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October 2008

Working Paper No. 08/204

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ISSN 1473-625X





Segregation and the Attainment of Minority Ethnic Pupils in England

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October 2008

Abstract

In this paper we ask whether ethnic segregation in schools and in neighbourhoods has a causal effect on differential school attainment. We ask two related but different questions. First, we look at the test score gap between White and minority ethnic students, separately for Black Caribbean, Indian and Pakistani ethnic groups. Second, we consider the absolute performance of students in each of these minority ethnic groups across cities with varying levels of segregation. We show that, in strong contrast to similar studies in the US, the test score gap is largely unaffected by segregation for any of the three groups we study, and we find no evidence of a negative impact of ethnic segregation on absolute attainment levels.

Keywords: ethnic segregation, schools

JEL Classification: I20

Electronic version: www.bristol.ac.uk/cmpo/publications/papers/2008/wp204.pdf

Acknowledgements

We gratefully acknowledge very useful comments from Rob McMillan, Carol Propper, Sarah Smith, Jacob Vigdor, Jane Waldfogel and Liz Washbrook, and seminar participants at ESPE and Bristol.

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1. Introduction

The accumulation of human capital is important for an individual's future life chances, both in terms of continuing in education and with regard to labour market outcomes. The qualifications achieved at the end of compulsory schooling provide an accurate marker for both. The differential attainment across ethnic groups through formal schooling is a cause for concern, given that there appear to be persistent differences across the different groups. In the US, for example, the long term focus has been on the underachievement of Black students relative to their White peers; more recently the Hispanic-White test score gap has also gained attention (see Neal (2005) for a recent review). In England the picture is more mixed: on average, White students outperform students from some minority ethnic groups (Black Caribbean, Pakistani, Bangladeshi, for example), but are outperformed by others, including Indian and Chinese (Wilson et al 2005; see also Modood 2005). There are many potential explanations for these observed differential education outcomes, not mutually exclusive. These include non-school factors such as poverty, social class and family background¹, school factors such as differential school quality², the quality of teachers and other educational inputs³ and teacher and/or system biases⁴.

In this paper we focus on the impact of the ethnic composition of the student's school and neighbourhood on test score outcomes. US evidence, discussed below, suggests strongly that segregation worsens the test score gap. But the context in England is different, in terms of the nature of the school system, the relative performance of minority ethnic students and the levels of segregation. Our results add to the wider debate about the 'effects of segregation' from this different perspective. We ask whether ethnic segregation in schools and in neighbourhoods has a causal effect on differential school attainment. Determining whether there is a causal effect is not straightforward since it is likely that the characteristics of students that are associated with attainment will be correlated with school composition: for example, more able minority ethnic pupils may attend schools with higher minority composition. We ask two related but different questions, which entail different assumptions for identification. First, we look at the score gap between White pupils and a minority group (separately for three different minorities). This is the question typically posed in the US and uses an identification strategy based on data aggregated to city level, and compared across cities. Secondly, we consider the absolute performance of minority students across cities with varying levels of segregation. This analysis relies on a matching approach to match minority pupils across cities and a regression on the matched pairs to control for a host of city characteristics.

Evidence for the US from a similar dataset to ours comes from Card and Rothstein (2007). They find that higher segregation increases the Black-White score gap, with a shift from a highly segregated city to a nearly integrated city removing about a quarter of the raw gap. They use student level data as we do, and deal with the endogeneity problem in the same way, by averaging up to city level, thereby side-stepping within-

¹ See Phillips et al (1998); Modood (2003); Bradley and Taylor (2004) and Friesen and Krauth (2007).

² See Fryer and Levitt (2004, 2005); Hanushek and Rivkin (2006).

³ See Clotfelter et al (2004), Hanushek et al (2005), and also Card and Rothstein (2007) and Reber (2007a, 2007b).

⁴ See Jencks (1998), Ferguson (2003) and Tikly (2005)

city non-random sorting. Other recent evidence comes from Ananat (2007), who uses 19th Century railway configurations to instrument for the extent to which cities became segregated during African-American immigration in the 19th Century. She finds that blacks are worse off across a range of education and income-related outcomes in areas that are more segregated compared to those that are less segregated. Echenique et al (2006) also find that segregation has a significant, negative relationship with test scores for Black, Asian and Hispanic students relative to Whites for a sample of around 90,000 7th -12th graders in the US in the mid 1990s. The authors stress, however, that their results may not be causal.

In what ways might school and neighbourhood ethnic composition affect schooling outcomes? It could be that the ethnicity of a student's peers is simply a proxy for their academic ability and/or their socioeconomic status, which in turn suggests a peer effects mechanism (Vigdor and Ludwig 2007; Cooley 2006). A more insidious peer effects mechanism is that of 'acting White', whereby Black peers and communities impose costs on their members who try to 'act White', thus creating a disincentive to engage in certain behaviours such as studying hard (Austen Smith and Fryer 2005 and references therein). Cook and Ludwig (1998) discuss how this can lead to academically successful Black students being disparaged and/or reducing their effort in order to avoid taunts. Thus the composition of the school influences individual effort. Modood (2003) notes that this is one common explanation for the underachievement of Black Caribbean male students in the UK.

There is a large literature on the importance of aspiration and expectation in explaining ethnic differences in educational attainment (Kao and Tienda 1998; Khattab 2003). While parents are an important source of educational and occupational aspiration (Schneider and Stevenson 1999), school composition – or levels of school segregation – may additionally impact on these aspirations in two opposing directions. The first stokes up aspirations as minority students face lesser competition from majority students and thus judge their performance relative to other minority students in their school (Shavit and Williams 1985). The second may restrict aspirations; areas with high concentrations of minorities are less likely to attract families from high socio-economic groups and high levels of resources/investment. Students in schools in such areas may be less focussed on academic activities and less likely to have high academic aspirations with a potential effect on performance. They may also be less exposed to aspirational role models within their locale⁵.

