ISSN 1832-8741

LABOUR ECONOMICS RESEARCH GROUP (LERG)

DISCUSSION PAPER SERIES

SCHOOL OF ECONOMICS

Discussion Paper No. 13

Do Peers Matter? Estimation of Peer Effects from Pupil Mobility Between Schools

by

Steve Bradley and Jim Taylor

November 2006

THE UNIVERSITY OF QUEENSLAND

The Labour Economics Research Group (LERG) Discussion Paper Series is currently hosted by the Centre for Economic Policy Modelling (CEPM) at the School of Economics, University of Queensland.

The LERG currently encompasses collaborative work on labour, education and related economic issues from researchers at the University of Queensland in Australia, as well as Lancaster University and the University of Ulster in the United Kingdom.

Specifically the LERG Discussion Paper Series can be split into four categories as follows and we encourage submissions that meet any of these requirements:

- Human and Social Capital
- Labour Market Flexibility and Transitions
- Comparative Analyses
- Economic Aspects of the Workplace

The current Joint Editors of the LERG Discussion Paper Series are Professor Jim Taylor (Lancaster University) and Professor Vani Borooah (University of Ulster). Any submissions or queries should be sent to Parvinder Kler at p.kler@economics.uq.edu.au or mailed to:

Parvinder Kler,
LERG,
CEPM,
School of Economics,
University of Queensland,
St. Lucia,
Queensland 4072,
Australia.

Do peers matter? Estimation of peer effects from pupil mobility between schools[1]

Steve Bradley and Jim Taylor

Department of Economics

Lancaster University

Lancaster LA1 4YW

e-mail: jim.taylor@lancaster.ac.uk

The peer effect on an individual's test score gain during the final two years of compulsory education is estimated. We address the problems of simultaneity and selection bias by estimating peer effects only for those pupils changing school. Simultaneity bias is reduced since each pupil in the sample has a different peer group at the beginning and end of their final two years of compulsory education. Selection bias is reduced by using test score gain during the last two years of compulsory education to measure the change in attainment rather than its level. We conclude that peer effects are present but that they benefit low ability pupils more than high ability pupils. We also find that ability heterogeneity at school level is beneficial only for low ability pupils and disadvantages pupils in middle ability groups.

Key words: Peer effects Schools Pupil sorting Test score gain

JEL classifications: I20, I21, I28

[1] The authors are grateful to the Department for Education and Skills for providing the data and to the Nuffield Foundation for supporting this research project. They are also grateful to Dave Stott for his help in preparing the database. The authors are responsible for all errors and omissions.

Do peers matter? Estimation of peer effects from pupil mobility between schools

1. Introduction

Interest in peer effects has increased in recent years as a consequence of the introduction of education policies designed to increase parental choice. The central issue is whether this increase in choice will result in an increase in educational inequalities as a consequence of greater sorting of pupils between schools. A crucial policy question is whether pupils should be *segregated* according to their ability or whether they should be organised into *mixed ability* groups. It is consequently important to know whether peer effects exist and if so how strong they are. Such information is essential since appropriate policy action depends on which of these two ways of organising schooling has the optimal impact on educational outcomes.

The proponents of segregation argue that the learning process is more effective if pupils are grouped according to their ability since high ability pupils will not then be held back by the slower rate of progress of low ability pupils; and low ability pupils will gain since they will not be disillusioned as a consequence of lagging behind their more able peers. The teaching process may also be more efficient in more homogeneous groups since lessons can be targeted and delivered at a level more closely aligned to the group's ability distribution than is possible in more heterogeneous ability groups. Segregation can occur within schools in the form of tracking or streaming pupils, or between schools, where schools are allowed to select on the basis of ability or some other characteristic such as aptitude. This kind of system has been described as elitist in the sense that segregation may lead to inequality of educational opportunity (Galindo-Rueda and Vignoles 2004).

The case for mixed ability schooling is based on the argument that low ability pupils benefit from the presence of high ability peers. As Hoxby (2000) notes, there are multiple channels through which a peer group may influence a pupil's learning. These channels include direct instruction by one pupil to another as well as indirect 'knowledge spillovers', such as the acquisition of better learning skills from their higher ability peers, and improvements in standards of behaviour in the classroom.[2] These potential benefits will be lost if low ability pupils are segregated from high ability pupils. There is the added danger that in a segregated system the 'best' teachers may be attracted towards schools with high ability pupils, leaving schools with low ability pupils to be taught by the 'worst' teachers (Hanushek, Rivkin and Taylor 1996). If these peer effects are powerful, a policy of mixed ability groups will result in a reduction in educational inequalities, thereby reducing the size of the educational underclass over the longer term.

Interest in estimating peer effects in education began with the Coleman Report (Coleman *et al*. 1966). This report, together with other studies that followed, suggested that peer effects were powerful (Summers and Wolfe 1977). These early estimates were subsequently deemed to suffer from serious upward bias due to problems with the estimation methods used. Manski (1993, 2000) identifies two potentially serious problems with estimating peer effects from the relationship between individual and group outcomes. First, simultaneity bias occurs because individuals in a peer group affect each other, resulting in correlated errors between pupils in the same group. If steps are not taken to address this 'reflection problem', it is consequently not possible to identify a causal relationship between the pupil and her peer group.

