findings and the sizes of the coefficient is very similar. However, in some instances, IV results are slightly bigger than OLS. It is possible that this difference is due to the fact that IV estimates represent Local Average Treatment Effects, i.e. the effects of peers' ability on outcomes for those students who are easily influenced by their peers. This effect is particularly interesting because these students are the ones whose behaviour might be changed by any educational reform focused on mixing childre from different ability groups in the classroom.

When we add the IMD score, the results in Model 2 suggest that the impact of peers' ability on performance at GCSE level (Age 16–17) is no longer statistically significant in the IV estimation. However, this could simply be due to the fact that the effect of peer ability on individual achievements is heterogeneous, and peer ability has a stronger impact on students with particular characteristics or ability level. We thus estimate the model using quantile-regression techniques in order to investigate heterogeneous effects of peers' ability on GCSE and A-level results.

As explained in Section 4, so far we have assumed that peer effects affect achievements in the same way for all students. However, it is possible that some students suffer (or benefit) more

Table 3 *OLS and IV estimates of the impact of average peers' quality on academic achievement*

	Model 1			**Model 2**			**Model 3**		
Outcomes	**OLS**	**IV**	**F**	**OLS**	**IV**	**F**	**OLS**	**IV**	**F**
# GCSE	0.327	0.576	29.95	0.286	0.376	20.53	0.258	0.454	16.42
A*–C	(0.099)***	(0.539)		(0.106)***	(0.698)		(0.117)**	(0.756)	
N	9,434	8,188		9,213	7,997		9,076	7,866	
5+ GCSE	0.057	0.134	29.95	0.045	0.108	20.53	0.039	0.151	16.42
A*–C	(0.011)***	(0.057)**		(0.012)**	(0.075)		(0.013)***	(0.086)*	
N	9,434	8,188		9,213	7,997		9,076	7,866	
Having	0.080	0.118	27.07	0.077	0.123	18.77	0.063	0.141	15.87
A levels	(0.009)***	(0.048)***		(0.009)***	(0.06)**		(0.011)***	(0.074)*	
N	7,291	6,387		7,098	6,220		6,986	6,113	
A-level	57.614	56.21	19.28	58.437	56.119	13.06	50.947	56.131	13.93
Points	(4.17)***	(19.00)***		(4.471)***	(24.212)***		(5.235)***	(28.151)**	
N	4,017	3,560		3,948	3,497		3,881	3,443	
Attend	0.079	-0.057	26.87	0.085	-0.102	18.38	0.085	-0.013	16.03
University	(0.011)***	(0.065)		(0.011)***	(0.089)		(0.012)***	(0.089)	
N	6,459	5,653		6,309	5,524		6,208	5,428	
Russell	0.042	0.097	20.33	0.041	0.101	16.23	0.050	0.166	15.65
University	(0.016)***	(0.077)		(0.017)***	(0.090)		(0.018)**	(0.100)*	
N	2,289	2,027		2,252	1,993		2,209	1,953	

Note: Std errors are in brackets. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***1%. Additional variables included are listed at p.14-15. IV Sample size, N, is different between IV and OLS because all students whose peers come from 1 primary school only do not have "peers of peers and are excluded. F is the Stock and Yogo test that suggests that, as a rule of thumb, one might consider instruments that result in an F below 10 as weak.

Table 4 *OLS and IV estimates of the impact of % of students not achieving basic standards in KS3 Mathematics on academic achievements*

	Model 1			Model 2			Model 3		
Outcomes	**OLS**	**IV**	**F**	**OLS**	**IV**	**F**	**OLS**	**IV**	**F**
# GCSE	-0.107	-0.190	84.31	-0.082	-0.017	71.33	-0.084	-0.187	49.82
A*–C	(0.042)**	(0.011)*		(0.046)*	(0.148)		(0.049)*	(0.162)	
N	9,410	8,135		9,168	7,947		9,168	7,947	
5+ GCSE	-0.018	-0.029	84.31	-0.012	-0.023	71.33	-0.012	-0.028	49.82
A*–C	(0.005)***	(0.012)**		(0.0057)**	(0.016)		(0.006)**	(0.018)	
N	9,410	8,135		9,168	7,947		9,168	7,947	
Having	-0.028	-0.027	87.73	-0.025	-0.022	71.58	-0.020	-0.031	50.87
A levels	(0.037)***	(0.012)**		(0.004)***	(0.015)		(0.0044)***	(0.018)*	
N	7,531	6,367		7,292	6,202		7,292	6,202	
A levels	-21.274	-22.31	80.94	-21.97	-23.68	65.12	-20.452	-21.30	49.22
Points	(1.98)***	(5.08)***		(2.187)***	(6.345)***		(2.308)***	(7.223)***	
N	4,082	3,537		4,005	3,475		4,005	3,475	
Attend	-0.028	-0.017	92.21	-0.030	-0.016	72.12	-0.029	-0.010	49.54
University	(0.004)***	(0.0138)		(0.004)***	(0.017)		(0.005)***	(0.020)	
N	6,642	5,638		6,461	5,510		6,461	5,510	
Russell	-0.017	-0.016	68.19	-0.018	-0.014	52.99	-0.019	-0.036	40.37
University	(0.006)***	(0.022)		(0.007)***	(0.027)		(0.007)***	(0.030)	
N	2,322	2,010		2,280	1,976		2,280	1,976	