In strong contrast to the US findings, we show that the test score gap between White and minority students is largely unaffected by segregation for the three groups we study (Black Caribbean, Indian, and Pakistani pupils). Furthermore, when we compare the performance of minority students across cities, we find no evidence of a negative impact of ethnic segregation on test score outcomes. There is considerable variation in school segregation across England for these ethnic groups, but it appears to have no detrimental impact on school attainment.

The rest of the paper is structured as follows. In the next section we outline our empirical model and derive the equations we estimate for the two different sets of results. Section 3 provides details of the data we use. In section 4 we present our

⁵ See Wilson (1987), Zhou (2005) and Cutler, Glaeser and Vigdor (2005).

results; first looking at the test score gap, then focusing on how segregation impacts on the absolute attainment of each minority group. Section 5 concludes and discusses the potential policy implications of our results.

2. Empirical Model

a) Basic Model

We start with a simple model to make the issues clear and then generalise to the model we actually implement; this largely follows the approach of Card and Rothstein (2007). We assume that a student's score depends on personal characteristics of the student, and characteristics of her school, local neighbourhood and city⁶. The key feature is that we also allow the composition of the school to affect students' test scores. For a student i in school s located in city c we assume that the test score g is generated by:

$$g_{isc}^{G} = X_{isc}\alpha^{G} + Z_{sc}\beta^{G} + S_{sc}\gamma^{G} + \left[\mu_{sc}^{G} + \varepsilon_{isc}^{G}\right]$$

$$\tag{1}$$

where superscript G refers to ethnic group, X is a set of observable personal characteristics, Z a set of observable school characteristics, and S is the proportion of the school's students from the ethnic minority. Unobservable school influences are μ_{sc}^G , the common error component for students of group G in school s in city c, and an individual error ε_{isc} , with zero mean within each school, city and ethnic group. City effects are implicit and absorbed by the school effects, observed and unobserved, as in Card and Rothstein (2007). For brevity in this section, we will refer to just two ethnic groups: a minority and White, so G = M, W.

There are obvious problems with estimating (1) straightforwardly on individual or school-level data since students are not randomly assigned to schools. It seems very likely that characteristics of students that are associated with educational performance will be correlated with school composition through the decisions of schools and/or families on which children go to which schools. This correlation could produce a bias of either sign for γ , depending on whether more able (or more supported) minority ethnic pupils go to schools with higher minority composition or not. The key statistical problem is the non-random sorting of families of different ethnicities across schools and neighbourhoods in an area.

Another potential problem with school-level estimation is reverse causality. For example, it may be that schools that do well for Indian pupils attract a disproportionate number of such pupils. We set out the approaches to deal with these two endogeneity problems below.

⁶ We refer to the aggregate geographical unit as a city for convenience. In the empirical work, we use two different definitions for this.

4

b) Modelling the test score gap

Continuing with the simple model in (1), we can eliminate the selection problems of within-city non-random sorting by averaging at the city level. This yields:

$$\overline{g}_{c}^{G} = \overline{X}_{c}^{G} \alpha^{G} + \overline{Z}_{c}^{G} \beta^{G} + \overline{S}_{c}^{G} \gamma^{G} + \overline{\mu}_{c}^{G}$$
(2)

The average test score of an ethnic group in a city depends on their characteristics, the average ethnic composition of schools in the city and the quality of the schools they go to. To make the point simply, assume for now that all the coefficients are the same for both groups: $\alpha^M = \alpha^W = \alpha$. Taking the difference between ethnic groups at city level, using the notation, $\overline{g}_c^M - \overline{g}_c^W \equiv \Delta \overline{g}_c$:

$$\Delta \overline{g}_{c} = \Delta \overline{X}_{c} \alpha + \Delta \overline{Z}_{c} \beta + \Delta \overline{S}_{c} \gamma + \Delta \overline{\mu}_{c}$$
(3)

Observed and unobserved city-wide influences disappear. $\Delta \overline{Z}_c$ measures differences in the characteristics of schools disproportionately attended by minority and White pupils, such as the gap in average school quality.

The term $\Delta \overline{S}_c$ is a measure of segregation. Fully segregated schools imply $\Delta \overline{S}_c = 1$ and fully integrated schools imply $\Delta \overline{S}_c = 0$. There is a vast literature on measuring segregation. Two key references are Duncan and Duncan (1955) who set out the formal foundations for measuring segregation, and Massey and Denton (1988) who delineate different dimensions of segregation, examine the links between them, and assess their empirical performance. The approach we use derives from the economic model set out above. Subtracting the city average school ethnic composition, weighted by minority pupils, from the same, weighted by White pupils $(\Delta \overline{S}_c)$, yields a measure that is closely related to the standard isolation index⁷. For example, this is the difference in the average school percentage of Black Caribbean students experienced by the average White student and that experienced by the average Black Caribbean student⁸.

Note that, given the model and definitions we adopt, the impact of school segregation on the distribution of test scores and the impact of school composition on individual scores is the same. While in this formulation these all come from the same model and represent different version of the same question, statistical issues mean that the more aggregated approach is more likely to provide robust estimates.

By estimating at city-level, we are by-passing the endogenous within-city sorting that would make school or individual level analysis problematic. By using differences

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⁷ It is in fact the *eta*-squared index.

⁸ Note that for both school and neighbourhood segregation we combine three cohorts to increase precision. We use segregation in the final year of schooling. An alternative would have been to produce school-year-specific measures for each 'city' and then average. But this was computationally cumbersome, and in other research we have shown that school segregation in much of England has been changing only very slowly, if at all (Johnston, Burgess, Harris and Wilson, 2008). This implies that the current level of segregation is a good proxy for the level that the students would have experienced throughout their time in school.

across ethnic groups within a city, we remove all within-city factors that affect the minority and White groups equally. However, there may be city-level factors that influence the two groups differently, so these will not net out. We need therefore to include city level variables to capture as much of this heterogeneity as we can. Similarly, there may be differences in the differences of averaged school errors over the different groups of pupils across cities, $\Delta \mu_c$, and any uncontrolled correlation of this with segregation will bias the results. Again, including city-level variables will deal with some of this heterogeneity. The key identification assumption is that families do not locate in cities for education reasons. Choosing neighbourhoods and schools within a city for education reasons is not a problem as that is averaged out. The difficulty we face in this paper is that there are relatively few areas ('cities') in England with sufficient numbers of minority ethnic pupils, thus limiting degrees of freedom quite severely. We can only include a much smaller number of city-level variables than Card and Rothstein (2007).