Second, selection bias occurs because peer groups are endogenous. Students self-select into peer groups through school choice exercised by parents (either as a result of an education policy based on parental choice or because of residential location decisions). This sorting of pupils into schools according to characteristics such as prior attainment, motivation or family background results in an upwardly biased estimate of the peer effect. This arises because selection into schools means that pupils with parents who are keen for their child to do well are more likely to have schoolmates who also have parents who are keen for their child to do well. High achieving pupils are more likely to have high achieving schoolmates; and conversely for low achieving pupils. Selection will therefore result in an *automatic* positive correlation between an individual's attainment and the attainment of the individual's schoolmates.

A variety of approaches have been used to overcome the problems of simultaneity and selection bias in order to estimate the peer effect. Needless to say, the many and varied attempts to measure the peer effect have produced different estimates of its magnitude. The results of some previous studies shown in Table 1 indicate two distinct clusters: one at 0.07 and another at 0.25. Some researchers have used the random assignment of pupils between schools (Hoxby and Weingarth 2005, Kang 2005) and

[2] More generally, Manski (2000) discusses three channels through which agents' actions can affect the actions of others, that is, through their effect on an agents' expectations, through the imposition of constraints and through revealed preferences.

between classes within schools (Ammermueller and Pischke 2006) to estimate the peer effect from administrative data. But such data are scarce and the more commonly-used approach is to control for selection effects by including a comprehensive set of personal, family background and school level covariates (Levin 2001, Betts and Zau 2004, Vigdor and Nechyba 2004, Schneeweis and Winter-Ebmer 2005, Schindler-Rangvid 2005). Instrumental variables have also been used to control for the endogeneity of the composition of the peer group (Figio and Page 2002, Fertig 2003, Robertson and Symonds 2003). The problem with IV estimation is that appropriate and reliable instruments are often unavailable. A device used in many studies of the peer effect is to control for fixed effects (data permitting) at pupil, class or school level in order to reduce endogeneity bias. Controlling for pupil fixed effects is deemed to be particularly important in order to control for factors such as innate ability and other personal characteristics. A further method aimed at combating simultaneity bias is to use lagged data for constructing the peer group variable (Hanushek *et al*. 2001, Betts and Zau 2004, Vigdor and Nechyba 2004).

This paper takes a different approach to overcoming the statistical problems arising from simultaneity and selection bias. One of the limitations of earlier studies is that they have to use a single peer group for estimating the peer effect on individual pupils. By selecting only those pupils who change school, however, we are able to use two entirely different peer groups for estimating the peer effect. We therefore select from the pupil population only those pupils who changed school during their final two years of compulsory secondary education. This allows us to obtain more reliable estimates of the peer effect since we are using the *difference* in test scores between two entirely different peer groups rather than the *change* in the test score of the same peer group. This should reduce simultaneity bias.

Previous research has focused not only on the size of the peer effect but also how it varies with the characteristics of the peer group. The issue of greatest concern is whether the peer effect varies across the conditional distribution of pupil attainment. In other words, is the peer effect linear or non-linear? A linear relationship is neutral with respect to the case for 'streaming' since it implies that any positive attainment effects of transferring a pupil from a high ability group to a low ability group will be exactly offset by transferring a low ability pupil in the opposite direction. If the peer effect is greater for low ability pupils than for high ability pupils, the total educational product will increase as a consequence of mixed ability schooling; and conversely if the peer effect is greater for high ability pupils than for low ability pupils.

A related issue concerns the effect of the heterogeneity of a pupil's peer group on her attainment. Do individual pupils perform better in groups with low dispersion in ability levels or in groups with high dispersion in ability levels? Previous studies investigating the effect of segregating pupils by ability (i.e. 'tracking') yield contradictory results. Although much of the empirical literature suggests that tracking has little effect on attainment outcomes, at least at school level (Rangvid 2003, Hanushek *et al*. 2001, Vignor and Nechyba 2004, Schneeweis and Winter-Ebmer 2005), several studies find that tracking has beneficial effects on both high and low ability groups. Hoxby and Weingarth (2005), for example, find that positive peer effects on individual attainment in maths are stronger in schools with more homogeneous ability groups. Other studies that find positive attainment effects from ability tracking include those by Fertig (2003) and Figlio and Page (2002) for US schools and by Levin (2001) for Dutch schools. Not all studies, however, obtain this result. Some find that tracking is beneficial to those in high ability groups but harmful to those in low ability groups (Argys *et al*. 1996, Betts and Shkolnik 2000, Robertson and Symonds 2003); and Hanushek and Wossmann (2006) find evidence that early tracking (in primary school) is associated with greater dispersion of attainment outcomes in later (secondary) schooling without having any positive effects on the aggregate level of attainment. There is therefore substantial disagreement over whether ability tracking has beneficial effects on attainment.

Our aim in this paper is to confront the following questions: To what extent, if any, is a pupil's attainment affected by the corresponding attainment of his or her peers? Does the strength of this effect vary according to a pupil's personal characteristics or family background, such as prior attainment, ethnicity and family income? Does the peer effect vary according to the dispersion of scholastic ability in a pupil's peer group? Briefly, our main findings are that peer effects are statistically significant and quite substantial in size and that they are stronger for low ability pupils than for high ability pupils. Low ability pupils are more likely to benefit from a non-selective (comprehensive) education system while the overall effect on attainment of a non-selective system is likely to be positive. We find mixed evidence, however, that a pupil's attainment is affected by the heterogeneity of a pupil's peer group. Peer group heterogeneity is positively related to an individual's test score gain for pupils in the lowest ability group and negatively related to an individual's test score gain for those in the middle of the ability distribution, which indicates that ability heterogeneity at school level is beneficial for low ability pupils but not for those in the middle ability range.

