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ESTIMATING PEER EFFECTS IN SWEDISH HIGH SCHOOL USING SCHOOL, TEACHER, AND STUDENT FIXED EFFECTS

by

Krister Sund

Estimating Peer Effects in Swedish High School using School, Teacher, and Student Fixed Effects*

Krister Sund‡
SOFI

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Abstract
In this paper I use a rich dataset in order to observe each student over time in different subjects and courses. Unlike most peer studies, I identify the peers and the teachers that each student has had in every classroom. This enables me to handle the simultaneity and selection problems, which are inherent in estimating peer effects in the educational production function. I use a value-added approach with lagged peer achievement to avoid simultaneity and extensive fixed effects to rule out selection. To be specific, it is within-student across-subject variation with additional controls for time-invariant teacher characteristics that is exploited. Moreover, I identify students that are attending classes in which they have no peers from earlier education which otherwise could bias the result. I find positive peer effects for the average student but also that there is a non-linear dimension. Lower-achieving students benefit more from an increase in both mean peer achievement and the spread in peer achievement within the classroom than their higher-achieving peers.

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‡ Swedish Institute for Social Research (SOFI), Stockholm University, SE-106 91 Stockholm, SWEDEN.
E-mail: Krister.Sund@sofi.su.se, phone: +46 (0)8 16 23 07.

1. Introduction

In economics of education, peer effects in the educational production function have increasingly become a point of interest over the years. Do peers influence student outcome and, if so, in what way? The presence of peer effects and their workings may have implications for education policy, such as how to allocate students with respect to their ability or whether you should allow for an increased latitude of school choice in society. Proponents of ability grouping (or tracking) argue that in classrooms with a homogeneous ability distribution the teacher is better able to reach all students in the classroom when teaching. However, there is not much evidence to support this view. Studies have found that tracking has differential effects; detracking schools has had positive effects for lower-achieving students but none or negative effects for high achievers (e.g. Betts and Shkolnik, 2000; Zimmer, 2003; Sund, 2006). This suggests that non-linear peer effects might be present, low-achieving students benefit more from being placed together with high-achieving peers while there are no or small effects on students at the high end of the ability distribution. If such non-linear peer effects are at hand, tracking policies would do more harm than good.

Estimating peer effects is difficult since there are confounding effects that are likely to bias the results. There are primarily two issues that are problematic, namely selection and simultaneity. Selection, in that students are not randomly assigned to schools. Parents actively choose where to reside so school composition will reflect neighborhood characteristics. High-achieving students end up going to the same schools due to their parents' choice, thus there will be a spurious correlation between student and peer achievement. If one can not control for this selection, peer achievement might seem important even though it is not. Different approaches to finding exogenous variation in peer composition have been used. Sacerdote (2001) uses the random procedure of pairing up students with their roommates in college. Others have exploited within-school variation and used school fixed effects (e.g. Schneeweis and Winter-Ebmer 2006). The idea behind this is to account for systematic differences in family background that are correlated with school choice. Age variation within neighborhoods has also been used. There is evidence that students born early in the year perform on average better than students born later. Thus, variation in birth month composition of peers within neighborhoods and across time is used in Goux and Maurin (2006).

The simultaneity problem arises from the fact that if the achievement of peers has an influence on a student's achievement, that student will also have an influence upon his or her peers. This is the so-called reflection problem (see Manski 1993). To avoid this, Hanushek et al., (2003) use lagged achievement as their peer measure to avoid simultaneity, whereas Ammermueller and Pischke (2006) use predetermined peer variables that are correlated with achievement such as the number of books at home.

Numerous studies have found evidence of positive peer effects in that achievement increases for students when they are placed together with high-achieving peers (see for instance Summers and Wolfe 1977; Hoxby 2000; Hanushek et al. 2003). The results in Vigdor and Nechyba (2005), however, were inconclusive. There are also studies that address the potential non-linear impact of peer effects (Schindler-Rangvid 2003; Winston and Zimmerman 2003). Peer effects might influence students differently depending on their initial ability. The findings suggest that peer effects are stronger for low-performing students. This supports the non-linear peer effects found in the tracking studies above to a certain extent. If it were true that in the classroom high-achieving peers directly help lower achievers, then this would suggest a non-linear peer effect. The students at the low end of the ability distribution within a classroom learn from better-achieving peers whereas the students at the high end do not have this advantage since there is no better-achieving peer for them to learn from.

In this paper, I use a fixed effects approach to avoid potential selection and lagged achievement to avoid simultaneity when estimating the peer influence on achievement for Swedish high school students at the classroom level. I start with a baseline model estimating peer impact on mean achievement and then move on to analyzing potential differential effects of peer achievement. I have rich data where I for several cohorts in the municipality of Stockholm observe each student over time in different subjects and courses. Unlike most peer studies, I identify the peers and the teachers that each student has had in every classroom. The dataset enables me to use within-student across-subject variation for each year in order to counteract potential selection but also enables me to control for unobservable teacher specific components.