We extend this basic model in two ways for estimation. First, we allow the effect of school quality and all individual characteristics to differ by ethnic group, so allowing α^M and α^W etc to differ. That is, we regress g_{isc} on all available pupil characteristics and school fixed effects, all interacted with ethnicity and take the residuals, r_{isc} , as the dependent variable. This method allows the most flexibility in allowing potentially different effects for different ethnic groups of gender, poverty and school fixed effects.

Second, we also include neighbourhood segregation as a potential explanatory of test score gaps. Neighbourhood ethnic composition, W_c . π^G , is added to (1), and treated symmetrically to S in reaching (3), so that the final regression includes $\Delta \overline{W}_c$, a measure of neighbourhood segregation. We also analyse a model with neighbourhood segregation and orthogonalised school segregation, the latter being the residual from a regression of school segregation on neighbourhood segregation. This allows us to separately address school and neighbourhood segregation.

The final term to deal with in (3) is $\Delta \overline{Z}_c$. This represents the difference in mean school factors as experienced by minority pupils relative to White pupils in each city. Arguably this is part of the effect of segregation: some groups disproportionately attending better schools. In any case, practically it is impossible to measure all relevant aspects of schools so this term becomes part of the error term and the estimated coefficient gives the direct effect of segregation *per se* – school ethnic composition on outcomes – plus the indirect effect of differential school quality. The model we finally estimate is therefore a reduced form:

$$\Delta \overline{r}_c = \gamma' . \Delta \overline{S}_c + \pi' . \Delta \overline{W}_c + \delta . \Sigma_c + e_c$$
 (4)

where Σ are city-level variables.

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⁹ There are then further interesting questions on the way school sorting is generated from neighbourhood sorting, but that is a topic for another paper.

c) Modelling ethnic minority test scores

Essentially we want to compare the distribution of educational outcomes across two cities where the school-age minority population is the same in terms of its basic individual characteristics, but is different in the degree of segregation experienced in schools.

We start from (1) with two minor differences: since we are now examining differences across cities within a minority group we leave the G superscript implicit as we estimate separately by group, so all the coefficients are implicitly different by group. We also use a dichotomous split between high segregation cities (treated; T) and low segregation cities (untreated; T). So the modified basic equation is:

$$g_{isc} = X_{isc}\alpha + Z_{sc}\beta + T\gamma + \left[\mu_{sc} + \varepsilon_{isc}\right]$$
 (5)

We match pupils on the basis of personal characteristics, and analyse the score gap between each minority pupil in a high segregation city and their match in a low segregation city¹⁰. Using the notation, $\nabla g_{isc} \equiv g_{isc=T} - g_{js'c=U}$ where j is i's match (and attends school s'), and $X_{isc} = X_{js'c}$, the model implies:

$$\nabla g_{isC} = \nabla Z_s \beta + \gamma + \left[\nabla \mu_s + \nabla \varepsilon_{is} \right] \tag{6}$$

We include city-level variables to pick up the heterogeneity between the high- and low-segregation cities. We make the standard assumption of conditional mean independence and, under that assumption, estimating (6) group by group gives an unbiased estimate of γ for each group. An important question, which we discuss below, is how to interpret the different results controlling for, and not controlling for, neighbourhood and school quality measures.

The analysis we implement is to match on pupil characteristics and to run the following regression on the difference between each pupil's score and that of her match:

$$\nabla g_{is} = \gamma + \pi \cdot \nabla \Sigma_c + \left\{ \delta \cdot \nabla N_i + \varphi \cdot \nabla Q_s \right\} + u \tag{7}$$

where N are neighbourhood variables and Q a school quality measure. As above, since we do not capture all the dimensions of school quality, the interpretation of the estimate of γ is as a reduced form parameter, picking up the direct and indirect effects of segregation.

7

¹⁰ A city is assumed to be treated if its school segregation measure is equal to or larger than the 90th percentile of the city school segregation measure. For Black Caribbean, Indian and Pakistani pupils mean city school segregation measure for treated cities is 0.10, 0.26 and 0.42 respectively while for untreated cities it is 0.03, 0.06 and 0.11 respectively.

3. Data

a) Datasets and Variables

Our key dataset is the Pupil Level Annual School Census (PLASC), part of the National Pupil Database (NPD) released to us by the Department for Children, Schools and Families (DCSF, formally the Department for Education and Skills (DfES)). PLASC is a census of all children in state schools in England, taken each year in January for the cohorts we use. Each cohort has approximately 0.5 million pupils. We use the first three PLASCs, taken in 2002, 2003, and 2004. We pool three cohorts of pupils, in their final year of compulsory schooling (age 16, year 11) respectively in 2002, 2003 and 2004. Given the low numbers in some minority ethnic groups this gives us more data. This yields a pupil-level dataset of approximately 1.6 million observations (see Table 1). Whilst at first glance this seems far more observations than are needed for the task, schools in England remain largely White – 88% of pupils are White. So even this very large dataset only yields a barely adequate number of minority ethnic pupils for the purposes of our analysis.

PLASC provides a number of personal characteristics, including gender, within-year age, free school meal eligibility (FSM, an indicator of poverty), whether English is a pupil's mother tongue, whether the pupil has special educational needs, and the pupil's ethnicity¹¹. The ethnic groups we use are shown in Table 1. As can be seen, the sample is mostly White, with only the following ethnic groups having more than 1% of pupils: Black Caribbean (1.4%), Black African (1.3%), Indian (2.6%) and Pakistani (2.5%). We have been given access to the full postcode (zipcode) of each pupil's home address¹². In the UK as a whole there are around 1.78m unit postcodes covering 27.5m addresses¹³. On average, there are 15 addresses in a unit postcode. We use this very precise information on a pupil's location when defining their neighbourhood. For example, we can match pupils' postcodes to the Mosaic classification of that address 14.

