Do Schools Make a Difference ?
The Respective Contributions of Pupils and Schools in Achievement in English Primary and Secondary Education

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Abstract

Coleman et al (1966) suggested that peers and pupils' backgrounds make more difference than schools in educational achievement. The economic literature has taken two path to reassess (i) the effect of peers on achievement (Hoxby 2000, Sacerdote 2001), and, separately (ii) the effect of school characteristics and school quality on achievement (Card, 1990). As Hanushek (1997, 1998, 2003) points out, these issues remain controversial. This paper combines strategies from Hoxby (2000) and Abowd et al. (1999) to jointly estimate school quality and peer effects, without relying on proxies for school quality. We assess the relative importance of school quality, peer effects and pupils' backgrounds in educational achievement. Test scores in English, Maths and Science are decomposed into contributions from schools, peers and pupils. Following Hoxby (2000), peer effects are identified assuming variations in year group composition in adjacent years are exogenous. Following Abowd et al. (1999), school and pupil effects are estimated using movers, assuming that mobility is not driven by time-varying endogenous shocks. Therefore our measure of school effectiveness does not rely on proxies such as school resources or pupil/teacher ratio.

1 Introduction

Knowledge of the effectiveness of educational inputs is crucial to good decision-making in education. Generally speaking, educational policies can target pupils, schools or promote desegregation. Choosing between these alternatives requires some knowledge on the relative impact of schools, pupils' backgrounds, and peers on educational achievement.

If schools make much of the difference, changing school inputs, management and teaching practices could lead to substantial reducations of inequalities. If, on the other hand, peers make much of the difference, segregation may be the number one issue to tackle. Finally, if pupils' background, ie pupils' specific problems, are the first determinant of achievement, policies aimed at low achieving may have the highest potential to narrow the gap between children.

However, there is no real consensus on what makes *much of the difference*. The sociology of education has long argued that peers are the most important determinant of test scores, at least since Coleman [1]. In The Concept of Equality of Educational Opportunity (1969), he asserts that:

> [...] those inputs characteristics of schools that are most alike for Negroes and whites have least effect on their achievement. The magnitudes of differences between schools attended by Negroes and those attented by whites were as follows: least, facilities and curriculum; next, teacher quality; and greatest, educational backgrounds of fellow students. The order of importance of these inputs on the achievement of Negro students is precisely the same: facilities and curriculum least, teacher quality next, and backgrounds of fellow students, most.

Following the Coleman report, a series of desegregation programs were initiated. Furthermore the report sparked research on the effects of peers, school quality and pupil's backgrounds on achievement.

A number of economic papers have challenged the view that peers are the most important determinant of educational achievement. A seminal paper by Manski [2] has highlighted the main problems of baseline estimation used by James Coleman. The selection bias is the most important one: if we observe good pupils together, are they good because they are together or are they together because they are good? Students may be partly selected on unobservable characteristics. Manski [3, 2] moreover pointed out that it is hard to disentangle the effect of peers' behaviour from the effect of peers' characteristics. And last, the econometrician should adress the simultaneity bias, since students influence each other simultaneously. Hoxby [4] has estimated the overall effect of race and gender composition on Texas primary school pupils. She finds significant and large peer-effects. In the context of the Boston METCO desegregation program, Angrist and Lang [5] estimate the effect of minority students on test scores. The estimated effects are modest and short-lived. Gould, Lavy and Paserman [6] assess the impact of immigrants on Israeli pupils. Even though the average effect they find are not significant, they do find that low-achieving pupils are more sensitive to their peers.

Another strand of the economic literature has focused on the relationship between school quality and achievement. Usually school quality has been proxied by the teacher/pupil ratio, teacher education, teacher experience, teacher salary or expenditures/pupil. The link between school resources and test scores is weak: on 147 studies published before 1987, not more than 20% find significant effects [7]. In the British context, Levacic and Vignoles [8] mention that the impact of school resources is small and very sensitive to misspecification. Dearden, Ferri and Meghir [9] suggest that, while the pupil-teacher ratio has no significant impact, attending selective schools improves both attainment and wages. Eventually the literature turns to less crude measures of school quality. Indeed,

> Schools differ dramatically in quality, but not for the rudimentary factors that many researchers (and policy makers) have looked to for explanation of these differences. (Hanushek, 1986)

In this paper, we measure the relative contributions of pupils, schools and peers without relying on observable proxies for peers' characteristics or school quality. We jointly estimate peer-effects, school effects and pupil effects in a single equation. The estimation strategy combines ideas from Abowd et al. [10] and Hoxby [4]. Following Abowd et al. [10], pupil and school effects are identified using movers, assuming no unobserved time-varying shock motivates mobility decisions. Following Hoxby [4], we argue that variations in the average quality of pupils in adjacent years are credibly idiosyncratic, due for instance to the randomness of the demographics. The paper goes one step further from previous literature, for (i) it assesses the relative contribution of peers, school quality and pupils' backgrounds in a single specification (ii) it estimates the overall effect of peers without relying on specific peer characteristics. We use an administrative database of English pupils. The dataset is comprehensive: six cohort of all English pupils in state schools are followed through primary education or through secondary education. The outcome measures are policy relevant: test scores are used for government targets and parents can freely read them in performance tables.