Further, by using the transition from compulsory school to high school additional variation is exploited. In Sweden this transition implies a considerable change for the students. Almost all students attend an entirely new school when they start high school at the age of 16. Moreover, the catchment areas for high schools are often larger than the catchment areas for compulsory schools. Thus, when students are allocated to different high school classes, they will be placed together with peers from compulsory schools and neighborhoods other than their own. In the sample used, around 40 percent of the students were allocated to classes in which they have no prior peers. Thus, not only am I able to link peers and teachers together at the classroom level but I can also estimate peer effects on students that attend classes in which they are altogether subjected to new classmates.

Furthermore, in 2000 there was a change in the high school admission rules in the municipality of Stockholm. Prior to this change, admission was based on grades and distance. Those residing in the catchment area of a high school had precedence over students that were not residents. In 2000, this changed. From then on, admission has been based on grades alone and students in the municipality of Stockholm are free to apply to whatever high school they want. If a school gets more applicants than there are slots, students will be admitted based on the ranking of their final grades from compulsory school. This implies that from 2000, the composition of peers in classrooms might have changed. Geographical selection is likely to have decreased but selection in terms of achievement and motivation is more likely to have increased after the reform. Thus, selection on achievement has most likely increased, which makes it even more important to be able to control for school fixed effects during this period.

From the baseline specification with school, teacher and student fixed effects my findings are that on average there are positive peer effects in Swedish high schools, one standard deviation increase in mean peer grade point average (GPA) within the classroom corresponds to a 0.08 standard deviation increase in student grades. Moreover, I find positive effects from increased classroom heterogeneity. On average, an increase in the standard deviation in peer GPA will have positive effects on student high school grades. One standard deviation increase in the spread corresponds to a 0.02 standard deviation increase in student grades. There is also evidence of non-linear peer effects. Students that graduated from compulsory school at the lower end of the achievement distribution will benefit from being placed in classes with a wider achievement distribution, i.e., there being a greater distance to the top achievers in the class.

The paper proceeds as follows. Section 2 describes potential problems when estimating peer effects and how previous work has dealt with this problem. In section 3 I proceed to present the dataset and the empirical strategy. The results and sensitivity analysis in section 4 are followed by conclusions.

2. Previous studies

Numerous attempts have been made to estimate the impact of peers in the educational production function. Common for all these attempts are the problems of selection and simultaneity discussed above. To organize the discussion of previous studies let us consider the following value-added specification as our baseline model

$$A_{it} = \alpha_1 S_{it} + \beta_1 F_{it} + \delta_1 P_{it} + \lambda A_{t-1} + \mu_i + \nu_{it} \,. \tag{1}$$

where A_{it} is individual i's achievement at time t. S_{it} and F_{it} is school and family input at time t. P_{it} captures peer effects and A_{t-1} is lagged achievement.

The idea here is that A_{t-1} serves as a sufficient statistic of past peer, school, and family inputs up to period t since in reality all past input variables are rarely available. μ_i captures individual or family specific effects and ν_{it} is the error term. Assume that there is selection present with high-achieving students ending up in the same school due to their parents' residential choice. This is captured by the family input variable F_{it}. Assume that this information is not at hand, what would the result be? The consequence will be that peer effects will appear important even if they are completely irrelevant. However, the lack in family input can be compensated by school input information. Using within-school variation will eliminate any such selection bias. In the specification above, this translates as replacing input F_{it} with a component γ_s that captures school specific effects. This approach is used by McEwan (2003), who can identify different classrooms in schools from a 1997 cross-section in Chile. He finds that peers have a positive impact on student achievement in math and Spanish. However, not every study has the advantage of data that allow for classroom identification. Hoxby (2000) and Hanushek et al. (2003), use across-cohort variation in schools in order to account for selection bias. The assumption is that even if parents actively decide which school to enroll their children in, there will be some variation in the composition of the student body between cohorts in schools which parents cannot foresee. The studies report evidence of positive peer effects. Even though they both use Texas panel data (grades three through six) they handle the simultaneity problem somewhat differently.

The problem of simultaneity is more of a two-way causality issue between A_{it} and P_{it}. For instance, if positive peer effects are present, consider the situation when a student is placed together with higher-achieving peers. This increases the student's performance, which in turn spills over to his/her peers and thus causes simultaneity. To counteract this, Hoxby

(2000) McEwan (2003) and Ammermueller and Pischke (2006) use predetermined variables as peer instruments for input P_{it}. Hoxby uses individual characteristics such as gender and race, which are correlated with achievement to avoid simultaneity, whereas McEwan uses information on the parents' education among other things. The challenge is finding exogenous variations that are correlated with student achievement. The number of books at home is used in Ammermueller and Pischke (2006), who present evidence of positive peer effects from their within-school estimations. They use PIRLS data on fourth-graders from six European countries. Others have simply avoided contemporary measures and used lagged peer variables, e.g. $\overline{A}_{-it-1}$ as their peer measure instead of *P* where *-i* indicates that it is the mean achievement ($\overline{A}$) among peers excluding student *i*, the student of interest. For example, Hanushek et al. (2003) use prior mean and standard deviation in math achievement as their peer measure.