PLASC can be linked to other datasets from the NPD, including a pupil's test score history and the characteristics of the school they attend. We use the pupil's total GSCE point score as our key outcome variable. The GSCE exams are nationally set and marked exams taken at the end of compulsory schooling, and are important for the pupil's future progress in education or the labour market. We proxy prior ability with scores from another set of nationally set and marked tests taken at age 11, just prior to entering secondary school; these are Key Stage 2 (KS2) tests.

 $^{^{11}}$ We use ethnicity reported in 2002 for all three cohorts. This is because most schools used broad ethnicity codes in PLASC 2002. However, from PLASC 2003 it was mandatory to use the more disaggregated ethnicity codes used in the 2001 population census. As each cohort is at the end of compulsory schooling we do not have the more recent ethnicity codes for the 2002 cohort. We do have the older ethnicity codes for the 2003 and 2004 cohorts.

¹² For further details see http://www.statistics.gov.uk/geography/postal_geog.asp

¹³ As of May 2005.

¹⁴ Mosaic classification is a postcode level dataset which therefore describes the area around 12 dwellings on average. The data categorises each postcode into one of 61 types on the basis of demographics, socio-economics and consumption, financial measures, and property characteristics and value. For more information see http://www.experian.co.uk/business/products/data/113/html.

b) Defining the geographical units

We locate each pupil in a neighbourhood using their postcode, and use two levels of definition for 'neighbourhood'. To compute neighbourhood segregation, we use Middle-Layer Super Output Areas (MSOA) as our definition of neighbourhood. There are just under 7,000 MSOAs in England, with a mean population of 7,200 and a minimum of 5,000; they are designed to be of roughly the same size. These are the rough equivalent of an electoral ward but are more homogeneous in size.

To characterise where people live, the data we use permits a smaller, more disaggregate definition. We use the Indices of Deprivation 2004 (ID 2004) produced by the Office of the Deputy Prime Minister (ODPM). The ID 2004 include several indices of deprivation along domains such as income, employment, health and disability, education and crime. In our analysis we exploit two of these indices, the index of income deprivation and the index of employment deprivation, both measured on a scale of 1 to 100 (with 100 indicating high deprivation)¹⁵. These indices are available at Lower-layer Super Output Area (LSOA) level. There are 32,482 lower SOAs in England with a mean population of 1,500 and a minimum of 1,000.

There are two main choices for defining the aggregate spatial units for the analysis, the 'cities' in the terminology of the model. One is the Local Authority (LA), which largely defines an education 'market' (over 90% of pupils attend a school in the LA in which they reside, less so in London). The LA is also to some degree a policy-making unit. There is a particular problem with London, however, if we adopt LAs as the aggregate unit. London is divided into 33 fairly small LAs. As we have seen above, the key assumption for our identification strategy is that families do not locate in a particular aggregate unit for education-related reasons. Any such differential sorting across LAs would jeopardise the interpretation of our estimates. This seems unlikely to hold for London: in fact 20% of pupils cross an LA border within London. So, after a degree of experimentation, we merged all the London LAs into one large unit. The disadvantage is that by doing this we lose a lot of aggregate units to compare across; however, the point is that some of these comparisons would have been confounded by selection. We tried other permutations such as splitting London into quadrants, or quadrants plus a centre. These did not dramatically affect the results but are less plausible in terms of identification. The fact that London is empirically defined as a single local labour market (see next paragraph) suggests that treating as a sngle entity is the safest approach.

The alternative is to define the aggregate units by where people live and work. This is in some ways closer to the spirit of the identification strategy and is also closer to the standard implementation of a cross-city research design. In particular, it is useful to have a definition that includes both city centre and some rural and suburban fringes in the same aggregate unit. This deals with the phenomenon of 'White flight' as the families moving out of the city centre will be retained in the same spatial unit. We

¹⁵ The income deprivation index is based on the numbers of adults and children in households claiming income contingent benefits, such as Income Support, Income Based Jobseekers Allowance and the Working Families Tax Credit. The employment deprivation index is based on; the unemployment claimant count, Incapacity Benefit claimants, Severe Disability Allowance claimants and participation in the New Deal (for 18-24s, 25+ and lone parents). We also compute median household income from Experian Mosaic data.

therefore also use Travel to Work Areas (TTWAs)¹⁶ as the definition of the aggregate unit in the cross-city analysis. TTWAs are labour markets and seem a natural implementation of a unit where people choose to live and work. They are defined by an algorithm that aims to identify areas where 75% of the people who live there also work there, and where 75% of the people who work there also live there. In fact, LAs and TTWAs offer quite different geographies: dense urban areas tend to be split into different LAs but be single TTWAs, while rural areas tend to be big LAs but split into many TTWAs. The pattern is shown in Figure 1. The major urban conurbations are split into a number of different LAs but are typically defined as single TTWAs.

We control for several LA level variables in the post-matching regression. These are the ethnic group proportion; average income deprivation (an average across LSOAs within the LA); proportion of lone parents; unemployment rate (gender and ethnicity specific); proportion of people with 'lower level' qualifications (ethnicity specific)¹⁸; proportion of people with 'higher level' qualifications (ethnicity specific)¹⁸; proportion of people of managerial or professional occupations (ethnicity specific)¹⁹; proportion of people born outside UK (ethnicity specific); and the score assigned to the LA by the Comprehensive Performance Assessments published by Ofsted. This provides a measure of the quality of education provision across the LA²⁰.

c) Defining the estimation sample

Minority ethnic populations are clustered in a relatively small number of urban areas around England. Most LAs and TTWAs have negligible minority populations. The historical patterns of migrant settlement in the UK mean that ethnic minority groups are not spread evenly across the country²¹. Black Caribbean communities are most prevalent in London and to a lesser degree in Birmingham and Manchester, but rarer elsewhere. Families of Indian, Pakistani and Bangladeshi ethnicity are also well represented in London, but are also found in significant numbers in northern and midlands cities such as Manchester, Leicester, Oldham, Bradford and Blackburn. We therefore have a trade-off in defining the areas to include in the sample. Only choosing areas with relatively large numbers of minority pupils will mean few areas in the estimation; having more areas means including some with few minority pupils to average over.