The remainder of this paper is structured as follows. Section 2 explains the model and estimation strategy. This is followed in section 3 by a description of the data and the variables used in the empirical analysis, the results of which are discussed in section 4. Section 5 concludes.

2. Model and empirical strategy

Our model is based on the education production function, which states that educational attainment is determined by personal characteristics, family background, peer effects and schooling (Hanushek 1979, 1986). A linear representation of the education production function is as follows[3]:

$$A_{i,t} = \alpha_i + \beta A^*_{-i,t} + \mathbf{F}^*_{-i,t}\boldsymbol{\lambda} + \mathbf{F}_{i,t}\boldsymbol{\gamma} + \mathbf{S}_{i,t}\boldsymbol{\delta} + e_{i,,t} \qquad (1)$$

A = attainment (e.g. test score) of pupil i at time t

A* = attainment of pupil's peer group (excluding pupil i)

F* = family background of pupil's peers

F = family background of pupil

S = school-related factors

α_i = individual fixed effects representing unobservable personal characteristics

The aim of the empirical analysis is to estimate β, which is the effect of a pupil's peer group on his or her educational attainment. Using equation (1) to estimate the peer effect on an individual pupil's attainment, however, runs into the twin problems of simultaneity and selection bias, as discussed above.

These two estimation problems can be mitigated in several ways. First, following the existing literature, the inclusion of variables reflecting the pupil's own family background and the family background of the pupil's peers will help to reduce the adverse effect of selection bias on β since these factors are correlated with unobservables that drive the sorting of pupils between schools. Second, equation (1) can be estimated in first differences in order to eliminate unobservable fixed effects (α_i) relating to each pupil, such as innate ability and motivation. Third, the potential bias in the estimated peer group effect that is induced by sorting into schools is likely to be reduced if the sample is restricted to *pupils who change school* during the period of compulsory schooling. This is the crucial innovation in our estimating procedure. Since pupils who change school also change their peer group, this means that the change in the peer group's test score relates to two entirely different peer groups. The second peer group can therefore only affect the pupil's final score and not the pupil's initial score. Simultaneity bias should consequently be less severe than if the same peer group were observed at the beginning and the end of a given period of schooling in a single school.

Since there has also been some interest in the effect of ability grouping (i.e. tracking) on an individual's attainment, we also include a measure of the *variation* in the ability of each pupil's peer group, as indicated by the variance of the peer group's prior attainment ($\text{var}A^*_{-i,t-1}$). This is included to capture the degree of heterogeneity in the peer group's scholastic ability. Note, however, that this

[3] We note that the education production function can also be written with initial attainment as an additional argument. We have estimated the model using both forms (see below).

measure of peer group heterogeneity is at school level and not at class level since the relevant class level data are not available.

After taking first differences of equation (1) and incorporating the variance in peer prior attainment into the model, our estimating equation becomes:

$$\Delta A_{i,t} = \beta \Delta A^*_{-i,t} + \theta \mathrm{var}A^*_{-i,t-1} + \mathbf{\Delta F^*}_{-i,t}\boldsymbol{\lambda} + \mathbf{\Delta F}_{i,t}\boldsymbol{\gamma} + \mathbf{\Delta S}_{i,t}\boldsymbol{\delta} + e_{i,t} \qquad (2)$$

where β is the peer effect and θ measures the influence of the heterogeneity in prior attainment of the pupil's peer group. Local area dummies and school level dummies can also be included in order to control for locality and school fixed effects. All equations are estimated using the Huber-White robust estimator, which allows for the errors of the within-school clusters of pupils to be correlated while assuming independence of the between-school errors.

3. Data and variables

The data used to estimate the model were obtained from two sources: the National Pupil Database (NPD) and the annual Schools' Census. Both datasets were obtained from the Department for Education and Skills and the data are for pupils who were in their final year of compulsory education in 2003. The NPD provides pupil level data for all pupils attending maintained (state funded) schools in England and the Schools' Census provides school level data. The dependent variable is constructed from national test and exam scores obtained by pupils at Key Stage 3 (for 13/14 year olds) and Key Stage 4 (for 15/16 year olds). The Key Stage 3 result for each pupil is the total test score for English, Maths and Science. The Key Stage 4 result for each pupil is the average points scored across all subjects in the GCSE and GNVQ examinations taken at the end of compulsory education. In both cases, the test and exam scores are converted into a standard normal variable.[4]

The explanatory variables of primary interest are those relating to the pupil's peer group, which is defined here as the pupil's schoolmates. The peer group variable is constructed in the same way as the dependent variable: it is the difference between the standardised test scores at Key Stages 3 and 4 for the pupil's peers (and excluding the pupil's own score). A further variable of interest is the dispersion in the ability of a pupil's peers, which is measured by the standard deviation in the Key Stage 2 test score (in tests taken in the final year of primary schooling) of the pupil's Key Stage 4 schoolmates.

[4] Pupils in compulsory schooling in England are tested at four Key Stages: Key Stage 1 (age 7/8), Key Stage 2 (age 10/11), Key Stage 3 (age 13/14) and Key Stage 4 (age 15/16). The latter is the General Certificate of Education (GCSE) and the General National Vocational Qualification (GNVQ). Both are normally taken at the end of compulsory schooling.