Note: Std errors are in brackets. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***1%. Additional variables included are listed at p.14-15. IV Sample size, N, is different between IV and OLS because all students whose peers come from 1 primary school only do not have "peers of peers and are excluded. F is the Stock and Yogo test that suggests that, as a rule of thumb, one might consider instruments that result in an F below 10 as weak.

from their peers' ability and in particular, it is possible that weaker students are more heavily influenced by their peers' behaviour and achievements in class. For this reason, we follow Kang (2007) and use quantile regressions in order to analyse the potential heterogeneity of peers' interaction. The potential endogeneity of peers' ability is taken into account by using quantile instrumental variable regression.

Results from the estimation of Model 2 using quantile regression are reported in Tables 5–10. Our results confirm the main findings in previous literature (e.g., Kang, 2007; and Carrell et al., 2009) and show that peer effects are stronger at the bottom of the grade distribution. In particular, Table 6 shows that a one-standard-deviation increase in average peers' KS3 score increases the number of GCSE A*–C by 0.93, and by 0.78 in Model 2 for students in the 10^{th} and 15^{th} percentile of the GCSE distribution, while the effect is lower and then vanishes for students at the top of the grade distribution. This effect is sizeable, especially considering that students in these bottom percentiles are particularly weak, as they only achieve an average of 0.5 GCSE passes while the average in the estimation sample is 6.4 GCSE passes.

Results from the estimation of quantile regression on the effect of low ability peers strongly confirm that increasing the percentage of low ability peers is significantly detrimental for students at the bottom of the GCSE grade distribution. An extra 10 percent of high school peers who do not achieve basic standards in Mathematics decrease the number of GCSEs at passing A*–C grades by about 0.3 for students in the 20^{th} percentile of the grade distribution, while the effect is significantly smaller and then vanishes for top students. These results are confirmed when we estimate instrumental variable quantile regression, using the STATA routine *cqiv*. The confidence intervals of the true estimates of the effect of peers' ability are wide, but include the values found using OLS and confirm that the effect of peers' ability is higher at the bottom of the grade distribution (Table 6 and 7).

Interestingly, we do not see such a clear pattern with respect to A-level results, and students from the whole of the grade distribution seem to benefit from increased peers' quality in a similar way, and the effect of low-ability peers is also consistent across the grade distribution. Table 8 shows that a one standard deviation increase in peers' average Key Stage 3 score increases A level results by 71 points at the 15th quantile, and by 49th points in the 75th quantile, so the effect does decrease but it is significant throughout the distribution. Further, these results are confirmed when we estimate quantile instrumental variable regression (Table 9 and 10), which shows that the effect of peers' ability is relevant across most quantiles above the 20th.

The effect of low-ability peers also seem relevant across the grade distribution for A level results and a 10% increase in the proportion of peers who do not achieve basic standards in mathematics has a negative effect that ranges from 24 (5th percentile of A level distribution) to 20 points (75th percentile) in the individual A level score.

This difference with respect to GCSE results might be partially due to the fact that students who undertake A-levels will usually study in a different school (often a Sixth Form College) from the one they attended in the junior high years, so this model is actually estimating the effect of "past peers", as we rely on peers at the beginning of high school. Furthermore, A-level exams require a higher level of preparation than GCSEs, and it is possible that the quality of high school peers has a stronger effect on the students' preparation at this higher level.

All our main findings are confirmed when we estimate Model 3, including a wider set of independent variables and some school characteristics. The pattern of results is unchanged and we notice a strong effect of peers' quality on chances to take A-levels and on A-levels score, as well as a significant effect on students in the bottom quartile of the GCSE grade distribution.

We further investigate the impact of low ability peers and estimate the effect of the proportion of peers not achieving basic standards in Maths on the probability of taking A-levels in Mathematics or Science[3] and on the A-level points in these subject. These results are presented in Table 11 and show that having studied in a high school with an extra 10 percent of low-ability peers

[3] We group the following subjects under ''Science'': Biology, Chemistry, Physics (and any combination of two of these three subjects), Environmental Science, Psychology (as a Science), Technology, Zoology, Meteorology, Engineering Science, and Other Science.

decrease the probability of taking A-level in Maths or Science by about 3–4 percentage points, and decrease the A-level points in these subjects by about 9–10 percent of an s.d.