Sass and Burke (2006) have classroom level information on peers and teachers for students in Florida, which enables them to include both student and teacher fixed effects. They exploit peer group variation in movement, age and disabilities which they argue are exogenous to student achievement when constructing their instrument for contemporaneous peer achievement. The results are mixed as regards peer influence on mean achievement, but nevertheless, they find evidence of non-linear peer effects when interacting previous achievement with mean peer achievement. Students situated in the lower quintile seem to benefit more from increases in peer achievement than students in higher quintiles.

Gibbons and Telhaj (2006) use the change in peer group composition caused by the transition from primary to secondary school in England. The data that they use enable them to compare student outcome of children that grew up in the same street and attended the same primary school but later on attended different secondary schools, thus they exploit within-neighborhood variation. Their outcome variable is test scores in math and English at the age of 14 whereas their peer measure is lagged test scores at the age of 11. They find small but positive effects of peer achievement; an increase of one standard deviation in peer achievement corresponds to a 0.05-0.08 standard deviation increase in student achievement.

My study combines the approaches in the two latter papers and takes the peer analysis one step further. Not only can I - like Sass and Burke (2006) - identify peers and teachers at the classroom level, but I can also - similarly to Gibbons and Telhaj (2006) - use the variation that arises from the transition from compulsory school to high school. This latter feature enables me to estimate peer effects for students who attend classes with completely new peers.

3. Data

The dataset I have constructed for this study stems from the municipality of Stockholm and their high school database (HANNA). The advantage of this dataset is that it is possible to identify each classmate with whom a student has taken a specific course. This enables me to match peers and teachers to every student in each and every course. Thus, I am not only able to use within-school variation to estimate peer effects, but also control for individual and teacher fixed effects. This is important since the strategy of using within-school variation hinges on the assumption that achievement is exogenous when students are allocated to different classes. Even if school officials say that they strive to obtain an equal mix within classrooms with respect to gender, ability and ethnic background when they allocate students in different schools this seems not to be the case.[2] When testing for equal coefficients of variation at the classroom and school level the hypothesis of equal coefficients does not hold. The coefficient of variation is larger at the school level as compared to classroom level which suggests that there might be systematic differences in achievement between classes within schools. However, this problem is dealt with by using within-student variation together with controls for time-invariant teacher characteristics.

[2] I have been in contact with school officials responsible for the allocation of students in different schools in the municipality of Stockholm. All the respondents said that when students are allocated a great effort is made to ensure that the classes are as equal in composition as regards achievement, gender, and ethnic background.

The database also contains information from which I can extract teacher age and gender, but also class size and classroom gender composition.

My outcome variable is the course grade in high school which – besides being a mere measure of achievement - determines admittance to higher education in Sweden. When applying to tertiary education, the GPA is one of two main screening devices, the other one being the national university aptitude test.[3] These two are interchangeable and cannot be used in combination, either a student applies for tertiary education using grades or using his or her test result. The grade is reported in four levels: "fail", "pass", "pass with distinction" and "pass with special distinction". I use the corresponding numerical values that are given to each grade when calculating the GPA; for application to university these values are 0, 10, 15 and 20. Obviously, an outcome that has more variance than the four scale grade measure would have been preferable, but the national tests[4] that are given in Sweden are not recorded in any database or register for the period of interest.

On to the dataset I have merged information from Statistics Sweden's *Student Register, Year 9* (*Årskurs 9-registret*), which contains compulsory school information (normally at the age of 16) such as grades, year of graduation, school identifier, foreign background and parental education. Parental education is divided into three different levels: at most 9 years of formal schooling, at most upper-secondary education and tertiary education. It is the parent with the highest level of education that I use as my measure of parental education. I use the final subject grade from compulsory school as my main peer measure when calculating the mean subject grade and the standard deviation in achievement - excluding student *i* - for peers within a classroom in high school. The assumption is that a student will benefit from having a

[3] At least two thirds of the slots in tertiary education are reserved for applicants in the grade or test score quota. Schools are free to choose how to use the last third of their slots so they could, for example, allocate two thirds of the slots to applicants using grades and one third of the slots to applicants applying with test scores.
[4] National tests are given in the core subjects math, Swedish and English to serve as a calibrating tool for teachers when grading students.

larger share of high-achieving students within the classroom, and possibly negative from the opposite. Moreover, the information in Statistics Sweden's register data together with the information in HANNA enable me to construct a measure of the share of students within a classroom with a foreign background. Additional teacher information from Statistics Sweden's *Teacher Register* (*lärarregistret*) has also been merged on to the dataset. The register provides information regarding whether the teacher has a foreign background or not.

The sample consists of students enrolled in upper-secondary education between 1998 and 2004, who graduated from compulsory school after 1997. The reason for the latter restriction is that there were schools that tracked their students in English and math up to 1997, which makes their grades incomparable. I use the grades from compulsory school to construct my peer measure and therefore limit the analysis to subjects that are given both at the compulsory and high school level. Thus, I estimate peer effects in the first course taken in the subjects math, Swedish, Swedish as a second language, English and sports. The courses usually stretch over two semesters. I have restricted the sample to those students attending any of the so-called 17 different national programs[5] in order to avoid potentially mixed classes where different subjects are taught within the same classroom. This is sometimes the case among the students enrolled in the so-called individual program.[6] Moreover, some students have multiple observations of the same subject grade but at different points in time. The reason is that some students retake a course in order to improve their grade. I only use the first high school grade reported for these students even though their grade from compulsory school is used when calculating the peer measures in courses they have retaken.