Since the statistical analysis is confined to those who change school, we are also interested in discovering whether any specific school switches are more favourable to the pupil's test score gain than others.[5] We therefore include a range of school-related variables that identify differences between the origin and destination school for each pupil (i.e. community v non-community schools, coeducational v non-coeducational schools, 11-16 v 11-18 schools). In addition, differences between schools in several operational variables are also included, namely differences in the pupil-teacher ratio between the origin and destination school, differences in the part-time to full-time staff ratio, and differences in school size (as indicated by pupil numbers).

We also investigate whether the peer effect varies between different types of mover. In particular, we distinguish between those pupils who move *within* the catchment area (approximated by local authority districts) and pupils who move *between* catchment areas. The crucial distinction between these two types of move is that moves between catchment areas are likely to be accompanied by a change of household residence. The most likely explanation for these inter-district moves is that one, or both, parents have changed their job. Having had to make such a move, it is likely that parents will seek a house close to a school with a peer group that is at least as good as the peer group in their child's previous school. Moves to another school within the same district are more likely to be motivated by a parental desire to find a more appropriate school because of problems faced by their child at the origin school. We have no specific prior for predicting the relative strength of the peer effect in these two distinct groups of movers.

The potential influence of the family background of a pupil's peer group on each pupil's educational attainment is estimated by including several variables to measure the difference in the family background of peers between a pupil's first and second peer groups. Peer effects arising from family composition are proxied here by using the proportion of a pupil's peers who were eligible for free school meals, the proportion with English as their second language and the proportion from an ethnic minority. We are unable to include the change in the pupil's own family background variables in the estimating equation since family background data are only available for pupils in their final year of compulsory schooling. This should have little effect on the results, however, since family background for the majority of pupils is unlikely to change much between Key Stages 3 and 4.

Before proceeding to the empirical results, it is useful to compare the characteristics of the movers with those of the stayers. Pupils who changed school during Key Stage 4 (i.e. pupils aged 14 to 16) differ in several respects to pupils who did not change school. The first clear difference between movers and stayers is that stayers achieved substantially better exam results than movers at all three

[5] We note that pupils attending Leicestershire schools are omitted from the analysis since all pupils in maintained (state funded) secondary schools in Leicestershire change from middle school to high school at age 14.

key stages (see Table 2). The exam gap is particularly large at the GCSE/GNVQ exams, which are taken at the end of compulsory education.

Movers and stayers also vary according to several other characteristics. For example, movers are more likely than stayers to be eligible for free school meals, particularly if they change school within the same district (24% compared to 14%). This indicates that disadvantaged pupils are far more likely to change school than non-disadvantaged pupils. Movers are also less likely to have special educational needs than stayers. Other pupil characteristics appear to be less important in determining the probability of being a mover rather than a stayer.

4. Empirical results

The results reported in this section fall into three broad categories. The first set, reported in Table 3, show the estimated peer effect on a pupil's test score gain between Key Stages 3 and 4. The second set of results, reported in Table 4, show the extent to which the peer effect varies between pupils according to their initial attainment, gender, ethnicity, eligibility for free school meals and the heterogeneity of the peer group. Finally, Table 5 presents some quantile regression results in order to test for differences in peer effects across the attainment distribution.

The peer group effect

Three regression equations are reported in Table 3. The first is based on all pupils changing school whereas the second and third equations are based on those moving *within* districts and *between* districts respectively. In all three cases, a highly significant positive relationship is found between an individual pupil's educational attainment (as measured by the *change* in exam results between Key Stages 3 and 4) and the attainment of the individual's peers. The estimated coefficient of around 0.17 for all three samples indicates that an increase of one standard deviation in the exam performance of a pupil's peer group is associated with an increase in an individual pupil's exam performance by around one-sixth of a standard deviation. This is equivalent to a shift in an individual pupil's exam performance from the median percentile to the 57th percentile, which indicates that the peer group effect is quite substantial in addition to being statistically significant. The results also indicate that the peer effect does not differ significantly between those who changed school *within* a district and those moving *between* districts, despite the probable differences in their reason for changing school.

A further result of interest with respect to a pupil's peer group relates to the degree of heterogeneity in the peer group's ability level. It has been argued that more homogeneous peer groups are easier to teach and that this will improve educational outcomes. Due to data availability, we necessarily focus here on the heterogeneity of ability at year group (not class) level. Using the standard deviation in the test score at Key Stage 2 as an indicator of the heterogeneity of the ability level of a pupil's year group, we find that the estimated coefficient is statistically insignificant. We therefore conclude that there is no evidence that a pupil's test score gain is related to the degree of heterogeneity of pupils at year group level.

The movement between different types of school and test score gain

Several variables used as controls are of interest. Pupils move between different types of school and in some cases the type of move is correlated with the test score gain of the movers. Pupils moving to a non-community school, for example, appear to benefit more (in terms of test score gain) than those moving to a community school.[6] This effect is particularly strong for those moving from a community to a non-community school within their own district. The estimated coefficient implies that such a move is associated with an increase of 0.19 standard deviations in test score gain (equivalent to a shift from the median to the 58th percentile in the test score gain distribution). There therefore appears to be a clear benefit in moving to a non-community school. Whether this improvement is due to school or peer group effects (such as peers having more support from parents in schools with a religious affiliation) is unknown, but it does seem likely that non-community schools offer something extra over community schools at least in terms of educational attainment. We also find that pupils transferring from an 11-18 school to an 11-16 school improve their test score gain compared to those moving between 11-18 schools. Moreover, the estimated effect for those moving within the same district is relatively large (0.25 of a standard deviation, which is equivalent to a shift from the median to the 60th percentile of the test score gain distribution). Although the estimated coefficients are not significant at the 5% level, there is also some evidence that pupils moving to non-coeducational schools have higher test score gains than those moving to coeducational schools.