We test our main results using three sensitivity analyses. First, we re-estimate the model excluding observations from smaller than average high schools (with less than 600 students).[4] Large schools will typically draw from a larger number of junior schools and this is likely to lessen the problem associated with socioeconomic sorting in primary schools (see Appendix, Table 12). Secondly, we re-estimate results excluding high schools that are in regions that are largely rural[5] (e.g., Essex, Gloucestershire, Lancashire, etc.), where the students' population is more likely to be homogeneous (see Appendix, Table 13). Both these sensitivity tests confirm the main findings.

As a final sensitivity test, we estimate a model with primary school fixed effects in order to take into consideration the common unobserved characteristics of children who attended the same primary school (see Appendix, Table 14). Unfortunately, our data do not allow estimating a model with high school fixed effects, as we only have one observation of average peer KS3 score for all children attending the same high school and therefore there would not be any variation in our main variable of interest. The results are consistent with the previous findings from the OLS and IV estimates. Interestingly, in the fixed-effects model, peer ability has a significant effect on the probability of attending university.

Results for other independent variables are reported in Appendix Table 17. Not surprisingly, family socioeconomic status (and, in particular, maternal education) is a strong determinant of academic achievements, and so are previous test scores. Students from Asian backgrounds and those from single-sex schools also seem to perform better in all their exams.

[4] We also re-estimate the model limiting the sample to students who have at least 10 peers from the same high school in LSYPE. The substantive results are unchanged.

[5] We used the definition of rural areas from the Family Resource Survey data. The complete list of rural areas is: Berkshire, Bournemouth, Dorset and Poole, Cambridgeshire, Cheshire and Warrington, County Durham, Cumbria

Derbyshire, Devon and Cornwall, Essex, Gloucestershire, Hampshire and Isle of Wight, Herefordshire and Worcestershire, Hertfordshire, Humberside, Kent and Medway, Lancashire, Leicestershire, Lincolnshire and Rutland, Norfolk, North Yorkshire, Northumberland, Shropshire, Somerset, Staffordshire, Suffolk, Sussex, West Yorkshire, West of England, Wiltshire and Swindon.

Table 5 *Quantile Regression of the impact of peers' quality on GCSE passes*

	Model 1		Model 2		Model 3	
# GCSE A*–C	**Average peers quality**	**% Low quality peers**	**Average peers quality**	**% Low quality peers**	**Average peers quality**	**% Low quality peers**
P5	0.358	-0.155	0.205	-0.078	0.255	-0.107
	(0.117)***	(0.052)***	(0.116)*	(0.037)***	(0.130)**	(0.037)***
P10	0.972	-0.319	0.935	-0.285	0.898	-0.262
	(0.183)***	(0.056)***	(0.209)***	(0.048)***	(0.199)***	(0.058)***
P15	0.869	-0.315	0.788	-0.293	0.853	-0.294
	(0.169)***	(0.051)***	(0.197)***	(0.047)***	(0.173)***	(0.051)***
P20	0.812	-0.320	0.764	-0.299	0.762	-0.274
	(0.153)***	(0.057)***	(0.178)***	(0.047)***	(0.161)***	(0.046)***
P25	0.680	-0.263	0.621	-0.231	0.641	-0.237
	(0.126)***	(0.062)***	(0.141)***	(0.046)***	(0.131)**	(0.048)***
P50	0.358	-0.155	0.205	-0.078	0.255	-0.107
	(0.116)**	(0.052)**	(0.116)*	(0.036)***	(0.130)**	(0.037)***
P75	0.004	-0.014 (0.032)	-0.020	0.001 (0.023)	-0.023	-0.017
	(0.086)		(0.095)		(0.117)	(0.028)
N	9,434	9,410	9,213	9,168	9,076	9,168

Note: Std errors are in brackets. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***1%. Additional variables included are listed at p.14-15.

Table 6 *IV Quantile Regression of the impact of average peers' quality on GCSE passes – Model 2*

# GCSE A*–C	P5	P10	P15	P20	P25	P50	P75
_b	0.968	0.668	1.231	1.613	0.725	0.092	-0.283
Mean	1.009	0.842	1.421	1.458	0.961	0.029	-0.179
Lower bound	-0.318	-0.432	0.145	-0.203	-0.449	-0.792	-1.208
Upper bound	2.234	2.366	3.191	3.171	2.715	0.870	1.145

Note: Confidence intervals are reported. Results have been estimated with Stata routine cqiv with uncensored option and 50 bootstrap replications.

Table 7 *IV Quantile Regression of the impact of % low ability peers on GCSE passes – Model 2*

# GCSE A*–C	P5	P10	P15	P20	P25	P50	P75
_b	-0.333	-0.441	-0.266	-0.443	-0.189	-0.151	-0.153
Mean	-0.301	-0.420	-0.362	-0.384	-0.255	-0.170	-0.180
Lower bound	-0.623	-0.646	-0.613	-0.629	-0.541	-0.423	-0.364
Upper bound	0.034	-0.087	-0.091	-0.092	0.038	0.069	0.041

Note: Confidence intervals are reported. Results have been estimated with Stata routine cqiv with uncensored option and 50 bootstrap replications.