Table 2 shows the number of LAs we have in our sample if we restrict our analysis to only those LAs that have a minority population that is at least 2% of the total population in that LA; we also show the situation with a cut-off of 1%. Note that there

¹⁷ 'Lower level' qualifications describe qualifications equivalent to levels 1. to 3. of the National Key Learning targets (i.e. GCSE's, 'O' levels, 'A' levels, NVQ levels 1. to 3.).

10

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¹⁶ See http://www.statistics.gov.uk/geography/ttwa.asp for more information.

¹⁸ 'Higher level' qualifications describe qualifications equivalent to level 4. and above of the National Key Learning targets (i.e. first degree, higher degrees, NVQ levels 4. and 5., HND, HNC and certain professional qualifications).

¹⁹ Managers, Senior Officials, Professional Occupations, Associate Professional and Technical Occupations.

²⁰ Note that at first approximation, LA budgets are centrally determined using a capitation formula which is designed to account for differences in deprivation etc. We therefore focus here on city-wide differences in quality rather than resources.

²¹ A history of immigration into the UK can be found in Winder (2004).

are 150 LAs in England. The table also shows the minimum number of the minority group across those LAs. This shows that even using the less stringent 1% cut off, most LAs are dropped for every minority group. Only for Indian, Pakistani, Other and Black Caribbean pupils are there more than 20 LAs in the sample. For this reason, the results focus solely on Indian, Pakistani and Black Caribbean pupils using the 1% cut off.

4. Results

a) Summary statistics

Table 1 provides some useful summary facts. On average, White pupils score 41 points at GCSE²². This is higher than some groups: 33 for Black Caribbean, 38 for Black African and 38 for Pakistani pupils. But it is lower than or similar to others: 48 for Indian pupils, 40 for Bangladeshi and 55 for Chinese pupils. This mixed pattern provides an interesting context for the analysis; of the two most numerous minority groups, one scores higher than Whites (Indian) and one less (Pakistani).

The table also provides two contextual variables. Pupils of White, Indian and Chinese ethnicity are the least poor in terms of free school meal eligibility (12, 13 and 13% respectively). The poorest groups are Bangladeshi, Pakistani and Black African. Unsurprisingly, this pattern is repeated in terms of neighbourhoods: Whites, Indian and Chinese pupils live on average in the least deprived neighbourhoods, Bangladeshi and Pakistani pupils the most deprived, and the Black communities intermediate.

b) Test-score Gaps

We first address the minority – White test score gap²³. Throughout, we present the results separately for the three selected minority groups: Black Caribbean, Indian and Pakistani. The model is given by (4) repeated here:

$$\Delta r_c = \gamma' . \Delta \overline{S}_c + \pi' . \Delta \overline{W}_c + \delta . \Sigma_c + e_c$$

Figure 2 plots the test-score gap, Δr_c , against first school segregation, $\Delta \overline{S}_c$, and then neighbourhood segregation, $\Delta \overline{W}_c$. We control for the city level variables, Σ_c , in the regressions shortly, but the Figure shows the broad structure of the data. The unit in the figure is a 'city': these plots are based on LAs as the 'city', but we present the regressions for both these and TTWAs. The units are weighted by the number of the respective minority ethnic pupils. School segregation is obviously computed over schools, and the neighbourhood segregation measure uses MSOAs as the definition of

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²² Each GCSE examination is given a grade, from A*, through A, B, C, ...G, and then U (unclassified). A*-G are passes and have the following point equivalents: A*=8, A = 7, G = 1. The average number of GCSEs taken by students in England is 8, so the maximum point score in that case is 64. A student needs a minimum of five passes at grade C or equivalent, i.e. 25 points, to progress to post-16 education.

Note that r is the residual test score gap after controlling for pupil characteristics and school fixed effects in a fully flexible way. The results of this regression are in Appendix Table 1.

neighbourhood. Note that there is an implicit assumption of a linear effect of segregation here; the second approach uses a dichotomous high/low specification.

Taking Black Caribbean pupils first, a number of points stand out. First, the points gap is always negative, ranging from less than 1 GCSE point in Nottingham to around 12 points in Reading. Second, there is little variation in segregation. Segregation varies between 0 and 0.1, with only two LAs (London and Birmingham which are clearly outliers) having values above 0.06. Third, there does appear to be evidence of a negative relationship between the Black Caribbean-White test score gap and segregation. However, there is one area that dominates the rest in terms of size – this is London, combining the small LAs as described above. Both this and the next largest, Birmingham, are substantially bigger than the others, and this causes problems throughout this analysis. In this case, the negative relationship in the Figure is dominated by the position of London. Looking at the neighbourhood segregation plot, again the slope is negative and largely driven by London.

A different pattern emerges for Indian pupils. There is much more variation in segregation; ranging from zero to over 0.4, and with the exception of Trafford the Indian-White test score gap is always positive. There is little clear evidence of a relationship between the test score gap and segregation, although if anything it is positive. The pattern for residential segregation is the same.

The Figures for Pakistani pupils show the most segregation out of these three groups (this echoes our earlier findings (Burgess and Wilson 2005)), ranging from zero to 0.5. There are a number of LAs with positive and a number with negative test score gaps, with the gap ranging from around +10 to -13 GCSE points. There is little evidence of a relationship between the test score gap and segregation but the evidence there is suggests it would be negative. Again, the pattern is very much the same using residential segregation.