Interaction effects

Does the peer group effect vary according to the personal characteristics of pupils? More information about the magnitude of peer effects can be obtained by including interaction terms in the estimated equation. Several interaction effects are reported in Table 4. First, since there is no reason to suppose that the effect of a pupil's peer group on attainment will be the same across the ability range, it is of interest (and policy relevant) to investigate whether the magnitude of the peer effect varies according to the *ability* of pupils. We investigate this by interacting the peer group variable with a pupil's Key Stage 2 (primary school) test score. The estimated coefficients on the interaction between the peer group variable and the five quintiles of the pupil's Key Stage 2 score indicate that the peer effect is significantly smaller at the upper end of the initial attainment distribution. For the full sample of movers, for example, the estimated peer effect is 0.09 in the fifth quintile of the initial attainment distribution compared to 0.15 in the lowest quintile and 0.18 in the middle quintile. Moreover, the

[6] Community schools are under the direct control of the local education authority whereas non-community schools, such as those with a religious affiliation, have more control over their intake of pupils.

estimated peer effect for those pupils in the top quintile of prior attainment who also changed districts is not significantly different from zero. In other words, the peer effect is lowest for those pupils who obtained the highest levels of prior attainment. The peer effect is therefore non-linear (and concave) according to the estimates obtained here.

Second, a similar analysis can be performed for other pupil characteristics, such as gender, ethnicity and eligibility for free school meals (see Table 4). Adding interaction terms based on these three characteristics indicates that the peer effect is slightly higher for girls and for non-whites than for boys and whites respectively. The significance levels on the estimated coefficients, however, are low. There is no evidence of any difference in the peer effect according to whether or not a pupil is eligible for free school meals.

Third, there is also evidence that the degree of heterogeneity in the ability level of a pupil's year group is related to test score gain, but the direction of this effect varies according to a pupil's prior attainment (see Table 4). The estimated coefficients indicate a positive relationship between a pupil's test score gain and the degree of heterogeneity for those in the lowest ability group, though this result is only obtained for those going to a new school in another district. This compares with a set of negative coefficients for those in the middle range of the ability distribution, which is consistent with the conventional view that a pupil's exam performance is adversely affected by an increase in heterogeneity. It is also worth noting that there is no relationship between a pupil's exam performance and the degree of heterogeneity in the ability of a pupil's peer group at the top end of the ability distribution.

Quantile regression estimates

Quantile regression methods can be used to estimate the peer effect at different points on the conditional distribution of the dependent variable (i.e. test score gain). This method relaxes the assumption that the estimated coefficients are constant across the entire distribution of the dependent variable. The results in Table 5 indicate that the peer effect is substantially weaker for those at the bottom end of the test score gain distribution than for those at the top. This result only holds, however, for those movers who did not change their school district. There was no significant difference across the attainment distribution for those pupils who moved to another district.

The result that the peer effect is higher for pupils at the upper end of the conditional distribution of the test score gain than at the lower end of the distribution contrasts (see Table 5) starkly with the result that the peer effect is lowest for those pupils who achieved the highest test scores at the end of primary education (see Table 4). It should, however, be remembered that the quantile regression results refer to the conditional distribution of the *change* in the test score whereas the interaction effects refer to the *level* of prior attainment. It is not inconsistent for the peer effect to be greatest for pupils with the lowest scores at the end of primary education at the same time that the peer effect is lowest for those with the smallest *change* in their test score during secondary schooling.[7]

5. Conclusion

There is general agreement that segregating pupils into schools by their ability is undesirable on social and equity grounds. There is less agreement, however, about the consequences of mixed ability schooling on the total educational product as measured by test and exam outcomes. Whether segregated or mixed ability schooling is most efficient in terms of the total educational product, however, depends on the magnitude of peer effects. This paper has therefore attempted to estimate the peer effect on an individual's educational attainment during the final two years of compulsory education. The statistical analysis is based on individual level data for a sample of pupils in state funded secondary schools in England.

Since attempts to estimate the size of the peer effect are plagued by the twin problems of simultaneity and selection bias, we have taken a different route to previous studies by focusing on the specific group of pupils who changed school during their final two years of compulsory schooling. Simultaneity bias is likely to be less serious if the sample is restricted to pupils changing school since two entirely different peer groups are used for each individual in estimating the peer effect. Selection bias is likely to be mitigated by using the test score *gain* as the dependent variable in order to control for individual fixed effects.

The main conclusions of this paper are as follows. First, we find strong evidence of peer effects on the individual's test score gain. Estimates suggest that an increase of one standard deviation in the test score gain of a pupil's peers is associated with an increase of 0.17 of a standard deviation of the pupil's test score gain. Second, there is some evidence that the peer effect is significantly larger for low ability pupils (0.15) than for high ability pupils (0.09). Third, there is evidence that peer group heterogeneity is positively related to an individual's test score gain for pupils in the lowest ability group and negatively related to an individual's test score gain for those in the middle of the ability distribution. This suggests that ability heterogeneity at school level is beneficial for low ability pupils but not for those in the middle ability range.