Table 8 *Quantile Regression of the impact of peers' quality on A level points*

	Model 1		**Model 2**		**Model 3**	
A-level	**Average peers**	**% Low quality**	**Average peers**	**% Low quality**	**Average peers**	**% Low quality**
P5	62.882 (4.875)***	-22.084 (2.596)***	64.956 (5.050)***	-23.975 (2.447)***	55.330 (6.155)***	-21.211 (2.616)***
P10	60.613 (7.297)***	-16.064 (2.570)***	61.652 (7.759)***	-15.862 (2.639)***	57.652 (8.477)***	-17.068 (3.525)***
P15	67.271 (6.862)***	-20.735 (3.120)***	70.917 (6.615)***	-21.747 (2.796)***	65.018 (7.719)***	-22.216 (3.971)***
P20	64.211 (5.875)***	-21.995 (3.080)***	65.974 (6.237)***	-21.930 (2.854)***	62.965 (7.728)***	-22.872 (3.567)***
P25	63.159 (5.654)***	-21.943 (2.877)***	62.097 (5.861)***	-21.913 (2.432)***	57.816 (6.786)***	-21.604 (3.244)***
P50	62.882 (4.875)***	-22.084 (2.596)***	64.956 (5.050)***	-23.975 (2.445)***	55.330 (6.155)***	-21.211 (2.616)***
P75	48.916 (4.727)***	-19.200 (2.547)***	49.316 (5.461)***	-20.282 (2.486)***	47.641 (6.931)***	-19.818 (2.684)***
N	4,017	4,084	3,948	4,005	3,881	4,005

Note: Std errors are in brackets. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***1%. Additional variables included are listed at p.14-15

Table 9 *IV Quantile Regression of the impact of average peers' quality on A level points – Model 2*

A level points	**P5**	**P10**	**P15**	**P20**	**P25**	**P40**	**P50**	**P60**	**P75**
_b	-3.750	45.554	67.669	33.728	29.574	76.649	61.906	55.955	43.184
Mean	11.959	36.984	64.887	47.381	47.004	71.455	79.560	64.045	56.964
Lower bound	-37.686	-23.068	13.389	-6.027	-20.923	16.712	29.462	12.774	12.596
Upper bound	66.775	101.735	115.815	112.045	116.093	132.924	131.954	116.603	103.704

Note: Confidence intervals are reported. Results have been estimated with Stata routine cqiv with uncensored option and 50 bootstrap replications.

Table 10 *IV Quantile Regression of the impact of % low quality peers on A level results– Model 2*

A level points	**P5**	**P10**	**P15**	**P20**	**P25**	**P50**	**P75**
_b	0.933	-7.449	-18.861	-16.498	-15.456	-27.413	-25.117
Mean	0.875	-8.758	-18.043	-18.982	-18.454	-27.667	-26.905
Lower bound	-9.701	-24.889	-32.963	-34.332	-34.860	-42.359	-43.852
Upper bound	13.286	5.870	0.151	-4.624	-2.433	-16.707	-11.663

Note: Confidence intervals are reported. Results have been estimated with Stata routine cqiv with uncensored option and 50 bootstrap replications.

Table 11 *OLS and IV estimates of the impact of % of low quality peers on A-level performance in Maths and Science*

	Model 2		
Outcomes	**OLS**	**IV**	**F**
Having A level in Maths	-0.028 (0.007)***	-0.0419 (0.016)***	80.94
A level points in Maths	-4.4764 (0.932)***	-6.236 (2.106)***	80.94
Having A level in Science	-0.041 (0.008)***	-0.046 (0.017)***	80.94
A levels points in Science	-6.717 (1.213)***	-6.529 (2.531)***	80.94
Sample size N	4,005	3,537	

Note: Std errors are in brackets. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***1%. Additional variables included are listed at p.14-15.

6. Conclusion

In this paper, we estimated the effect of peers' ability in English high schools using data from the Longitudinal Study of Young People in England (LSYPE) and measuring peers' ability using results in Key Stage 3 test scores at Age 14. While we focused our attention on the effect of average peers' ability, we also considered the effect of being in a school with a high proportion of low-achieving peers, and we have investigated the effect of peers' ability across the grade distribution using quantile-regression methods.

The main contributions of the work are that we analyse peers' effects on high-stakes outcomes at the end of high school using a very rich and recent dataset as well as using a new identification strategy based on the peers of peers. Briefly, we use information on primary school peers of individual's high school peers who attended different primary and high schools from the individual to instrument average high school's peers' ability. Peers of peers have never been in school with the individual and therefore could never have had a direct effect on her or his achievements.

Our findings show that average peers' ability does have a moderate effect on performance in GCSE exams at Age 16, and most of the effect is found for students at the bottom of the grade distribution. In particular, being in a school with a high proportion of low-achieving peers is particularly detrimental for the achievements of students in the bottom quartile of the GCSE distribution.