However, as equation (4) makes clear, we need to control for other influences on test score gaps at city level. The regressions doing this are presented in Tables 3a, 3b and 3c, using both the LA and TTWA as the 'city' unit. All these regressions are run using weighted least squares, the weights being the number of the relevant ethnic minority group in that area. Each table reports six specifications. The first two regress the test score gap on school segregation and the city proportion of that group. Specification 2 adds to specification 1 by adding the city average minority-White difference in the income deprivation index. Specifications 3 and 4 are analogous to specifications 1 and 2 but use neighbourhood as opposed to school segregation. In specifications 5 and 6 we use the part of school segregation that is orthogonal to neighbourhood segregation (the residuals from a regression of school segregation on neighbourhood segregation) as our school segregation measure when we include both school and neighbourhood segregation; specification 6 also includes the city average minority-White difference in neighbourhood income deprivation.

Focussing first on Table 3a, the regressions for Black Caribbean pupils, there is a consistently negative and significant relationship between the test score gap and school segregation using LAs as the definition of the 'city'. In fact, this is the one consistently significant coefficient across the specifications: neighbourhood segregation is only negative and significant when we do not include school

segregation or average neighbourhood income deprivation differences, and income deprivation is only significant in two. Looking at the results with the TTWA definition of a city, we see that segregation has no significant effect in any of the specifications. However, we are now down to just 13 observations, so this may simply be because of so little information.

Table 3b reports the results for Indian pupils. For Indian pupils there appears to be no robust relationship between the test score gap and either school or neighbourhood segregation, either with LA or TTWA. The income deprivation term is consistently negative and significant. Over and above neighbourhood differences in income deprivation there is little or no relationship between the test score gap and segregation at school or home for Indian pupils.

We report results for Pakistani ethnicity pupils in Table 3c. Again there appears to be no relationship between the test score gap and school segregation after controlling for neighbourhood segregation and neighbourhood income differences.

c) Ethnic Minority Attainment

This set of results addresses the question about the absolute attainment of minority ethnic students and segregation. The equation we estimate is given by (7), repeated here:

$$\nabla g_{isc} = \gamma + \pi . \nabla \Sigma_c + \{ \delta . \nabla N_i + \varphi . \nabla Q_s \} + u$$

The main threat to the identification of the true impact of levels of school segregation within a city on the test scores of a particular ethnic group is that the mix of families differs across cities in ways that matter for educational attainment, and that are correlated with city-level segregation. This includes factors such as parental resources, child ability, parental human capital and so on. The idea is that by controlling for these background factors we isolate the effect of living in a city in which schools are more segregated. We maintain the assumption of conditional mean independence; that conditional on the city-level variables we include, the distribution of other family influences on outcomes are uncorrelated with the degree of segregation.

Note that we are not attempting to model attendance at particular schools – the 'treatment' is living in a particular type of city, not a particular school. The selection problems for the city-level decision seem less than that for a school-level decision, and indeed a cross-city research design has been often used (Hoxby 2000).

It seems very likely that there are heterogeneous effects of segregation. The most obvious source of this is poverty. In a highly segregated city, poor pupils are more likely to be in a particularly low income school and/or neighbourhood than non-poor pupils. Whilst regression and matching approaches both require the same conditional independence assumption, a matching approach works much better if there are heterogeneous treatment effects (see Cobb-Clark and Crossley, 2003). We use matching procedures to focus on observationally equivalent pupils. The 'treatment' is

living in a high segregation city and the 'control' is living in a low segregation city²⁴. An LA is assumed to be treated if its school segregation measure is equal to or larger than the 90th percentile of the ethnicity-specific LA school-segregation distribution.

We chose to perform the match on pupil characteristics and to deal with differences between cities (LAs) with post-matching regression. It proved infeasible to match on LA variables as there was little overlap between the propensity score distributions. In essence this is because the LAs are few and are rather different. Our main specification is pupils matched on pupil characteristics, controlling for LA characteristics by regression. Figure 3 confirms that there is sufficient common support for each of these groups – we find sufficient 'treated' (high segregation) and untreated pupils at all levels of the propensity score.

We then matched each treated observation to their untreated counterpart using radius matching with a caliper of zero. The variables used to match were: gender, FSM-eligibility, age within year, cohort year. With these samples we then regressed the difference in the test-score on the differences in LA-level covariates, the constant in these regressions giving us our treatment effect.

We again make the distinction between the total effect of segregation and the effect coming through assignment to particular qualities of school and neighbourhood. Our main specifications refer to the first. But we also present results controlling for the quality of school and neighbourhood whilst emphasising that they are very likely to be endogenous.

We first present results from the naïve straightforward OLS regressions on all the data – see Tables 4a, b, c. These are for comparison to the matched results below. The point is that with heterogeneous effects of segregation, the matched estimates offer a more meaningful estimate, the average effect of treatment on the treated (ATT).

For each group we offer four specifications: the first simply includes the high segregation dummy; the second adds pupil characteristics and is therefore the equivalent of the unconditional treatment effect below; the third adds city level variables and is our preferred specification; and the fourth adds local neighbourhood controls. The key coefficient is on school segregation. The city level controls relate to deprivation (average income deprivation, the unemployment rate and the proportion of lone parents), city-wide educational quality (the Ofsted LA report) and the ethnic group proportion. Local controls are income and employment deprivation, average household income and school quality²⁵.

Table 4a reports outcomes for Black Caribbean pupils. In column 1 with no controls we find a positive effect and this remains in column 2 adding just pupil characteristics. Once we control for city characteristics the coefficient increases substantially but the standard error also increases. The big fall in precision is largely because of the problem noted above: the Black Caribbean population is concentrated

for Pakistani ethnicity pupils Birmingham, Bradford, Calderdale, Luton, Slough. ²⁵ We use the value added of White pupils at the school as our measure of school quality, in attempt to

²⁴ The highly segregated cities are for Black Caribbean pupils London and Birmingham only; for Indian ethnicity pupils Birmingham, Blackburn with Darwen, Leicester, London, Wolverhampton; and for Pakistani ethnicity pupils Birmingham, Bradford, Calderdale, Luton, Slough.

avoid the issue of selection into schools and replicating the dependent variable respectively.

in very few LAs once London is aggregated into one. In column 4 the introduction of local controls has a substantial effect on the coefficient and it becomes insignificant. We see the same pattern for pupils of Indian ethnicity in Table 4b. Including only pupil characteristics we find a small positive relationship. Once we control for city differences the estimated coefficient increases and remains significant. Finally, with local controls, the effect of segregation is eliminated. For Pakistani pupils the pattern is different. In columns 1 and 2, the naïve regressions yield a negative effect but adding in city variables turns it small and positive. For this group, the effect is not all eliminated by the addition of local controls in specification (4).