Preliminary results show that pupil heterogeneity is the first determinant of achievement inequalities. Differences in school quality come second. And peer effects come third. Estimated peer-effects are small though significant.

The outline of the paper is as follows: section 2 introduces the reader to the specific british policy context and describes the dataset. Section 3 presents the specification and the estimation strategy. Section 4 analyzes the regression results. Inequalities in test scores are decomposed into a school contribution, a pupil contribution and the contribution of segregation. School effects and pupil effects are correlated with observable characteristics.

2 Context and Dataset

2.1 Policy Context: the National Curriculum, Schools, and Pupils

The English educational system has two interesting features. Schools have a diversity of different management structures but, at the same time, a national examination system closely monitors the performance of pupils.

We use this series of examinations in this paper. The contents of teaching is set out in the National Curriculum. This curriculum is divided into four 'Key Stages', and we will use the first three of them: Key Stage 1, from 5 to 7, Key Stage 2 from 7 to 11, Key Stage 3, up to 14. At the end of each of these Key Stages, pupils take an examination in English, Maths, and Science – the latter beginning at Key Stage 2. We follow the educational career of English pupils in state schools throughout primary education and the first years of secondary education, up to age 14. These examinations are national, externally set and marked.

On the other hand, schools can have very different management structures. The private sector caters for less than 7% of the pupils, which is relatively small compared to other European countries. State schools have a large range of different management practices and intakes. *Community schools*, which represent more than half of pupils, are fully controlled by the Local Education Authority

(LEA): the LEA owns the buildings and employs the staff. On the other hand, in voluntary aided and foundation schools, teachers are employed by the school governing body and the LEA has no legal right to attend proceedings concerning the dismissal or appointment of staff.[1] Funding differs from school to school too. While most state schools are funded by the government, voluntary aided schools contribute 10% of the total capital expenditure.[2]

2.2 Dataset

The dataset is panel data from the National Pupils Database, a comprehensive administrative register of all english pupils in state schools. Data is collected by the Department for Education and Skills; it is mandatory for all state schools to provide accurate data on pupils, who are followed from year to year through a Pupil Matching Reference.

The dataset provides rich information on pupils' characteristics: gender, free school meal status, special educational needs, and the ethnicity group. It also provides some information on school management, ie whether they are community schools, foundation schools, voluntary aided or voluntary controlled schools, and so forth.

Test scores in English, Maths and Science are also included – the latter field only for Key Stage 2 and 3 – . These tests are externally set and marked. We have standardized test scores to a mean of 50 and a standard deviation of 10 to make results comparable from one level to the other and from year to year.

Due to the richness of available pupil characteristics, test scores can be used to compare the performance of pupils across genders, ethnicities and family backgrounds. The ethnicity variable has been coded such that it takes the following values: White, Black Carribbean, Other Black, Pakistani, African Black, Mixed background, Bangladeshi, Indian, Chinese, Other Background. A proxy for economic deprivation is given by the Free School Meal status[3].

[1] Code of Practice on LEA Schools Relationships, DfES 2001

[2] Source: Eurybase, 2006.

[3] Free School Meal pupils, as defined by the Department for Education and Skills (DfES): Children whose parents receive Income Support (IS); Income-based Job Seekers Allowance (IBJSA); support under Part VI of the Immigration and Asylum Act 1999; or Child Tax Credit, but who are not entitled to Working Tax Credit and whose annual income (as assessed by the Inland Revenue) that from 6 April 2005 does not exceed £13,910 are entitled to freeschool meals. Children who receive IS or IBJSA in their own right are also entitled to freeschool meals. All other pupils must be charged the same amount for the same quantity of the same item, although the meals may be subsidised. Neither the governing body nor the LA has the power to provide free meals to any other pupils.

	Primary School		Secondary School
	Key Stage 1	Key Stage 2	Key Stage 3
Age	7	11	14
Grade	2	6	9
Available topics	Maths	Maths	Maths
	English	English	English
		Science	Science
Available years	2000	2004	
	1999	2003	
	1998	2002	
		2001	2004
		2000	2003
		1999	2002
Schools	State Schools Only		

Sources: Department for Education and Skills, Pupil Level Annual School Census (PLASC) 2002 to 2004, National Pupils Database 1998 to 2004. Some school characteristics are taken from the Annual School Census.

Table 1: A overview of the dataset

3 Estimation Strategy

3.1 School and pupil effects

To estimate pupil contributions and school contributions into educational achievement, we start with the simple specification - however powerful - of Abowd et al. [10]. Test scores are decomposed into a pupil effect and a school effect, and a set of controls for the grades and years. Thus test score $y_{i,f,t}$ can be written:

$$y_{i,f,t} = D_{i,f,t}\beta + \theta_i + \psi_{J(i,t)} + \varepsilon_{i,f,t} \tag{1}$$

With $i = 1, ..., N$ indexing pupils, $j = 1, ..., J$ indexes schools, $f \in Maths, English$ indexing fields, and t indexing years. For the list of years for each cohort, see table (2.2). $J(i,t)$ is the school of pupil $i$in year t. θ_i is the pupil effect, ψ_j is the school effect, $D_{i,f,t}$ is a set of controls for grades, years and fields, and $\varepsilon_{i,f,t}$ is the residual.