Results for A levels are less heterogeneous and show that increased peers' quality is significantly beneficial for all students across the grade distribution. Our results are stable to the introduction of a more detailed set of independent variables, including individual, family and school characteristics, and robust as well to IV regression and primary school fixed effects. Our results are broadly consistent with previous findings from the literature and in particular with Gibbons and Telhai (2015) and Lavy et al. (2012).

Our results imply that there are some indications of complementarities between students of different abilities. Even if it is particularly complex to draw clear policy implications related to students' ability mixing, we believe that these results show the detrimental effect of grouping low ability students with peers from similar ability level.

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Appendix

Table 12 Sensitivity to excluding students from small high schools (<600 students) Model 2

	Average peers quality			% Low quality peers		
Outcomes	**OLS**	**IV**	**F**	**OLS**	**IV**	**F**
# GCSE A*–C	0.393 (0.114)***	0.233 (0.743)	17.90	-0.158 (0.051)***	-0.140 (0.151)	70.07
5+ GCSE A*–C	0.071 (0.011)***	0.091 (0.078)	17.90	-0.028 (0.005)***	-0.019 (0.016)	70.07
Having A levels	0.073 (0.011)***	0.108 (0.064)*	17.09	-0.023 (0.005)***	-0.021 (0.015)	72.85
A levels Points	59.069 (4.486)***	54.322 (24.395)***	12.87	-22.843 (2.202)***	-22.649 (6.394)***	63.63
Having A levels in Maths	0.091 (0.017)***	0.147 (0.085)*	12.87	-0.030 (0.007)***	-0.044 (0.019)**	63.63
A levels Points in Maths	14.128 (2.324)***	24.973 (9.935)**	12.87	-4.659 (0.936)***	-6.308 (2.521)**	63.63

Note: Std errors are in brackets. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***1%. Additional variables included are listed at p.14-15.

Table 13 - Sensitivity to excluding students from rural areas – Model 2

	Average peers quality			% Low quality peers		
Outcomes	**OLS**	**IV**	**F**	**OLS**	**IV**	**F**
# GCSE A*–C	0.281 (0.158)*	1.041 (0.819)	25.67	-0.113 (0.066)*	-0.174 (0.189)	60.77
5+ GCSE A*–C	0.0319 (0.017)*	0.1503 (0.081)*	25.67	-0.011 (0.008)	-0.019 (0.020)	60.77
Having A levels	0.0773 (0.013)***	0.173 (0.065)***	22.59	-0.023 (0.006)***	-0.038 (0.018)***	59.31
A levels Points	55.611 (6.628)***	52.099 (22.461)***	15.06	-18.549 (2.856)***	-19.418 (7.01)***	61.90
Having A levels in Maths	0.099 (0.020)***	0.117 (0.079)	15.06	-0.028 (0.087)***	-0.041 (0.021)***	61.90
A levels Points in Maths	15.731 (3.139)***	18.530 (9.521)***	15.06	-4.557 (1.193)***	**-6.726 (3.078)*** **	61.90

Note: Std errors are in brackets. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***1%. Additional variables included are listed at p.14-15.

Table 14 Primary school fixed effects estimates of the effect of peers' ability on academic achievements – Model 2

Outcomes	Average peers quality	% Low quality peers
# GCSE A*–C	-0.032 (0.153)	-0.176 (0.063)***
5+ GCSE A*–C	0.00096 (0.021)	-0.017 (0.008)**
Having A levels	0.065 (0.027)***	-0.041 (0.011)***
A levels Points	34.051 (11.293)***	-23.284 (5.102)***
Attended University	0.0612 (0.032)*	-0.045 (0.013)***
Russell University	-0.046 (0.056)	-0.0052 (0.026)

Note: Std errors are in brackets. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***1%. Additional variables included are listed at p.14-15.

Table 15 - First stage results – Endogenous variable: average peers' quality (KS3 score) – Model 2(See Table 3)