It should be stressed that the HANNA database is not primarily intended for research and is thus not flawless. The information in the database is recorded by principals, teachers

[5] Swedish high school education consists of 17 different programs (tracks), 14 with a vocational orientation, such as construction and auto shop, and three programs with a more academic orientation.
[6] The individual program consists of students who have had problems in compulsory school and graduated with poor grades, failing several subjects. These students do not qualify for any of the national programs in high school but are placed in the individual program. There they get assistance in order to later on be integrated into any of the national programs.

and other administrative staff at the different schools, which means there is room for errors. There are, for example, observations with missing teacher information. Even if these errors occur randomly they will still cause missing values and force me to drop observations. I have restricted class size to no smaller than 10 students; small classes might be reporting errors or possibly classes in which different subjects are taught simultaneously. Taken together, these restrictions reduce the number of unique individuals in the sample by almost 10 percent.

Descriptive statistics are presented in table 1. From the table we see that women are slightly overrepresented at the high school level both among students and teachers. However, what is more interesting is that the share of students that are subjected to entirely new peers increased by 50 percent after the implementation of the new admission rules in 2000. The share of students attending classes in which they have no prior peers was around 30 percent before the reform and almost 45 after.

4. Empirical strategy

Consider the cumulative achievement production function following Todd and Wolpin (2003) and Sass (2006), who model student achievement as a function of contemporary and past inputs from family and school.[7] We can then describe the achievement production function using the equation:

$$\begin{aligned} A_{it} &= \alpha_1 S_{it} + \alpha_2 S_{it-1} + \cdots + \alpha_t S_{i1} \\ &\quad + \beta_1 F_{it} + \beta_2 F_{it-1} + \cdots + \beta_t F_{i1} + \delta_1 P_{it} + \delta_2 P_{it-1} + \cdots + \delta_t P_{i1} + \phi_i + \varepsilon_{it} \end{aligned} \tag{2}$$

where A_{it} is individual i's achievement at time t, S_{it} is school input, F_{it} and P_{it} are family and peer input for individual i at time t and ϕ_i represents time-invariant student specific effects.

Estimating equation (2) requires data on current and all past school and family inputs that are rarely available. However, it is reasonable to assume that recent school, family and peer input will have more weight on current achievement than earlier input. Thus, one can

[7] For a more general exposition see Hanushek (1979)

assume that all prior input will decline in weight with distance to the outcome measure. If we assume that past inputs decline with λ from *t-1* to *t* and λ^2 from *t-2* to *t* so that $\alpha_2 = \lambda\alpha_1$ and $\alpha_3 = \lambda^2\alpha_1$ and that the achievement production function at *t-1* is:

$$\begin{aligned} &A_{it-1} = \alpha_1 S_{it-1} + \alpha_2 S_{it-2} + \cdots + \alpha_t S_{i1} \\ &+\beta_1 F_{it-1} + \beta_2 F_{it-2} + \cdots + \beta_t F_{i1} + \delta_1 P_{it-1} + \delta_2 P_{it-2} + \cdots + \delta_t P_{i1} + \phi_i + \varepsilon_{it-1}. \end{aligned} \tag{3}$$

Taking first the differences between achievement at *t* and achievement at *t-1* yields

$$\begin{aligned} A_{it} - \lambda A_{it-1} = {} & [\alpha_1 S_{it} + \lambda\alpha_1 S_{it-1} + \cdots + \lambda^{t-1}\alpha_1 S_{i1} \\ & +\beta_1 F_{it} + \lambda\beta_1 F_{it-1} + \cdots + \lambda^{t-1}\beta_1 F_{i1} + \delta_1 P_{it} + \lambda\delta_1 P_{it-1} + \cdots + \lambda^{t-1}\delta_1 P_{i1} + \phi_i + \varepsilon_{it}] \\ & -\lambda[\alpha_1 S_{it-1} + \lambda\alpha_1 S_{it-2} + \cdots + \lambda^{t-2}\alpha_1 S_{i1} \\ & +\beta_1 F_{it-1} + \lambda\beta_1 F_{it-2} + \cdots + \lambda^{t-2}\beta_1 F_{i1} + \delta_1 P_{it-1} + \lambda\delta_1 P_{it-2} + \cdots + \lambda^{t-2}\delta_1 P_{i1} + \phi_i + \varepsilon_{it-1}]. \end{aligned} \tag{4}$$

By simplifying and rewriting this, we get

$$A_{it} = \alpha_1 S_{it} + \beta_1 F_{it} + \delta_1 P_{it} + \lambda A_{t-1} + \mu_i + \nu_{it} \tag{5}$$

where λ represents the influence from achievement at time *t-1* on achievement at *t*, $\nu_{it} = \varepsilon_{it} - \lambda\varepsilon_{it-1}$ is the error term and $\mu_i = \phi_i - \lambda\phi_i$ represents the family/individual specific component.