This specification is estimated by OLS. Given the large number of two-way fixed effects, the normal form equation cannot be solved by the usual inversion of the matrix of covariates. Thus we employ a conjugate gradient algorithm described in Abowd, Creecy, Kramarz [11].

The identification of equation (1) relies on the movement of pupils between schools. Indeed one needs a conterfactual for each pupil, comparing his results in the first and the second school. Thus only pupil and school effects in the same group of mobility can be compared. Mobility groups are defined by the following rule:

Rule SC: Pupil i and school j are in the same mobility group if pupil i attended school j once.[4]

Observations i, f, t of the dataset are split into mobility groups. Since this partition practically leads to one large group including more than 99.9% of the observations, we throw the remaining smaller mobility groups. The selection bias is likely to be small. The pupil effects are therefore estimated under the identification restrictions that $\sum_{i=1}^{N} \theta_i = 0$ and that $\psi_J = 0$.

More details and a proof that this rule leads to the identification of pupil and school/year-group effects can be found in Creecy ([11]).

[4]Formally, denote by $\mathcal{P}$the set of pupils. $\mathcal{S}$ is the set of schools. R is the equivalence relation on $\mathcal{P} \cup \mathcal{S}$ such that $i \in \mathcal{P}$ and $j \in \mathcal{S}$ are equivalent, iRj, if and only if i attended school j at least once. Mobility groups are the equivalence classes of this equivalence relation.

Where does this pupil mobility come from? One can broadly distinguish two types of mobility: (1) *institutional mobility*, due to the fact that pupils have to move because their school does not cater for them next year (2) *chosen mobility*, when parents move their children because they find that another school would be better given the cost of moving, under current conditions.

We believe that institutional mobility is likely to be a more exogenous source of mobility than chosen mobility. It is true, however, that parents can choose to register their child in a school that accepts only pupils aged 7.

Table A2 presents descriptive statistics on the mobility of pupils. Around 64% of the observed pupils were attending a school for both Key Stage 1 and Key Stage 2 at age 7. Around a third of the sample comes from a school that they could not stay in for Key Stage 2. This is therefore a sizeable part of the sample that experiences what we have called *institutional mobility*. Finally, around 5% of the sample enters the dataset at Key Stage 2.

Formally the identification hypothesis for the OLS specification is written:

$$E(\varepsilon_{i,f,t}|i, J(i,t), f, t) = 0$$

Which means that no time-varying variable should be correlated with the pupil effect, the school effect, or the control variables. This implies *exogenous* mobility: mobility should not be driven by time-varying variables. This condition is for instance violated in the following case: if unemployment shocks affect both mobility and test scores; that is, pupils whose parents become unemployed go to lower quality schools and their test scores are directly affected by the change of their parents' income, then the school effects of low quality schools will be underestimated. Hence the identification hypothesis does not allow for such *endogenous* mobility.

Once school effects are estimated, one can compare school effects across school status, taking Community Schools as the reference point. School effects are regressed on a set of school characteristics S_j.

$$\psi_j = S_j s + \eta_j$$

The identification of the s parameters requires the orthogonality between the school characteristics and the residual. Given the limited amount of information available on schools, this simple regression is essentially descriptive. To go one step further, however one can compare schools with different status within the same Local Education Authority, by adding LEA fixed effects in the school effects analysis.

$$\psi_j = S_j s + LEA_j + \eta_j$$

LEA_j is a Local Education Authority fixed effect. Results are analyzed in the next sections.

The main advantage of specification (1) is its simplicity. However, this specification can be extended in two ways: (i) to capture the variation of school effects from year-to-year. School effectiveness is indeed likely to vary from year to year due to the changing school composition, and other time-varying inputs like teacher quality. (ii) to take into account that school heterogeneity in the first observed grade has an impact on test scores in the next observed grade. The next section presents a year-group effect specification that attempts to tackle the first issue.

3.2 Year-group and pupil effects

This section presents a specification that decomposes test scores into a pupil contribution and a year-group composition. Since the year-group effect is both time and grade-specific, this effect should capture both the time-varying school inputs (e.g. school resources, teacher quality, peer quality), and the time-invariant inputs. With the same notations as in the previous section, the test score $y_{i,f,t}$ is decomposed in the following way.

$$y_{i,f,t} = D_{i,f,t}\beta + \theta_i + \psi_{J(i,t),g(i,t),t} + \varepsilon_{i,f,t} \tag{2}$$

As before, $i = 1, ..., N$ indexes pupils. $j = 1, ..., J$ indexes schools, $g = 2, 6, 9$ indexes grades, and $t$indexes years. $f \in English, Maths$ is the topic. $J(i, t)$ is the school of pupil i in year t. $g(i, t)$ is the grade of pupil i in year t. Thus θ_i is the pupil effect, $\psi_{J(i,t),g(i,t),t}$ is a year-group effect, $D_{i,f,t}$ is a set of controls for grades, years and fields. $\varepsilon_{i,f,t}$ is the residual.