However, the results using the matched sample represent our main findings, in Table 5a, b, c. The dependent variable is the difference between the GCSE points of the focus pupil (cell) in a high segregation city and the average of the pupils in the equivalent cell in low segregation cities. The coefficient in column (2) is the full effect of segregation, including both the direct effect and the indirect effect arising from differences in the characteristics of the local neighbourhood and school, as in Card and Rothstein (2007).

When performing matching we introduce additional source of variability, beyond the normal sampling variation, through estimating a propensity score and performing the matching process. This implies that we cannot use standard errors from our regressions to determine the statistical significance of the treatment effects (Heckman, Ichimura and Todd 1998). Much of the matching literature uses bootstrap techniques to find valid standard errors (Smith 2000). This entails drawing samples with replacement from the population of pupils. The number of draws equals the number of pupils in the original population. The matching process and post matching regressions are then performed for the sample. This process is repeated a sufficient number of times (500 times in our analysis), yielding 500 estimates of ATT (average treatment on the treated). The bootstrap standard error we provide is the standard error in this generated sample of ATT estimates.

The results for Black Caribbean pupils are in Table 5a. Column 1 is the unconditional ATT, and implies a significant positive effect of segregation. Adding city controls in column 2 increases the size of this substantially, but using the boot-strapped standard error it loses significance. As in the naïve regression, adding in the local controls in column 3 reduces the size and significance further. We discuss specifications 4 and 5 in the next sub-section. The unconditional effect of segregation for Indian pupils is also significantly positive, but adding city controls pushes the effect to zero. The inclusion of local neighbourhood characteristics has an interesting effect, and the estimated effect is now negative and significant. Turning to Pakistani pupils, the negative unconditional treatment effect becomes insignificant once we include city controls, and remains so when we add the local controls.

To summarise: our main specification is column (2) of Table 5. We find a positive but insignificant effect of school segregation on test score outcomes for Black Caribbean pupils, and negative and insignificant effects for Indian and Pakistani pupils.

d) Robustness checks on matching

We now focus on the role of prior attainment in the results. This potentially fulfils two roles, and the interpretation of the results is different for each. First, by controlling for prior attainment, we are focussing all attention on pupils' educational progress from age 11 to age 16; by not controlling for it, we are picking up the entire impact of segregation, rather than partialling it out into before and after age 11. This interpretation of any change in the estimated segregation effect is therefore about the timing of the impact of segregation. Second, analysing absolute attainment in this approach, it is harder to deal with heterogeneity between the different cities, particularly in terms of household characteristics that are positively related to educational attainment. The inclusion of the prior attainment with the other personal characteristics goes some way to absorbing some of that heterogeneity. Given these two interpretations, the implications of the results are as follows: a positive result whilst including prior attainment means that there is an effect during secondary school, even controlling for parental support; a negative result might mean that all the effect comes before secondary school, or that the estimated effect is simply due to correlation with household characteristics.

We deal with this issue in two ways, which reveal essentially the same story. First, we simply control for KS2 scores in the post-matching regressions. This is reported in columns 4 and 5 in Table 5. For Black Caribbean pupils, inclusion of KS2 scores reduces the size of the segregation coefficient in columns 3 and 5 and they remain insignificant. For Indian students, the inclusion of KS2 scores raises the size of the coefficient in column 4 but it remains insignificant. For Pakistani pupils it has no effect. Second, we explicitly focus on progress during secondary schooling and model value-added (progress from KS2 to GCSE). The results unsurprisingly mirror those above (results available from the authors).

We finally perform the matching on personal characteristics plus the Mosaic code for each pupil (results not reported here). This is exact matching, though for Black Caribbean students the match is very poor with only a sample of around 6000 rather than 15000. For Pakistani and Indian students, the main results hold up with slightly reduced but significant coefficients. Perhaps unsurprisingly, for Black Caribbean students, no significant results were found (results available from the authors).

5. Conclusions

The segregation of minority ethnic students in schools and neighbourhoods remains an issue of great public policy interest. In this paper we explore one of the potential effects of this – on the educational attainment of minority ethnic students. We investigate whether segregation influences the test score gap between White and minority students, and whether it has an effect on the absolute attainment of minority students. Our analysis throughout allows for different effects on the different groups we analyse: Black Caribbean, Indian and Pakistani. The dataset that we start with is a census of all students in state schools in England, and we combine three cohorts from that census containing in total some 1.5m students. Nevertheless, schools in England are overwhelmingly White, and the minority ethnic students are concentrated in a relatively small number of cities. This concentration means that the effective amount

of information in the data is quite limited, and this needs to be borne in mind as a caveat to our findings.

We show that the test score gap between White and minority ethnic students is largely unaffected by segregation for all three groups. Once we control for differences in prosperity and use a geography that best fits our identification strategy, we find that segregation has no impact on the test score gap. This is in stark contrast to findings for the US, where the equivalent study (Card and Rothstein, 2007) shows that segregation raises the gap. Comparing the performance of a particular minority group across cities with varying levels of segregation, we find different results for different groups, but overall there is no tendency for significant negative effects of school segregation.