Equation (5) is the unrestricted value-added specification with a lagged dependent variable on the right hand side. The lagged variable might introduce autocorrelation due to correlation between the lagged variable and part of the error term. If autocorrelation is present, the OLS estimate will be biased. In order to avoid this problem one can rewrite the equation in terms of achievement gains:

$$\Delta A_{it} = \alpha_1 S_{it} + \beta_1 F_{it} + \delta_1 P_{it} + \pi_{it}. \tag{6}$$

Both specifications have been used in previous studies even though (6) is the more prevalent one. Even if the potential problem of autocorrelation is avoided in the latter specification, the model with gain scores hinges on the assumption that $\lambda = 1$, which implies that past input have an immediate one-time impact that does not decay over time. As described by Sass

(2006), this implies that the impact of a child's kindergarten teacher on achievement is the same at the age of 18 as at the age of 5.

None of the specifications is flawless. The unrestricted model might introduce autocorrelation and the restricted one makes unrealistic assumptions about the impact of past input. Due to the fact that my outcome variable only takes four different values and that I utilize within-individual across-subjects variation, the achievement gains measure will introduce problems. There are floor and ceiling effects when estimating using student fixed effects. For example, a student with top grades can only move in one direction. Moreover, I will also lose variation in cases where individuals have the same subject grade in compulsory and high school even if there are variations across subjects.

Therefore I use the unrestricted specification with lagged achievement on the right hand side when estimating peer effects. The empirical model estimated is

$$\begin{aligned} A_{isyfTt} = {} & \beta_1 F_{isyfTt} + \delta_1 \overline{A}_{-isyfTt-1} + \delta_2 SDA_{-isyfTt-1} + \delta_3 P_{-isyfTt} + \chi T_{isyft} + \gamma_1 A_{isfyTt-1} \\ & + \phi_i + \gamma_s + \eta_y + \mu_T + \nu_{it}, \end{aligned} \tag{7}$$

where A_{isyfTt} is the subject grade in the first course taken in high school for individual *i*, in school *s*, in school year *y*, in subject *f*, with teacher *T*. *F* is parental education level as explained above. $\overline{A}_{-isyfTt-1}$ is one of my peer measures of interest. It is the prior mean achievement in subject *f* of all peers within a classroom except peer *i*. The achievement measure is the final subject grade in subject *f* from compulsory school. The other peer measure is the within classroom standard deviation in peer achievement in the subject of interest, $SDA_{-isyfTt-1}$. The idea is that this measure captures effects that the mean value overlooks. Consider two different classrooms with the same mean value in achievement but where one class has a larger spread in the achievement distribution. In this classroom students at the low end of the distribution will have students above them that are considerably higher achieving as compared to students in the classroom with the tighter spread in achievement.

$P_{-isyfTt}$ is a vector of other peer measures such as share of female students and share of peers with a foreign background. T_{isyft} contains teacher characteristics such as age and foreign background. I use the lagged grade for individual i $A_{isfyTt-1}$ to capture past input.

Individual and possibly family time-invariant effects are represented by ϕ_i, γ_s and η_y capture school and school year specific effects. Since the dataset enables me to identify the teacher in each classroom, I can also use teacher fixed effects estimation with μ_T capturing time-invariant teacher specific effects.

In order to capture any non-linear effects, I interact mean and standard deviation in peer achievement within the classroom with student *i*'s lagged achievement variable. Others have used quantile regression (see Hanushek et al. 2003), but since I only have a four scale grade outcome that is not possible. The idea here is to see whether the mean and/or the spread within the classroom have different effects on student achievement conditional on initial achievement. Lower-achieving students might benefit from a wider spread, i.e., a larger share of higher-achieving students above them to learn from, while the opposite effect might be present for high-achieving students. They might suffer from being in classrooms with a greater spread in achievement, i.e., a greater share of lower-achieving students taking teacher time and forcing instruction to be held at a lower level. The omitted category in lagged achievement is students that received the subject grade "pass with special distinction" when graduating from compulsory school. Thus, in this specification the single coefficients of the peer variables, $\overline{A}_{-isyfTt-1}$ and $SDA_{-isyfTt-1}$ capture the effects of an increase in the mean and standard deviation in peer achievement for students that received subject grade "pass with special distinction" when graduating from compulsory school.

5. Results

My interest in this paper is to ascertain whether there are linear and non-linear peer effects in Swedish high school education. I start with the linear specification (equation 7) and then move on to the extended model with interactions capturing non-linear effects.

In table 2 column 1, I present the average peer effects within the classroom without controlling for time and school, teacher and student fixed effects. The result shows positive effects on student achievement from an increase in mean and the standard deviation in peer achievement. In columns 2 to 4, I introduce step-by-step time and school, teacher and student fixed effects.

Comparing column (1) and (2) we see that introducing time and school controls causes the estimated peer effects to decrease somewhat. There is evidence of some grade inflation in Swedish high school education (Wikström and Wikström, 2004), which might explain the observed drop. However, there is a larger drop in the coefficients when moving from column (2) to (3). Including teacher fixed effects in column (3) shows that not considering teacher specific effects when using between classrooms variation is likely to bias the result, the coefficients decrease from 0.38 to 0.32 when controlling for time-invariant teacher characteristics. This is in line with the result from testing whether there are any systematic differences between classes at the school level. The allocation of students and teachers in schools might not be exogenous and only considering school specific effects would not have been sufficient to obtain unbiased estimates. Proceeding to the full fixed effects model in column 4 controlling also for teacher and students fixed effects further reduces the estimated coefficients.