The main finding of this paper is that peer effects are present and that they tend to benefit low ability pupils rather more than they benefit high ability pupils. This suggests that low ability pupils are more

[7] The correlation between the Key Stage 2 score at the end of primary education and the change in the test score between Key Stage 3 and Key Stage 4 is -0.012.

likely to benefit from a non-selective (comprehensive) education system and that the overall effect on attainment of a non-selective system is likely to be positive.

References

Argys, L. M., Rees, D. I. and Brewer, D. J. (1996) Detracking Amerca's schools: Equity at zero cost?', *Journal of Policy Analysis and Management*, Vol. 15, 623-645.

Betts, J. R. and Shkolnik, J. L. (2000) 'The effects of grouping on student math achievement and resource allocation in secondary schools, *Economics of Education Review*, Vol. 18, 1-15.

Betts, J. R. and Zau, A. (2004) 'Peer groups and academic achievement: panel evidence from administrative data', Public Policy Institute of California, San Francisco.

Coleman, J., Campbell, E. Q. and Hobson *et al*. (1966) *Equality of Educational Opportunity*, Washington, D.C.: US Government Printing Office.

Fertig, M. (2003) 'Educational production, endogenous peer group formation and class composition: evidence from the PISA 2000 study', Discussion Paper 714, February, IZA, Bonn.

Figlio, D. N. and Page, M. E. (2002) 'School choice and the distributional effects of ability tracking: does separation increase inequality?', *Journal of Urban Economics*, Vol. 51¸497-514.

Galindo-Rueda, F. and Vignoles, A. (2004) 'The heterogeneous effect of selection in secondary schools: Understanding the changing role of ability', Centre for the Economics of Education, London School of Economics.

Hanushek, E. A. (1979). Conceptual and empirical issues in the estimation of educational production functions, *Journal of Human Resources*, 14, 351-388.

Hanushek, E. A. (1986). The economics of schooling: production and efficiency in public schools, *Journal of Economic Literature*, 24, 1141-77.

Hanushek, E. A., Kain, J. F., Markman, J. M. and Rivkin, S. G. (2001) 'Does peer ability affect student achievement?', National Bureau of Economic Research, Working Paper 8502.

Hanushek, E. A., Rivkin, S. G. and Taylor, L. L. (1996a). Aggregation and the estimated effects of school resources, *Review of Economics and Statistics*, 78, 611-627.

Hanushek, E. A. and Woessmann, L. (2006) 'Does educational tracking affect performance and inequality? Differences-in-differences evidence across countries', *Economic Journal 116 (510)*, 2006, C63-C76. (Working Paper 1415, Institute for Economic Research , University of Munich.)

Hoxby, C. M. (2000) 'Peer effects in the classroom: learning from gender and race variation', NBER Working Paper 7867, Cambridge, Massachusetts.

Hoxby, C. M. and Weingarth, G. (2005) 'Taking race out of the equation: School reassignment and the structure of peer effects', Department of Economics, Harvard University, mimeo.

Kang, C. (2005) Classroom peer effects and academic achievement: quasi-randomization evidence from South Korea, mimeo, Department of Economics, National University of Singapore.

Levin, J. (2001) 'For whom the reductions count: A quantile regression analysis of class size effects on scholastic achievement' *Empirical Economics*, Vol. 26, 221-246.

Manski, C. F. (1993) 'Identification and endogenous social effects: the reflection problem' *Review of Economics and Statistics*, Vol.60, 531-542.

Manski, C. F. (2000) Economic analysis and social interactions', *Journal of Economic Perspectives*, Vol. 14, 115-136.

Robertson, D, and Symons, J. (2003) 'Do peer groups matter? Peer group versus schooling effects on academic attainment', *Economica*, Vol. 70, 31-53.

Schindler-Rangvid, B. S. (2003) 'Educational Peer Effects: Quantile Regression Evidence from Denmark with PISA 2000 Data', Institute for Local Government Studies, Copenhagen.

Schneeweis, N. and Winter-Ebmer, R. (2005) 'Peer effects in Austrian schools', Discussion Paper Series 5018, Centre for Economic Policy Research, London.

Summers, A. A. and Wolfe, (1997) 'Do schools make a difference?' *American Economic Review*, Vol. 67, 639-652.

Taylor, J. and Bradley, S. (2000). 'Resource utilisation and economies of size in secondary schools', *Bulletin of Economic Research*, vol. 52, pp. 123-150.

Vigdor, J. and Nechyba, T. (2004) 'Peer effects in North Carolina Public Schools', mimeo., Sanford Institute of Public Policy, Duke University, Durham, North Carolina.