The identification constraints for the pupil effects and the year-group effects imply that year-group effects and pupil effects can only be compared within the same mobility group. Mobility groups are defined by the following rule:

Rule YG: Pupil i and year-group j, g, t are in the same mobility group if pupil i attended school j in grade g in year t.

Rule YG is more restrictive than rule SC. However applying rule YG to the dataset again leads to one large group covering more than 99.9% of the observations. Hence we drop the remaining mobility groups, assuming that the implied selection bias is likely to be small.

The identification hypothesis formally requires the orthogonality between the residual and the explanatory variables:

$$E(\varepsilon_{i,f,t}|i, J(i,t), g(i,t), f, t) = 0$$

This is again exogenous mobility, the difference with the previous specification being that mobility occurs from one year-group to another year-group. Exogenous mobility here means that there is no time varying variable correlated with the pupils effect or the year-group effect.

How do we disentangle peer-effects and school quality in the year-group effects ? The constant part of the year-group effect is attributed to school quality. The year-group effect is indeed decomposed as the sum of a constant school effect and the effect of the social composition of the school.

$$\psi_{j,g,t} = \psi_j + E(Z|J(i,t), g(i,t), t)\gamma + G_{j,g,t}\delta + \eta_{j,g,t} \tag{3}$$

As before, $\psi_{j,g,t}$ is the year-group effect. $\psi_j$is a school effect, common to all years and grades. $E(Z|J(i,t), g(i,t), t)$ is the average characteristics of the students of the year-group. $G_{j,g,t}$ is a set of year-group characteristics, dummy variables for the grades 2, 6 and 9, and school types. γ is the effect of the social composition on year-group quality.

The identification of this second-step equation requires that variations in year-group composition within a school are exogenous, which is similar to the identification hypothesis used by Hoxby [4] and Gould, Lavy and Paserman [6]. To make clear the identification hypothesis for peer-effects, let us write the within specification of regression (3).

$$\psi_{j,g,t} - \psi_{j,\cdot,\cdot} = [E(Z|j,g,t) - E(Z|j)]\gamma + (G_{j,g,t} - G_{j,\cdot,\cdot})\delta + \eta_{j,g,t} - \eta_{j,\cdot,\cdot} \tag{4}$$

Where the dot means the average over the specified index. In the language of Manski [2],γ includes both the exogenous and the endogenous contextual effects. The identification hypothesis requires that variations in year-group composition between years are exogenous, formally:

$$Cov(E(Z|j,g,t) - E(Z|j,g), \eta_{j,g,t} - \eta_{j,\cdot,\cdot}|G_{j,g,t} - G_{j,\cdot,\cdot}) = 0 \tag{5}$$

Variations in year-group composition across years and grades are assumed to be exogenous, ie not correlated with time-varying school unobserved characteristics. This can be due to the randomness of the demographics, the finite number of students in each year-group being the source of identification.

In a word, the year-group effects - pupil effects specification presented in this section goes on step further than specification (1) by allowing for year-group specific school effects that capture both non-time varying and time varying school inputs. A second step analysis of the year-group effects can be performed to suggest a decomposition of the year-group effect into the contribution of the social composition of the school and the contribution of invariant school inputs.

3.3 Controlling for past inputs: (A) year-group effects with value-added

At the end of section 3.1, we highlighted the two potential issues that needed to be addressed in specification (1). One of them, the fact that school inputs are time-varying due to changing social compositions and changing school quality, has found one possible solution in the previous section. The second issue is that we are comparing pupils at different times without controlling for past inputs. Indeed, specification (2) lacks controls for past school quality. In this section and the following, we propose two alternative ways of controlling for past inputs: the first path could be a value-added specification, which nevertheless suffers from the Nickell bias. The second path is the estimation by controlling for past peers' achievement.

Specification is enhanced one step further by the inclusion of a control for past educational inputs $P_{i,f,t}$:

$$y_{i,f,t} = D_{i,f,t}\beta + \theta_i + \psi_{J(i,t),g(i,t),t} + P_{i,f,t}\lambda + \varepsilon_{i,f,t}$$

For the definitions of the notations and symbols, see section (3.2). $P_{i,f,t}$ is a control for past inputs for the observation of pupil i in year t for field f. In this section, we attempt to estimate this specification with $P_{i,f,t} = y_{i,f,t-1}$.

$$y_{i,f,t} = \lambda y_{i,f,t-1} + D_{i,f,t}\beta + \theta_i + \psi_{J(i,t),g(i,t),t} + \varepsilon_{i,f,t} \tag{6}$$

In the first year of the cohort, we assume that the lagged test score is 0, i.e. $y_{i,f,t} = 0$ for the initial year of the cohort. We need, as in previous specifications, the assumption of *exogenous* mobility.