Altogether, the mean peer coefficient decreases from an effect of 0.42 in the specification without controls to 0.16 when using the full fixed effects specification. The result suggests that there are positive peer effects of an increase in mean peer achievement but not nearly as large as when only using time and school controls. Thus not accounting for time-invariant teacher and student characteristics will bias the result at least when considering mean peer achievement.

A somewhat surprising result is the coefficients of the two variables share of male students and share of students with a foreign background. Both report a positive effect in the full fixed effects specification which is not what I would have expected. In an attempt to gain an understanding of these results I have squared and cubed the variable share of students with a foreign background. The results show that there might be differential effects dependent on the size of the share of students with a foreign background in the classroom. The result suggests a positive effect of a small share of students with a foreign background. However, as the share increases the effect becomes negative to finally become positive again.

From column (3) we see that there is a negative effect of increasing teacher age. This can be explained by a differential pattern similar to what I observe in the share of students with foreign background. Otherwise, the results are not surprising. Increasing class size will have a negative impact on student achievement, students from academic family backgrounds tend to perform better, and native students outperform students with a foreign background.

Taken together the results from the baseline model show that on average, an increase in peer achievement will have a positive impact on student achievement. Further, an increase in the standard deviation in peer achievement - controlling for mean peer achievement - will also have a positive impact. This already suggests that tracking policies or other ability (achievement) grouping might cause inefficiencies.

In an attempt to further control for selection and correlated effects, I have estimated peer effects for students that do not have any prior peers from compulsory school in the classroom in high school (see table 3). The notion is here that these students do not share any correlated effects from previous school and neighborhood characteristics with his or her peers that might bias the result. The corresponding results from the same linear specification as used in table 2 are more or less the same. The estimated coefficient for mean peer achievement is almost 0.18 but with larger standard errors, still significant at the 1 percent level. The effect of an increase in the spread in peer achievement in the classroom is also similar as compared to the result in table 2. It decreases from 0.12 to 0.10, but here only significant at the 5 percent level. Thus, there seems to be no bias due to correlated effects and therefore I stick with the larger sample.

The next question is whether there are non-linear peer effects. Are students with different initial achievement affected differently by an increase in mean peer achievement and/or the spread in peer achievement or does everyone benefit in the same way from it? In table 4, I present estimations capturing non-linear peer effects. In this specification, I have interacted the mean and standard deviation in peer achievement within the classroom with pupil *i*'s subject grade from compulsory school, i.e., lagged achievement.

The omitted reference category is students that received the subject grade "pass with special distinction" when graduating from compulsory school so it is in comparison to these students the coefficients should be interpreted. The results imply that there are non-linear peer effects and that students at the lower end of the achievement distribution benefit more from a wider spread in peer achievement as compared to the students at the top end. Students that failed a subject in compulsory school gain more than students in the other categories. The effect of an increase in the standard deviation in peer achievement is decreasing and small and insignificant for students at the top end of the achievement distribution.

The non-linear effects are relative to students that received the subject grade "pass with special distinction" when graduating from compulsory school. Therefore we need to take the linear specification into consideration in order to say anything about the total effect. From table 2 we see that there is an overall positive effect of an increase in the achievement spread within the classroom. Therefore, even though there might be none or negative effects of increased achievement spread for high achievers, the total effect is still positive. A similar pattern is also evident for the interactions with mean peer achievement. Students at the lower end benefit more from an increase than their higher achieving peers.

6. Sensitivity Analysis

Since I use a four-grade scale outcome variable floor and ceiling effects might be present. Students allocated at the top and bottom can only change their grades in one direction, towards the mean. Therefore I have replicated the analysis from table 2 on a restricted sample in which I only use students that have graduated from compulsory school with the grades "pass" or "pass with distinction". This to provide students with the possibility of improving or reducing performance in high school. The estimated coefficients are the same as the results presented in table 1, which suggests that floor and ceiling effects do not impose any problems.

Another issue is the use of OLS instead of ordered probit that would have been more appropriate for a four-grade scale outcome variable, had it not been for the fixed effects estimation. I have estimated the specification used in table 2, column 2, i.e., the specification without teacher and student fixed effects to see whether the method used imposes a problem or not. The coefficients from the ordered probit estimations are positive and significant both for mean achievement and achievement spread.

I have also evaluated whether the admission reform in 2000 has had an impact on peer influence. Since 2000 admission to high school has solely been based on grades and students are free to apply to whatever high school they want. This might have caused the peer composition to have changed. I have constructed a dummy variable that takes the value one after the reform and interacted it with my peer measures. The result shows no effects from the reform which is reassuring in that, if constructed correctly, the peer measure should be insensitive to changes in the distribution of students.

There might be objection to the use of the subject sports. Therefore I have estimated peer effects using the baseline equation excluding sports. The result is that I get larger coefficients of the peer measures but otherwise similar results.