TABLE 1 Some recent estimates of the peer effect on pupils' test scores

Source	Context	Grade / year	Outcome indicator	Peer indicator or treatment	Peer group	Identification	Effect of change in peer group variable by one standard deviation
Hoxby (2000)	Public schools, Texas	3rd to 6th grade	Test scores (reading, math)	Test scores	Class	Gender variation between cohorts	0.40
McEwen (2003)	Secondary schools, Chile	8th grade	Test scores in Spanish language	Mothers' education of classmates	Class	School fixed effects	0.27
Hanushek *et al*. (2003)	Public schools, Texas	5th to 6th grade	Test score gain in math	Math score of peers (lagged 2 years)	Grade (school level)	Student and shcoll-by-grade fixed effects	0.05
Schindler-Rangvid (2003)	Secondary schools, Denmark	Age 15	Test scores in reading	Mothers' education of classmates	Grade (school level)	Extensive set of controls	0.07
Hoxby and Weingarth (2005)	Public schools, Wake County, South Carilina	3rd to 8th grade	Test scores for reading and math	Test scores for reading and math	Class	Random re-assignment of students to new peers	0.25
Gibbons and Telhaj (2005)	Secondary schools, England	Age 14 (year 9)	Test scores in English and maths	Test scores at age 11 (year 6) of schoolmates	Grade (school level)	Random variation in transition to secondary school	0.08
Schneeweiss and Winter-Ebmer (2005)	Secondary schools, Austria	Age 15	Test scores in reading	Socio-economic status of schoolmates	Grade (school level)	Type of school fixed effects	0.06
Kang (2005)	Secondary schools, South Korea	Age 13	Test scores in maths and science	Test scores (maths and science)	Class	School fixed effects	0.27
Ammermueller and Pischke (2006)	Primary schools, European countries	Age 9 to 10	Test scores in reading	Test scores in reading	Class	School fixed effects	0.07

Note: The estimated peer effect on a pupil's attainment given in the final column is measured in standard deviations.

TABLE 2 Descriptive statistics: mean test scores and some personal characteristics

Pupil characteristics	'Stayers'	'Movers'	
		Moved to new school within district	Moved to new school between districts
Pupil's own test and exam results			
KS2 score (age 11)	59.4	54.7	56.4
	(14.8)	(14.8)	(14.7)
	[474056]	[4051]	[7138]
KS3 score (age 14)	51.2	48.4	49.1
	(11.2)	(11.7)	(11.3)
	[465518]	[3414]	[6400]
Mean GCSE/GNVQ score (age 16)	41.5	28.1	33.0
	(20.4)	(20.7)	(20.6)
	[512159]	[4702]	[7992]
GCSE total score (age 16)	37.8	25.6	29.8
	(18.4)	(18.8)	(18.3)
	[512159]	[4702]	[7992]
Personal/family characteristics of pupil			
Boy	50.7	48.4	49.4
Girl	49.3	51.6	50.6
English second language	7.7	6.5	4.4
Ethnic minority	10.8	13.2	10.3
Special needs (not statemented)	15.7	10.1	8.8
Special needs (statemented)	3.4	5.0	4.7
Eligible for FSM	14.4	24.2	17.2

Note: KS2 = age 11; KS3 = age 14; KS4 = age 16. (   ) = standard deviation, [   ] = number in sample. Pupils changing school at the end of year 9 due to the local practice of having 'middle' schools and 'upper' schools (i.e. schools in Leicestershire) are not included in the above table.

TABLE 3 OLS regressions: dependent variable = pupil's test score gain (between Key Stage 3 and Key Stage 4)

Explanatory variables	Dependent variable = test score gain between Key Stage 3 and Key Stage 4		
	All movers	Movers within district	Movers between districts
Peer group attainment			
Test score gain of peer group	0.176***	0.176***	0.171***
	(0.014)	(0.021)	(0.018)
Standard deviation of peer group's pre-secondary school test score	-0.154	-0.181	-0.057
	(0.129)	(0.257)	(0.151)
Change in type of school attended			
Moved from community to non-community school	0.125***	0.189**	0.078*
	(0.033)	(0.063)	(0.039)
Moved from non- community to community school	0.070*	-0.050	0.092**
	(0.031)	(0.069)	(0.035)
Moved from non-community to non-community school	0.201***	0.166**	0.168***
	(0.032)	(0.061)	(0.043)
Moved from 11-18 to 11-16 school	0.089*	0.248**	0.029
	(0.037)	(0.085)	(0.040)
Moved from 11-16 school to 11-18 school	-0.020	0.087	-0.049
	(0.034)	(0.073)	(0.039)
Moved from 11-16 school to 11-16 school	0.018	0.101	0.031
	(0.035)	(0.073)	(0.041)
Moved from coed to non-coed school	0.074#	0.176#	0.036
	(0.040)	(0.091)	(0.047)
Moved from non-coed school to coed school	0.030	-0.113	0.106#
	(0.052)	(0.093)	(0.059)
Moved from non-coed to non-coed school	0.140	0.299#	0.071
	(0.097)	(0.171)	(0.103)
Constant	-0.023	-0.240	0.119
	(0.229)	(0.350)	(0.252)
R-squared	0.09	0.15	0.10
N	8857	3067	5790

Notes: (i) The results for the explanatory variables controlling for differences in school inputs between the 'new' school and the 'old' school are not reported since none of the coefficients are significant at 5%. The results for differences in the family background of peers are also not reported. The results are available on request to the authors. (ii) The standard errors (in parentheses) are estimated using the Huber-White robust estimator, which allows for the errors of the within-school clusters of pupils to be correlated while assuming independence of the between-school errors. (iii) #, *, **, *** = significant at 10%, 5% 1% and 0.1% respectively. (iv) Pupils who change school at the end of year 9 due to the local authority's practice of having 'middle' schools and 'upper' schools (i.e. schools in Leicestershire) are not included in the analysis.