Controlling for past achievement makes it clear that achievement at a certain date is the outcome of a cumulative process. However, as Todd and Wolpin [12] point out, the value-added specification imposes constraints on the impact of past inputs on current achievement. This appears when plugging the expression for $y_{i,f,t-t}$ into equation (6) to get the reduced form specification:

$$y_{i,f,t} = (1+\lambda)\theta_i + \psi_{J(i,t),g(i,t),t} + \lambda\psi_{J(i,t-1),g(i,t-1),t-1} + D_{i,f,t}\beta + \lambda D_{i,f,t-1}\beta + \varepsilon_{i,f,t} + \lambda\varepsilon_{i,f,t-1}$$

This reduced form equation shows that the coefficient λ on past inputs is constrained to be equal across different inputs.

One potential identification problem of specification (6) has been exposed by Nickell [13]. The introduction of the lagged dependent variable leads to a bias in the estimation of the λ since within deviations of the lagged variable are correlated with the within deviations of the residuals. In simple words, the progress of the child $y_{i,f,2} - y_{i,f,1}$ is correlated with the variation of the shock $\varepsilon_{i,f,2} - \varepsilon_{i,f,1}$.

In our case, with a zero test score as the initial condition, the bias takes a simple form. It is $1 - R_1^2$, ie one minus the R-square of the specification for the first year of each cohort. In order to try to overcome the identification problem, we estimate this R-square and the biased value of λ, to get an estimate of the structural λ. Thus $\hat{\hat{\lambda}} = \hat{\lambda} + (1 - R_1^2)$. We therefore estimate instead the following specification :

$$\begin{aligned} y_{i,f,2} - \hat{\hat{\lambda}} y_{i,f,1} &= D_{i,f,2}\beta + \theta_i + \psi_{J(i,2),g(i,2),2} + \varepsilon_{i,f,2} \\ y_{i,f,1} &= D_{i,f,1}\beta + \theta_i + \psi_{J(i,1),g(i,1),1} + \varepsilon_{i,f,1} \end{aligned}$$

However, the estimated R-square of the first step is dependent on the first estimate of λ. This estimation procedure does not lead to the identification of θ_i, $\psi_{j,g,t}$ andλ. However one could see the estimation as the estimation of the contribution of pupils and schools in the value-added of the pupil, in which the value-added is computed using an approximate discounting factor.

The value-added specification (6) is a first attempt to control for the past educational career. However the model fails to be identified, as has been shown in Nickell [13]. The next section provides a specification in which past peers' average achievement is a control for past educational inputs.

3.4 Controlling for past inputs: (B) past peers' achievement

The previous section has put forward one way of controlling for past inputs. This section presents a way to control for past by including the average achievement of peers in the previous key stage.

$$y_{i,f,t} = \lambda E[y|J(i,t-1), g(i,t-1), t-1] + D_{i,f,t}\beta + \theta_i + \psi_{J(i,t),g(i,t),t} + \varepsilon_{i,f,t}$$

Which, in reduced form, is:

$$y_{i,f,t} = D_{i,f,t}\beta + \lambda E[D|yg(i,t-1)]\beta + \theta_i + \lambda E[\theta|yg(i,t-1)] + \psi_{yg(i,t)} + \lambda\psi_{yg(i,t-1)} + \varepsilon_{i,f,t} + \lambda E[\varepsilon|yg(i,t-1)]$$

Notations are defined in the previous sections. $yg(i,t)$ is the year-group of pupil i in year t. Assuming that shocks are not correlated across individuals in the same year group, the effect λ of past inputs is identified. Formally, λ is identified under the assumption:

$$\forall t, f \quad \forall i \neq i' \qquad Cov(\varepsilon_{i,f,t}, \varepsilon_{i',f,t}) = 0$$

Intuitively, pupils should not have topic-specific shocks at the same time – non topic specific shocks should be captured by the year-group effect –.

4 Analysis of the Results

In this preliminary draft, we present results of the estimations for Key Stage 1 and Key Stage 2 cohorts.

4.1 Decomposing Inequalities

Once educational achievement has been decomposed into contributions of schools, and pupils' backgrounds, it is possible to assess the contribution of these inputs into inequalities of achievement. Broadly speaking, inequalities are both due to the heterogeneity of inputs and the assignment of the best inputs to advantaged pupils. If good schools are assigned to low performing pupils, schools narrow inequalities. In a word, heterogeneity and assortative matching cause inequalities.

Inequalities in achievement are due to (i) school quality, (ii) segregation and (iii) pupils' backgrounds. This can be seen in the following equality, where the variance of equation (3.2) is taken:

$$Var(y) = Cov(y,\theta) + Cov(y,\psi) + Var(\varepsilon)$$

For the sake of clarity, this decomposition ignores the presence of the other control variables. Moreover, we assume that the residual is orthogonal to the explanatory variables.

Under the identification hypothesis, the first component of the sum can be interpreted as the inequality caused by pupil effects, the second one is the inequality caused by year-group effects.