7. Conclusions

In this paper, I estimate peer effects in Swedish high school education. I use a rich dataset that enables me to handle the well-known problems of selection and simultaneity. I use lagged achievement to account for simultaneity and an extensive fixed effects framework to rule out selection. The baseline results suggest a presence of positive peer effects on student achievement. Both mean peer achievement and the spread in peer achievement among classmates have a positive effect. From the full fixed effects specification, it follows that one standard deviation increase in peer GPA leads to a 0.08 standard deviation increase in high school grades. Similarly, one standard deviation increase in the spread within the classroom in peer GPA leads to a 0.02 standard deviation increase in student grades.

I extend the analysis by interacting lagged achievement of student *i* with the mean and standard deviation in peer achievement to see whether there are non-linear effects present. The analysis provides evidence of non-linear peer effects in that students situated at the lower end of the achievement distribution will benefit more from an increase in both the mean and standard deviation in peer achievement as compared to students higher up in the distribution. From one standard deviation increase in the spread in peer achievement within the classroom students that failed a subject in compulsory school gain 0.11 standard deviations more than students that received a “pass with special distinction”.

This result together with the earlier linear specification results suggests that all in all, lower-achieving students benefit more than higher achievers lose from being in a classroom with a larger spread in achievement.

So it seems that there are peer effects present and that they are positive to a larger extent than negative (externalities) and that they primarily go from the top down. Higher-achieving peers help their lower-performing class-mates, directly and/or as role models, whereas being placed in a class with a greater or lesser share of low-performing students does not seem to matter for the top achievers.

This has policy implications concerning whether you should group students according to ability or not. The use of tracking - or ability grouping - will do more harm than good. Differentiating students according to achievement or ability is not the most efficient way to allocate students in terms educational output in high school.

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Table 1. Descriptive statistics

Variable	Mean (Standard deviation)	
Classroom characteristics	Before the admission reform in 2000	After the admission reform in 2000
Mean peer achievement	12.71 (2.70)	13.55 (2.89)
Standard deviation peer achievement	3.47 (1.06)	3.53 (1.08)
Class size	26.55 (4.83)	25.83 (5.94)
Share of male students	.49 (.20)	.48 (.25)
Share of students with a foreign background	.19 (.16)	.24 (.19)
Share of students with no prior peers in the classroom	.29 (.45)	.44 (.50)
Teacher characteristics		
Age	49.77 (10.50)	49.68 (11.22)
Male	.41 (.49)	.46 (.50)
Foreign background	.07 (.26)	.11 (.31)
Individual characteristics		
Achievement	13.79 (5.17)	13.39 (5.49)
Lagged achievement	13.99 (3.90)	13.89 (4.42)
Male	.48 (.50)	.47 (.50)
Foreign background	.17 (.38)	.22 (.42)
Family level of education, at most 9 years of compulsory school	.06 (.24)	.08 (.26)
Family level of education, at most high school	.29 (.46)	.34 (.47)
Family level of education, college	.64 (.48)	.59 (.49)
Year	1998.98 (.14)	2001.99 (1.37)
N	9145	73751

Note: The achievement measure can take on four different values 0, 10, 15 and 20. Classes with less than ten students are dropped. A student is coded as having a foreign background if he or she was born abroad or if both parents were born abroad. It is the parent with the highest level of education that sets the value for the family.

Table 2. Unrestricted value-added estimation of the influence from mean peer achievement and the standard deviation in peer achievement within the classroom on the subject grade in high school, standard errors in parentheses.

	(1)	(2)	(3)	(4)
	No controls	Time and school fixed effects	Time, school and teacher fixed effects	Time, school, teacher and individual fixed effects
Mean peer	0.424 (0.031)***	0.383 (0.025)***	0.318 (0.030)***	0.158 (0.042)***
Std peer	0.268 (0.030)***	0.283 (0.039)***	0.146 (0.027)***	0.120 (0.026)***
Share of male students		-0.018 (0.236)	-0.052 (0.293)	0.777 (0.389)*
Share of students with a foreign background		0.888 (0.265)***	0.778 (0.324)**	1.131 (0.428)**
Class size		-0.006 (0.007)	-0.009 (0.007)	-0.021 (0.008)**
Age teacher		0.010 (0.004)**	-0.270 (0.030)***	- (-)
Male teacher		0.041 (0.095)	- (-)	- (-)
Teacher foreign background		0.194 (0.137)	- (-)	- (-)
Lagged achievement	0.562 (0.012)***	0.531 (0.014)***	0.526 (0.014)***	0.399 (0.014)***
Male Student		-0.049 (0.068)	-0.046 (0.070)	- (-)
Student foreign background		-0.718 (0.090)***	-0.728 (0.093)***	- (-)
Parental level of education at most high school		0.408 (0.055)***	0.453 (0.057)***	- (-)
Parental level of education college education		1.016 (0.078)***	1.034 (0.082)***	- (-)
Constant	-1.024 (0.461)**	0.760 (0.593)	15.537 (1.618)***	-0.357 (1.169)
No schools	27	27	27	27
No classes	4181	4181	4181	4181
Observations	82896	82896	82896	82896
R-squared	0.35	0.37	0.41	0.70

* significant at 10%;
** significant at 5%;
*** significant at 1%

Note: Standard errors are clustered at high schools. The omitted level of parental education is no more than 9 years compulsory school.