TABLE 4 Interaction effects

Explanatory variables	Dependent variable = test score gain between Key Stage 3 and Key Stage 4		
	All movers	Movers within district	Movers between districts
Prior attainment			
Test score gain x pupil in first quintile at KS2	0.147***	0.183***	0.123***
	(0.027)	(0.041)	(0.036)
Test score gain x pupil in second quintile at KS2	0.172***	0.203***	0.162***
	(0.023)	(0.039)	(0.029)
Test score gain x pupil in third quintile at KS2	0.180***	0.180***	0.183***
	(0.031)	(0.055)	(0.035)
Test score gain x pupil in fourth quintile at KS2	0.141***	0.115**	0.149***
	(0.024)	(0.041)	(0.031)
Test score gain x pupil in fifth quintile at KS2	0.087**	0.149*	0.058
	(0.032)	(0.059)	(0.035)
Personal characteristics			
Girl	0.128***	0.110***	0.139***
	(0.018)	(0.034)	(0.021)
Test score gain x girl dummy	0.038*	0.036	0.037#
	(0.018)	(0.032)	(0.021)
Non-white	0.139***	0.198***	0.126***
	(0.029)	(0.058)	(0.038)
Test score gain x non-white	0.052*	0.030	0.055#
	(0.023)	(0.039)	(0.030)
Eligible for free school meals	-0.149***	-0.165***	-0.125***
	(0.026)	(0.043)	(0.033)
Test score gain x pupil eligible for free school meals	-0.005	-0.026	0.004
	(0.025)	(0.038)	(0.032)
Dispersion in prior attainment			
KS2 standard deviation x pupil in first quintile at KS2	0.115**	0.042	0.170**
	(0.044)	(0.081)	(0.056)
KS2 standard deviation x pupil in second quintile at KS2	-0.177***	-0.286***	-0.112*
	(0.043)	(0.077)	(0.051)
KS2 standard deviation x pupil in third quintile at KS2	-0.181***	-0.269**	-0.125**
	(0.043)	(0.086)	(0.047)
KS2 standard deviation x pupil in fourth quintile at KS2	-0.072#	-0.176*	-0.006
	(0.039)	(0.076)	(0.045)
KS2 standard deviation x pupil in fifth quintile at KS2	-0.044	0.066	-0.086
	(0.049)	(0.085)	(0.058)
Constant	-0.219	-0.302	-0.165
	(0.203)	(0.253)	(0.232)
Controls included?	Yes	Yes	Yes
R-squared	0,12	0.20	0.12
N	8831	3055	5776

Notes: (i) KS2 = Key Stage 2 (final year in primary school) (ii) The same variables were included in the above equations as in Table 3. (iii) The standard errors (in parentheses) are estimated using the Huber-White robust estimator, which allows for the errors of the within-school clusters of pupils to be correlated while assuming independence of the between-school errors. (iv) #, *, **, *** = significant at 10%, 5% 1% and 0.1% respectively.

TABLE 5 Quantile regressions: estimated coefficient on the peer group variable across the conditional distribution of the pupil's test score gain

Explanatory variables	Estimated coefficients at each quantile (standard errors)				
	0.10	0.25	0.50	0.75	0.90
All movers (n=8828)	0.149	0.183	0.192	0.209	0.202
	(0.025)	(0.015)	(0.010)	(0.012)	(0.012)
Movers within district (n=3055)	0.125	0.141	0.201	0.187	0.202
	(0.039)	(0.027)	(0.017)	(0.018)	(0.027)
Movers between districts (n=5773)	0.175	0.188	0.187	0.204	0.196
	(0.026)	(0.017)	(0.014)	(0.013)	(0.016)

Notes: (i) Only the estimated coefficient on test score gain is reported in the above table. *Notes*: (ii) The same variables were included in the above equations as in Table 3. (iii) The standard errors (in parentheses) are estimated using the Huber-White robust estimator, which allows for the errors of the within-school clusters of pupils to be correlated while assuming independence of the between-school errors.

APPENDIX

Means and standard deviations of variables included in the regression analysis

Variable	Mean	Standard deviation
Test score gain of pupil's peer group	-0.13	0.81
Test score standard deviation of pupil's KS4 peer group at KS2	0.89	0.08
Change in proportion of pupil's peer group eligible for free school meals	-0.01	0.14
Change in proportion of pupil's peer group with English 2nd language	0.00	0.17
Change in proportion of pupil's peer group from an ethnic minority	-0.02	0.18
Difference between 'new' and 'old' school's pupil/teacher ratio	0.07	1.85
Difference between 'new' and 'old' school's total number of pupils	0.05	3.70
Difference between 'new' and 'old' school's PT/FT staff ratio	0.00	0.08
Moved from 11-18 to 11-16 school	0.11	0.32
Moved from 11-16 to 11-18 school	0.12	0.32
Moved from 11-16 to 11-16 school	0.29	0.45
Moved from non-coed school to coed school	0.03	0.18
Moved from coed to non-coed school	0.05	0.22
Moved from non-coed to non-coed school	0.02	0.13
Moved from community to non-community school	0.11	0.31
Moved from non- community to community school	0.12	0.32
Moved from non-community to community school	0.26	0.44

Note: The number of observations is 8828 for all variables. This is the number of observations which are available for all variables in the above table. Only those changing school are included in the regression analyses. Test score gain is the difference between the exam score (measured as a standard normal variable) of the pupil's Key Stage 4 year group minus the exam score of the pupil's Key Stage 3 peer group.

Definitions:

Coed = single gender admissions

Non-coed = mixed gender admissions

Community = state school under local education authority (LEA) control

Non-community = voluntary-aided, voluntary controlled or foundation school (selection criteria usually based on religious affiliation)

Comprehensive = no selection criteria

Selective = grammar school (selection based on academic achievement)

Modern = admits pupils not admitted to a selective school

11-16 school = schools whose pupils leave at 16

11-18 school = schools whose pupils leave at 18.