In turn, each component can be written as the sum of (i) the heterogeneity of input qualities and(ii) the degree of assortative matching:

$$\begin{aligned} Cov(y,\theta) &= Var(\theta) + Cov(\theta,\psi) \\ Cov(y,\psi) &= Var(\psi) + Cov(\psi,\theta) \end{aligned}$$

Estimates of the correlation between achievement and pupil effects, school effects are shown in table A3.

They first suggest that pupils are more heterogeneous than year-groups. The standard deviation of pupil effects is around twice as large as the standard deviation of year-group effects. Moreover, good year-groups tend to be correlated with good pupils.

There is an issue in the estimation of empirical correlations since the measurement error on the pupil effect and the year-group effect are negatively correlated. Our bootstrap computations suggest that the true correlation is around 0.10 higher than the empirical correlation. For more on that, see Abowd et al. [14].

Overall, the inequality attributed to the pupil effects is higher than the inequality attributed to the year-group effects: the correlation between the test score and the pupil effect is 0.79, while the correlation between the test score and the year-group effect is 0.07.

4.2 Pupil effects and pupil's backgrounds

We now turn to the analysis of pupil effects. The correlation table suggests that pupil effects are much more correlated with test scores than year-group effects. How are pupil effects correlated with observable characteristics such as gender, ethnicity, free school meal status and disability ? Regression results are presented in table 4. The identification hypothesis for this regression is the exogeneity of the observable characteristics.

Free School Meal pupils is a proxy for economic deprivation, including the poorest 16% of the Key Stage 1/ Key Stage 2 sample. Free school meal status is associated with lower test scores, around 41% of a standard deviation lower. Special Educational Needs is a generic status for various kinds of disability. The variable can be broken down into finer types of disability, but here only a dummy for this status is included. Special Educational Needs status corresponds to test scores 120% of a standard deviation lower than non Special Educational Needs pupils. Speaking English at home is linked to test scores higher by 20% of a standard deviation.

The correlations between ethnicity and pupil effects rank ethnicities in the same way as descriptive statistics do, Chinese pupils being better pupils, wih a higher pupil effect, by 33% of a standard deviation. At the bottom of the list of ethnicities, Black Carribeans have lower pupil effects. The under performance of black carribeans is a public policy issue, notably emphasized by Trevor Phillips, the chairman of the commission for racial equality.

Around half of the variance of the pupil effects is left unexplained. This might be due to the absence of controls for family background and resources.

4.3 Year-Group effects analysis

Even though year-group effects explain a smaller share of the total variance of the test scores, it is interesting to look at the share of the year-group effects that is explained by school effects and by year-group composition. As explained in the specification part of this paper, the contextual can have a causal interpretation provided year-to-year variations in year-group composition is exogenous, which is similar to Hoxby [4]. This holds, of course, provided the year-group effect is correctly identified.

Results of the regressions of year-group effects on exogenous contextual characteristics of pupils are presented in table A5. Broadly speaking, the correlation between year-group composition and year-group effects is much higher than the correlation between school effects and year-group effects: in the specification with school fixed effects, the share of the variance explained by year-group composition is .

The correlation between the share of chinese pupils and the year-group effect is in line with the above-the-mean performance of chinese pupils which is presented in the pupil effects analysis. The fraction of black carribeans has an adverse contextual effect (under the identification hypothesis) that is in line with their own performance.

However, two surprising contextual effects emerge from regression (2) in table A5. The fraction of pakistani pupils and the fraction of bangladeshi pupils has a positive effect on year-group effects. This might indicate that Pakistani pupils have a positive *exogenous* contextual effect, ie an effect on year-group quality that does not go through achievement.

5 Conclusion

The economics of education literature and the sociological literature on education both strive to estimate the impact of peers, school quality and pupils' background on achievement. However, the relative effectiveness of these three inputs is little known. In this paper, we suggest a way to estimate the impact of pupils, peers and school quality on achievement without relying on proxies. Estimation is done in two steps by combining ideas from Hoxby [4] and Gould et al. [6], and Abowd et al. [10]. Though suffering from a bias as explained in Nickell [13], we propose a workaround to compute value-added test scores.

Preliminary results indicate that pupils explain the largest share of the variance of test scores. The correlation between pupil effects and year-group effects is positive but small. Under the assumption that year-to-year variations in year-group composition are exogenous, we find that year-group composition explains most of the variance of year-group quality, far above the share of the variance explained by time-invariant school effects.