	5+ GCSE A*-C		**# GCSE A*-C**		**Having A levels**		**A level Points**		**Attend university**		**Russell university**	
Male	-0.007	(0.023)	-0.007	(0.023)	0.0124	(0.029)	0.030	(0.045)	0.014	(0.032)	0.066	(0.053)
Imd score	-0.010	(0.001)***	-0.010	(0.001)***	-0.010	(0.000)***	-0.012	(0.001)***	-0.011	(0.001)***	-0.010	(0.001)***
KS2 score	0.140	(0.018) ***	0.140	(0.018)***								
5+ GCSE A*-C					0.217	(0.026)***	0.197	(0.030)***				
Taking A levels									0.195	(0.026)***		
A level Points											0.001	(0.000)***
Maternal Uni degree	0.200	(0.033) ***	0.200	(0.033)***	0.239	(0.039)***	0.250	(0.049)***	0.244	(0.040)***	0.186	(0.044)***
Other HE qual	0.095	(0.023) ***	0.095	(0.023)***	0.131	(0.027)***	0.167	(0.038)***	0.140	(0.029)***	0.158	(0.043)***
Senior high school graduate	0.065	(0.023)***	0.065	(0.023)***	0.099	(0.027)***	0.119	(0.042)***	0.112	(0.030)***	0.140	(0.050)***
Junior high school graduate	0.014	(0.018)	0.014	(0.018)	0.031	(0.021)	0.037	(0.032)	0.034	(0.023)	0.047	(0.042)***
Level 1 or below	0.011	(0.022)	0.011	(0.022)	0.010	(0.029)	0.018	(0.044)	0.015	(0.032)	0.037	(0.063)
Other qual	0.040	(0.033)	0.040	(0.033)	0.058	(0.041)	0.159	(0.064)**	0.071	(0.043)*	0.148	(0.086)*
Mother self-emp	0.028	(0.026)	0.028	(0.026)	0.019	(0.031)	0.023	(0.044)	0.015	(0.032)	0.045	(0.054)
Mother unemp	-0.047	(0.039)	-0.047	(0.039)	-0.091	(0.051)*	-0.061	(0.076)	-0.101	(0.051)**	-0.035	(0.111)
Mother out of labour force	-0.041	(0.016)**	-0.041	(0.016)***	-0.055	(0.020)***	-0.043	(0.026)*	-0.069	(0.023)***	-0.051	(0.032)
Father self-emp	0.036	(0.016)**	0.036	(0.016)**	0.032	(0.020)*	0.038	(0.027)	0.030	(0.021)	0.009	(0.032)
Father unemp	0.016	(0.033)	0.016	(0.033)	0.026	(0.037)	-0.006	(0.054)	0.022	(0.042)	-0.001	(0.077)
Father out of la-bour force	-0.009	(0.016)	-0.009	(0.016)	-0.024	(0.020)	-0.025	(0.028)	-0.022	(0.022)	-0.082	(0.036)**
Mother divorced	0.017	(0.019)	0.017	(0.019)	0.029	(0.024)	0.043	(0.042)	0.037	(0.027)	0.093	(0.051)*
Mother widow	0.016	(0.039)	0.016	(0.039)	0.021	(0.047)	0.115	(0.060)*	0.030	(0.050)	0.051	(0.080)
Maternal age	0.004	(0.001)***	0.004	(0.001)	0.004	(0.001)***	0.005	(0.002)***	0.005	(0.001)***	0.005	(0.002)***
Peers of peers average KS2	0.125	(0.028)***	0.125	(0.028)***	0.143	(0.033)***	0.157	(0.044)***	0.147	(0.034)***	0.176	(0.044)***
F stat	20.53		20.53		18.77		13.06		18.38		16.23	

Note: standard errors are in brackets. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***1%.

Table 16 - First stage results – Endogenous variable: % of Peers not achieving basic standards in KS3 Mathematics – Model 2 (See Table 4)

	5+ GCSE A*-C		**# GCSE A*-C**		**Having A levels**		**A level Points**		**Attend university**		**Russell university**	
Male	0.011	(0.043)	0.011	(0.043)	-0.033	(0.053)	-0.056	(0.072)	-0.039	(0.056)	-0.112	(0.084)
Imd score	0.031	(0.002)***	0.031	(0.002)***	0.031	(0.002)***	0.033	(0.003)***	0.032	(0.002)***	0.031	(0.003)***
KS2 score	-0.321	(0.043)***	-0.321	(0.043)***								
5+ GCSE A*-C					-0.492	(0.060)	-0.408	(0.067)***				
Taking A levels									-0.421	(0.059)***		
A level Points											-0.002	(0.000)***
Maternal Uni degree	-0.380	(0.064)***	-0.380	(0.064)***	-0.471	(0.066)***	-0.465	(0.081)***	-0.478	(0.067)***	-0.335	(0.092)***
Other higher education	-0.253	(0.056)***	-0.253	(0.056)***	-0.335	(0.063)***	-0.371	(0.078)***	-0.349	(0.066)***	-0.291	(0.096)***
Senior high school graduate	-0.179	(0.059)***	-0.179	(0.059)***	-0.253	(0.065)***	-0.297	(0.086)***	-0.282	(0.070)***	-0.254	(0.111)***
Junior high school graduate	-0.096	(0.049)**	-0.096	(0.049)**	-0.125	(0.057)***	-0.132	(0.075)*	-0.116	(0.061)*	-0.134	(0.098)
Level 1 or below	-0.069	(0.058)	-0.069	(0.058)	-0.077	(0.072)**	-0.151	(0.101)	-0.076	(0.078)	-0.185	(0.140)
Other qualification	-0.028	(0.087)	-0.028	(0.087)	0.069	(0.111)	-0.147	(0.140)	0.014	(0.115)	-0.094	(0.183)
Mother self-emp	-0.001	(0.049)	-0.001	(0.049)	0.006	(0.057)	0.060	(0.075)	0.022	(0.059)	-0.013	(0.099)
Mother unemp	0.244	(0.112)**	0.244	(0.112)**	0.305	(0.146)**	0.092	(0.181)	0.331	(0.151)**	0.077	(0.245)
Mother out of the labour force	0.204	(0.045)**	0.204	(0.045)**	0.247	(0.056)**	0.212	(0.055)***	0.280	(0.061)***	0.253	(0.069)
Father self-employed	-0.069	(0.037)*	-0.069	(0.037)*	-0.046	(0.043)	-0.038	(0.051)	-0.043	(0.045)	0.045	(0.061)
Father unemployed	0.036	(0.087)	0.036	(0.087)	-0.016	(0.094)	0.040	(0.134)	0.015	(0.103)	0.155	(0.178)
Father out of the labour force	0.016	(0.043)	0.016	(0.043)	0.036	(0.051)	0.012	(0.064)	0.031	(0.056)	0.124	(0.082)
Mother is divorced	0.012	(0.048)	0.012	(0.048)	-0.022	(0.061)	-0.052	(0.090)	-0.046	(0.065)	-0.107	(0.114)
Mother is a widow	-0.032	(0.099)	-0.032	(0.099)	0.040	(0.117)	-0.106	(0.136)	0.024	(0.131)	0.072	(0.190)
Maternal age	-0.007	(0.003)***	-0.007	(0.003)***	-0.008	(0.003)***	-0.007	(0.004)***	-0.009	(0.004)***	-0.008	(0.005)
% Peers of peers not basic Maths	0.278	(0.033)***	0.278	(0.033)***	0.300	(0.035)***	0.318	0.039	0.304	(0.036)	0.312	(0.043)***
F stat	71.33		71.33		71.58		65.12		72.12		52.99	