Table 3. Unrestricted value-added estimation of the influence from mean peer achievement and the standard deviation in peer achievement within the classroom on the subject grade in high school for students with no prior peers in the classroom, standard errors in parentheses.

	(1)	(2)	(3)	(4)
	No controls	Time and school fixed effects	Time, school and teacher fixed effects	Time, school, teacher and individual fixed effects
Mean peer	0.426 (0.035)***	0.370 (0.032)***	0.298 (0.040)***	0.178 (0.060)***
Std peer	0.275 (0.039)***	0.265 (0.048)***	0.112 (0.037)***	0.101 (0.044)**
Share of male students		-0.250 (0.271)	-0.312 (0.390)	0.777 (0.460)
Share of students with a foreign background		0.797 (0.284)***	0.623 (0.346)*	1.396 (0.520)**
Class size		-0.002 (0.008)	0.001 (0.007)	-0.006 (0.010)
Age teacher		0.007 (0.004)*	-0.264 (0.029)***	- (-)
Male teacher		-0.011 (0.121)	- (-)	- (-)
Teacher foreign background		0.169 (0.194)	- (-)	- (-)
Lagged achievement	0.544 (0.009)***	0.509 (0.011)***	0.502 (0.011)***	0.377 (0.010)***
Male student		-0.070 (0.095)	-0.082 (0.102)	- (-)
Student foreign background		-0.737 (0.102)***	-0.736 (0.104)***	- (-)
Parental level of education at most high school		0.451 (0.075)***	0.505 (0.076)***	- (-)
Parental level of education college education		0.915 (0.109)***	0.942 (0.113)***	- (-)
Constant	-1.013 (0.549)*	1.697 (0.470)***	15.868 (1.516)***	10.531 (1.530)***
No schools	27	27	27	27
No classes	4107	4107	4107	4107
Observations	35454	35454	35454	35454
R-squared	0.33	0.35	0.40	0.74

* significant at 10%
** significant at 5%
*** significant at 1%

Note: Standard errors are clustered at high schools. The omitted level of parental education is no more than 9 years compulsory school.

Table 4. Unrestricted value-added estimation of non-linear effects of the mean and standard deviation in peer achievement within the classroom on the subject grade in high school, standard errors in parentheses.

	(1)	(2)	(3)	(4)
	No controls	Time and school fixed effects	Time, school and teacher fixed effects	Time, school, teacher and individual fixed effects
Mean peer	0.245 (0.034)***	0.223 (0.036)***	0.182 (0.042)***	0.069 (0.038)*
Std peer	-0.049 (0.046)	-0.038 (0.043)	-0.083 (0.043)*	-0.056 (0.035)
Lagged achievement = fail X mean peer	0.054 (0.093)	0.071 (0.095)	0.122 (0.085)	0.132 (0.067)*
Lagged achievement = pass X mean peer	0.181 (0.042)***	0.164 (0.043)***	0.153 (0.040)***	0.096 (0.034)***
Lagged achievement = pass with distinction X mean peer	0.086 (0.021)***	0.069 (0.023)***	0.061 (0.024)**	0.051 (0.022)**
Lagged achievement = fail X std peer	0.793 (0.165)***	0.750 (0.159)***	0.701 (0.115)***	0.577 (0.130)***
Lagged achievement = pass X std peer	0.258 (0.071)***	0.283 (0.069)***	0.260 (0.062)***	0.221 (0.056)***
Lagged achievement = pass with distinction X std peer	0.077 (0.049)	0.102 (0.042)**	0.082 (0.049)	0.058 (0.042)
Share of male students		-0.040 (0.225)	-0.101 (0.290)	0.661 (0.390)
Share of students with a foreign background		0.759 (0.242)***	0.651 (0.301)**	0.870 (0.419)**
Class size		-0.005 (0.007)	-0.010 (0.007)	-0.022 (0.008)**
Lagged achievement = fail	-12.916 (1.477)***	-12.065 (1.484)***	-12.385 (1.232)***	-9.789 (1.043)***
Lagged achievement = pass	-10.170 (0.760)***	-9.749 (0.815)***	-9.406 (0.700)***	-7.097 (0.487)***
Lagged achievement = pass with distinction	-4.540 (0.430)***	-4.290 (0.471)***	-4.053 (0.492)***	-3.302 (0.414)***
Constant	14.297 (0.649)***	15.543 (0.582)***	29.967 (1.634)***	11.605 (2.746)***
No schools	27	27	27	27
No classes	4181	4181	4181	4181
Observations	82896	82896	82896	82896
R-squared	0.37	0.39	0.42	0.71

* significant at 10%
** significant at 5%
*** significant at 1%

Note: Standard errors are clustered at high schools. The omitted level of parental education is no more than 9 years compulsory school. Reference category lagged achievement is students that graduated from compulsory school with the grade "pass with special distinction". Thus, the coefficients of the interactions should be interpreted with reference to these students.