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Table A1: Descriptive Statistics : Pupils

		Number	Percentage
Number of Pupils		1,776,953	
Number of Year-Groups		95,225	
Sample Size		6,883,393	(100.00 %)
Of Which:			
Key Stage 1 observations		3,394,160	(49.31 %)
Key Stage 2 observations		3,489,233	(50.69 %)
Of Which :			
Key Stage 1:	1998	1,117,878	(16.24 %)
	1999	1,155,557	(16.79 %)
	2000	1,119,722	(16.27 %)
Key Stage 2:	2002	1,127,948	(16.39 %)
	2003	1,211,081	(17.59 %)
	2004	1,150,216	(16.71 %)

	Number	Percentage
Boy	783,449	(50.52 %)
Free School Meal	252,702	(16.30 %)
Special Educational Needs	324,601	(20.93 %)
Foreign Language	88,401	(5.70 %)

	Mean	(Std. Dev.)	Min.	Max.
All Test Scores	50.00	(10.00)	11.04	81.21
Key Stage 1 Test Scores	50.00	(10.00)	11.04	81.21
English	50.00	(10.00)	20.28	81.21
Maths	50.00	(10.00)	11.03	79.01
Key Stage 2 Test Scores	50.00	(10.00)	11.23	76.30
Maths	50.00	(10.00)	19.39	67.84
English	50.00	(10.00)	11.23	76.30

	Simple Correlation with			
	Key Stage 1		Key Stage 2	
	English	Maths	English	Maths
Key Stage 1 Test Scores				
English	1.00			
Maths		1.00		
Key Stage 2 Test Scores				
English			1.00	
Maths				1.00

Note: Test scores were standardized with mean 50 and standard deviation 10. Foreign Language: does the pupil speak another language than English at home ? The Normal Age is 10 in the second cross-section (2002 to 2004) and 6 in the first cross-section (1998 to 2000)

Table A2 :School Mobility between ages 7 and 11 (using observations of English test scores)

To a school for pupils aged…	*Not in the dataset in Key Stage 1*	*From a school catering for pupils aged …* 7	7 and 11	Total
11	24,837	471,474	61,102	557,413
	(1.43 %)	(27.08 %)	(3.51 %)	(32.01 %)
7 and 11	56,803	71,438	1,055,469	1,183,710
	(3.26 %)	(4.10 %)	(60.62 %)	(67.99 %)
Total	81,640	542,912	1,116,571	1,741,123
	(4.69 %)	(31.18 %)	(64.13 %)	(100.00 %)

In grey: mobility from schools that cater only for pupils aged 7, called *institutional mobility*

Table A3: Summary Statistics for the Decomposition of Variance for Pupil Data, Key Stage 1, Key Stage 2

Specification with School Effects

Variable description	Mean	Std. Dev.	Simple Correlation with y	θ	ψ
y Standardized grade	50.000	10.000	1.000		
θ, Pupil Effect	0.000	9.675	0.802	1.000	
ψ, School Effects	1.145	1.897	0.105	-0.085	1.000
ε, Residual	0.000	4.464	0.448	0.000	0.000

Specification with Year-Group Effects

Variable description	Mean	Std. Dev.	Simple Correlation with y	θ	ψ
y, Standardized grade	50.000	10.000	1.000		
θ, Pupil Effect	0.000	9.866	0.778	1.000	
ψ, Year-Group Effect	12.936	6.026	0.069	0.035	1.000
ε, Residual	0.000	4.288	0.432	0.000	0.000

Specification with Year-Group Effects and value added

Variable description	Mean	Std. Dev.	Simple Correlation with y	θ	ψ
y, Standardized grade	50.000	10.000	1.000		
θ, Pupil Effect	0.000	9.916	0.791	1.000	
ψ, Year-Group Effect	13.142	5.727	0.073	0.034	1.000
ε, Residual	0.000	7.434	-0.068	0.000	0.000

Source: National Pupils Database, 1999-2004, Department for Education and Skills.
The identification constraint for the pupil effects is that the mean is equal to zero.One of the school effects

Specification with Year-Group Effects and lagged average achievement

Variable description	Mean	Std. Dev.	Simple Correlation with y	θ	ψ
y, Standardized grade	50.000	10.000	1.000		
θ, Pupil Effect	0.000	9.959	0.780	1.000	
ψ, Year-Group Effect	12.928	6.004	0.063	0.034	1.000
ε, Residual	0.000	4.288	0.432	0.000	0.000

Source: National Pupils Database, 1999-2004, Department for Education and Skills.