Note: standard errors are in brackets. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***1%.

Table 17 – Results from OLS regression for the effect of other independent variables - Model 2 (see Table 3)

	#GCSE A*-C	5+ GCSE A*-C	Having A levels	A level Points	Attend university	Russell university
Male	-0.061 (0.008)***	-0.832(0.069)***	-0.044 (0.010)***	-18.026 (3.978)***	-0.033 (0.011)***	0.023 (0.017)
Imd score	-0.002(0.000)***	-0.007 (0.003)**	-0.000 (0.000)	0.015 (0.148)	0.000 (0.000)	0.000 (0.001)
KS2 score	0.287 (0.005)***	2.663 (0.037)***				
5+ GCSE A*-C			0.493 (0.012)***	131.428 (4.855)***		
Taking A levels					0.347 (0.013)***	
A level Points						0.002 (0.000)***
Maternal **u**ni degree	0.078 (0.016)***	0.515 (0.129)***	0.078 (0.020)***	39.258 (7.255)***	0.013 (0.022)	0.081(0.032)**
Other higher education	0.025 (0.015)	0.170 (0.123)	0.049 (0.019)***	6.197 (7.552)	-0.011 (0.021)	0.022(0.032)
Senior high school grad	0.004 (0.016)	-0.041 (0.127)	0.001(0.019)	-2.646 (6.887)	-0.024 (0.022)	-0.025 (0.033)
Junior high school grad	-0.033 (0.012)***	-0.314 (0.107)***	0.010(0.016)	-9.315 (6.415)	-0.053 (0.017)***	-0.073 (0.027)***
Level 1 or below	-0.056 (0.017)***	-0.608 (0.147)***	-0.065 (0.021)***	-42.563 (9.660)***	-0.054 (0.026)**	-0.053 (0.041)
Other qualification	-0.070 (0.026)***	-0.285 (0.205)	0.031 (0.033)	7.238 (12.080)	-0.019 (0.036)	-0.070 (0.049)
Mother self-employed	-0.006 (0.017)	-0.066 (0.128)	-0.018 (0.022)	4.976 (7.604)	-0.024 (0.025)	0.012 (0.036)
Mother unemployed	-0.027 (0.030)	-0.322 (0.232)	-0.018 (0.039)	8.665 (18.515)	-0.021 (0.039)	-0.069 (0.062)
Mother out of labour force	0.026 (0.011)**	0.190 (0.085)**	0.033 (0.013)***	12.670 (5.169)**	-0.014 (0.015)	-0.011 (0.021)
Father self-employed	0.006 (0.011)	0.052 (0.084)	-0.009 (0.014)	-5.741 (4.628)	-0.012 (0.017)	0.007 (0.023)
Father unemployed	-0.026 (0.023)	0.234 (0.214)	0.004 (0.031)	4.111 (12.215)	-0.104 (0.032)***	-0.002(0.054)
Father out of labour force	-0.052 (0.012)***	-0.733 (0.097)***	-0.058 (0.014)***	-26.636 (5.817)***	-0.049(0.017)***	-0.015 (0.028)
Mother is divorced	-0.025 (0.015)*	-0.180 (0.117)	-0.036 (0.017)**	-2.429 (7.673)	-0.026 (0.020)	0.008 (0.033)
Mother is a widow	0.023 (0.031)	0.307 (0.268)	0.027 (0.039)	4.966 (12.380)	-0.020 (0.046)	0.114 (0.073)
Maternal age	0.004 (0.001)***	0.039 (0.006)***	0.005 (0.001)***	1.839 (0.379)***	0.001 (0.001)	-0.001 (0.002)

Note: standard errors are in brackets. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***1%.