Table A4: Pupil Effects Analysis - Key Stage 1 / Key Stage 2 sample

	Dependent Variable: Pupil Effects *Sample : Key Stage 1 / Key Stage 2* Specification			
	School Effects	Year-Group Effects	Value-Added	Lagged Average *y*
Boy	**-0.036**	**-0.038**	0.009	**-0.037**
	(0.012)	(0.013)	(0.011)	(0.013)
Free School Meal Status	**-4.087**	**-4.091**	**-4.072**	**-4.198**
	(0.016)	(0.017)	(0.015)	(0.017)
First Language English	**1.916**	**2.083**	**2.199**	**2.587**
	(0.033)	(0.034)	(0.030)	(0.035)
Special Educational Needs	**-11.620**	**-11.530**	**-12.043**	**-11.611**
	(0.015)	(0.015)	(0.013)	(0.015)
Month of Birth	**-0.303**	**-0.305**	**-0.311**	**-0.307**
	(0.002)	(0.002)	(0.002)	(0.002)
Ethnicity				
Chinese	**3.003**	**3.077**	**3.256**	**3.112**
	(0.112)	(0.115)	(0.101)	(0.117)
Mixed	**-1.807**	**-2.009**	**0.550**	**-2.095**
	(0.045)	(0.046)	(0.040)	(0.046)
Indian	**1.076**	**1.097**	**1.225**	**1.334**
	(0.050)	(0.052)	(0.045)	(0.052)
White	Ref.	Ref.	Ref.	Ref.
Bangladeshi	**-1.549**	**-1.719**	**-1.510**	**-1.549**
	(0.070)	(0.072)	(0.063)	(0.072)
Black African	**-1.307**	**-1.502**	**-1.129**	**-1.911**
	(0.054)	(0.056)	(0.049)	(0.056)
Pakistani	**-2.328**	**-2.171**	**-1.888**	**-1.988**
	(0.049)	(0.050)	(0.044)	(0.051)
Black Other	**0.685**	**0.624**	**-0.831**	**0.416**
	(0.084)	(0.086)	(0.076)	(0.087)
Other	**-0.238**	**-0.256**	**-0.241**	**-0.381**
	(0.031)	(0.032)	(0.028)	(0.032)
Black Carribean	**-1.607**	**-1.757**	**-1.740**	**-2.027**
	(0.050)	(0.052)	(0.045)	(0.052)
Other controls	Cohort dummies			
R-Squared	0.337	0.322	0.486	0.324
F Statistic	53,403.61	49,740.61	84,144.00	50,141.00
Number of Observations	1,782,768	1,776,953	1,776,953	1,776,953

Month of birth coding: 1: September, 2:October, … 12: August

Special Educational Needs: The Child has special learning difficulties, compared to pupils of the same age,or has a disability (for a formal definition, see the Education Act 1996, par. 312).

Table A5 : School Effects Analysis - Key Stage 1 / Key Stage 2 Sample

	Specification:				
	School Effects	Year-Group Effect		Value-Added	
	Dependent Variable:				
	Ψj School Effect	Ψj,g,t Year-Group Effect		Ψj,g,t Year-Group Effect	
School Status					
Community	Ref.	Ref.	-	Ref.	-
Voluntary Aided	**0.151** (0.049)	**0.247** (0.028)	-	**0.257** (0.027)	-
Voluntary Controlled	**-0.300** (0.056)	**-0.140** (0.033)	-	**-0.132** (0.032)	-
Foundation	-0.015 (0.138)	**0.213** (0.082)	-	**0.220** (0.081)	-
Community Special	**-1.644** (0.098)	**-1.936** (0.095)	-	**-2.254** (0.093)	-
Non-Maintained Special	**-3.455** (0.467)	**-2.367** (0.448)	-	**-2.877** (0.439)	-
Foundation Special	**-3.101** (0.834)	**-5.320** (0.534)	-	**-5.531** (0.523)	-
School Composition					
% with English as first language	-	**-0.556** (0.154)	**-0.662** (0.219)	**-0.515** (0.151)	**-0.615** (0.215)
% with Free School Meal	-	**-3.111** (0.760)	-1.340 (0.879)	**-2.918** (0.744)	-1.191 (0.862)
% with Special Needs	-	2.424 (1.786)	1.514 (1.874)	2.478 (1.749)	1.598 (1.837)
% of Boys	-	**0.313** (0.084)	**0.256** (0.093)	**0.306** (0.082)	**0.246** (0.092)
Ethnic composition					
% Chinese	-	0.864 (0.822)	**2.659** (0.932)	0.941 (0.805)	**2.679** (0.913)
% Mixed	-	**-0.779** (0.278)	-0.094 (0.325)	**-0.683** (0.271)	-0.045 (0.318)
% Indian	-	**-0.822** (0.235)	-0.963 (0.509)	**-0.770** (0.229)	-0.922 (0.498)
% White	-	Ref.	Ref.	Ref.	Ref.
% Bangladeshi	-	**1.225** (0.268)	**1.755** (0.685)	**1.266** (0.263)	**1.646** (0.671)
% Black African	-	0.534 (0.301)	0.693 (0.458)	0.485 (0.294)	0.547 (0.449)
% Pakistani	-	0.032 (0.200)	**1.187** (0.460)	0.089 (0.196)	**1.111** (0.451)
% Black Other	-	-0.956 (0.503)	-0.227 (0.602)	-0.944 (0.493)	-0.268 (0.590)
% Other	-	**-0.386** (0.122)	0.248 (0.152)	**-0.374** (0.119)	0.216 (0.149)
% Black Carribean	-	0.273 (0.275)	**-1.042** (0.496)	0.275 (0.269)	**-1.097** (0.487)
School Fixed Effects	No	No	Yes	No	Yes
Key Stage dummies	No	Yes	Yes	Yes	Yes
Year dummies	No	Yes	Yes	Yes	Yes
R-Squared	0.05	0.73	0.85	0.72	0.84
F Statistic	81.93	7046.04	13558.05	6621.48	11656.54
Number of observations	20,658	95,198	95,225	95,225	95,225