Table 18 – Results from OLS regression for the effect of other independent variables - Model 3(see Table 3)

	N. GCSE A*-C	**5+ GCSE A*-C**	**Having A levels**	**A level Points**	**Attend university**	**Russell university**
Male	-0.058 (0.008)***	-0.819 (0.067)***	-0.041 (0.010)***	-16.798 (3.991)***	-0.034 (0.011)***	0.023 (0.017)
Imd score	-0.002 (0.000)***	-0.015 (0.003)***	-0.001 (0.000)**	-0.205 (0.155)	-0.002 (0.000)***	-0.000 (0.001)
KS2 score	0.288 (0.005)***	2.656 (0.037)***				
5+ GCSE A*-C			0.485 (0.012)***	130.789 (5.035)***		
Taking A levels					0.328 (0.013)***	
A level Points						0.002 (0.000)***
Mixed gender school	-0.004 (0.017)	0.048 (0.158)	-0.044 (0.017)***	-16.494 (6.300)***	-0.018 (0.019)	-0.023 (0.026)
Asian	0.133 (0.014)***	1.491 (0.136)***	0.114 (0.015)***	19.448 (6.585)***	0.150 (0.017)***	0.047 (0.023)**
Black	0.026 (0.022)	0.635 (0.189)***	-0.003 (0.027)	-2.158 (8.608)	0.086 (0.028)***	0.037 (0.040)
Religious schools	0.036 (0.016)**	0.096 (0.148)	0.010 (0.017)	-3.262 (6.237)	0.017 (0.020)	0.010 (0.028)
Total n. students	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)***	-0.001 (0.006)	0.000 (0.000)	0.000 (0.000)
Maternal Uni degree	0.114 (0.016)***	0.914 (0.125)***	0.118 (0.020)***	48.240 (7.604)***	0.068 (0.023)***	0.104 (0.034)***
Other higher education	0.061 (0.015)***	0.554 (0.120)***	0.088 (0.019)***	14.881 (7.987)*	0.039 (0.022)*	0.044 (0.032)
Senior high school graduate	0.046 (0.016)***	0.370 (0.122)***	0.041 (0.020)**	6.786 (7.475)	0.032 (0.022)	-0.010 (0.034)
Junior high school graduate	0.009 (0.012)	0.122 (0.099)	0.050 (0.016)***	0.113 (6.898)	0.002 (0.018)	-0.061 (0.028)**
Level 1 or below	-0.008 (0.018)	-0.133 (0.143)	-0.029 (0.021)	-34.494 (9.846)***	-0.001 (0.026)	-0.042 (0.041)
Other qualification	-0.044 (0.026)*	0.010 (0.197)	0.053 (0.033)	13.270 (12.479)	0.014 (0.036)	-0.059 (0.050)
Mother self-employed	-0.007 (0.017)	-0.074 (0.126)	-0.013 (0.022)	4.754 (7.741)	-0.021 (0.025)	0.014 (0.037)
Mother unemployed	-0.041 (0.030)	-0.393 (0.228)*	-0.007(0.040)	6.057 (18.523)	-0.033 (0.039)	-0.049 (0.065)
Mother out of the labour force	-0.000 (0.011)	-0.076 (0.082)	0.015 (0.013)	8.464 (5.342)	-0.035 (0.015)**	-0.009 (0.021)
Father self-employed	0.000 (0.011)	-0.025 (0.082)	-0.017 (0.014)	-6.456 (4.714)	-0.017 (0.017)	0.009 (0.023)
Father unemployed	-0.044 (0.023)*	0.080 (0.213)	-0.001 (0.030)	1.832 (11.815)	-0.129 (0.032)***	0.016 (0.055)
Father out of the labour force	-0.051 (0.012)***	-0.703 (0.094)***	-0.050 (0.015)***	-26.348 (5.873)***	-0.050 (0.016)***	-0.014 (0.029)
Mother is divorced	-0.016 (0.015)	-0.101 (0.116)	-0.033 (0.018)*	0.095 (7.691)	-0.011 (0.020)	0.004 (0.034)
Mother is a widow	0.013 (0.031)	0.172 (0.260)	0.013 (0.039)	2.978 (12.557)	-0.040 (0.044)	0.117 (0.072)
Maternal age	0.004 (0.001)***	0.038 (0.006)***	0.005 (0.001)***	1.902 (0.386)***	0.001 (0.001)	-0.000 (0.002)

Note: standard errors are in brackets. * indicates that the underlying coefficient is significant at 10% level, ** at 5% and ***1%. Coefficients of Government Office Regions are available on request