We can speculate on the reasons for the difference between the results in England and in the US, but this would surely merit more formal analysis as well. There are of course a number of important differences between the education systems in the two countries. One candidate is the much greater importance of centralised education funding in the UK, which actively attempts to equalise educational spending per head. A second relevant point is that the nature of the academic performance of the relevant minority groups is very different. In the US, the Black-White score gap is very stark, whereas the overall differences in England are smaller, with some minority ethnic groups out-scoring Whites. This means that, for example, Indian pupils in schools with many other Indian pupils may experience a positive peer effect relative to Indian students learning with mostly White peers. As Cutler, Glaeser and Vigdor (2005) note, the outcome of segregation depends on who you are segregated with. Thirdly, levels of school and neighbourhood segregation are lower in England than in the US. It could be that the deleterious effects of segregation found for the US only occur at very high levels. Our results show, therefore, that the 'effects of segregation' are contingent on context, and the rather different context studied here provides an additional piece of evidence to the US case.

The results need to be interpreted cautiously for reasons explained in detail above. Nevertheless, taken at face value, they have interesting implications. We find that segregation does not have a negative impact on school outcomes, but nor does it positively impact on the attainment of different ethnic groups. Looking at the broader picture, low levels of segregation are often considered a contributory factor in raising social and cultural cohesion. Indeed, the Ouseley Report (2001) on disturbances in several northern English cities in 2001 argued that these occurred in part because of 'a segregated school system that has failed to challenge negative attitudes and stereotypes and that has played a marginal role in brokering cultural shifts between family, school, and public life' (Amin 2002 page 962; see also Amin 2003). More recently, a UK Government Select Committee inquiry into social cohesion emphasised that the fact schools do not reflect the range of groups in the locality hindered the promotion of social cohesion (House of Commons 2004; para. 49). Recent research using a robust randomised design confirms that social interaction with students from minority ethnic groups engenders a more sympathetic attitude from Whites to that group (Boisjoly et al 2006). Low levels of segregation are consistent with higher levels of interaction and so potentially greater social cohesion. The fact that our results suggest that levels of segregation do not impact - either positively or negatively – on test score outcomes adds weight to the call for increasing

integration of different ethnic groups at school in order to increase the potential for improved social cohesion.

References

Amin, A. (2002) Ethnicity and the multicultural city: living with diversity, *Environment and Planning A*, 34: 959-980.

Amin, A. (2003) Unruly strangers? The 2001 urban riots in Britain, *International Journal of Urban and Regional Research*, 27: 460-463.

Ananat, E.O. (2007) The wrong side(s) of the tracks: estimating the causal effects of racial segregation on city outcomes, *NBER Working Paper 13343*.

Austen-Smith, D. and Fryer, R. (2005) An economic analysis of 'acting White', *Quarterly Journal of Economics*, 120: 551-583.

Boisjoly, J., Duncan, G., J., Kremer, M., Levy, D., M., and Eccles, J. (2006) Empathy or antipathy? The impact of diversity, *American Economic Review*, 96: 1890-1905.

Bradley, S. and Taylor, J. (2004) Ethnicity, educational attainment and the transition from school, *The Manchester School*, 72: 317-346.

Burgess, S. and Wilson, D. (2005) Ethnic segregation in England's schools, *Transactions of the Institute of British Geographers*, 30: 20-36.

Card, D and J Rothstein (2007) Racial segregation and the Black-White test score gap, *Journal of Public Economics*, 91: 2158-2184.

Clotfelter, C., Ladd, H. and Vigdor, J. (2004) Teacher quality and minority achievement gaps, *Terry Sanford Institute of Public Policy Working Paper Series San04-04;* Duke University.

Cook, P. and Ludwig, J. (1998) The burden of 'acting White': do Black adolescents disparage academic achievement?. in Jencks, C. and Phillips, M. (eds.), *The Black-White Test Score Gap*, Washington D.C.: The Brookings Institute.

Cooley, J (2006) *Desegregation and the achievement gap: do diverse peers help?*, unpublished manuscript, available from http://www.duke.edu/~jcc23/ (accessed 14 July 2008).

Cutler, D.,M., Glaeser, E. and L., Vigdor, J.,L., (2005) Ghettos and the transition of ethnic capital, in Loury, G., C., Modood, T., Teles, S., M. (eds.) *Ethnicity, Social Mobility, and Public Policy: Comparing the US and UK*, Cambridge: Cambridge University press: 204-221.

Duncan, O.D. and Duncan, B. (1955) A methodological analysis of segregation indexes, *American Sociological Review*, 20: 210-217.

Echenique, F., Fryer, R., G. and Kaufman, A., (2006) Is school segregation good bad?, *American Economic Review*, 96: 265-269.

Ferguson, R. (2003) Teachers' perceptions and expectations and the Black-White test score gap, *Urban Education*, 38: 460-507.

Friesen, J and B Krauth (2007) Sorting and inequality in Canadian schools, *Journal of Public Economics*, 91(11-12): 2185-2212.

Fryer, R. and Levitt, S. (2004) Understanding the Black-White test score gap in the first two years of school, *The Review of Economics and Statistics*, 86: 447-464.

Fryer, R. and Levitt, S. (2005) The Black-White test score gap through third grade, *NBER Working Paper 11049*.

Hanushek, EA and SG Rivkin (2006) School quality and the Black-White achievement gap, *NBER Working Paper 12651*.

Hanushek, E., A., Kaine, J., F., O'Brien, D., M., and Rivkin, S., G. (2005) The market for teacher quality, *NBER Working Paper 11154*.

Heckman, J., J., Ichimura, H., Todd, P., (2008), Matching as an econometric evaluation estimator, *Review of Economic Studies*, 65: 261-294.

House of Commons (2004) Social Cohesion. London: The Stationery Office.

Hoxby, C., M. (2000) Does competition among public schools benefit students and taxpayers?, *American Economic Review*, 90: 1209-1238.

Jencks, C. and Phillips, M. (1998) *The Black-White Test Score Gap.* (eds.), Washington D.C.: The Brookings Institute.

Johnston, R., Burgess, S., Harris, R. and Wilson, D. (2008) 'Sleep-walking towards segregation?' The changing ethnic composition of English schools, 1997-2003: an entry cohort analysis, *Transactions of the Institute of British Geographers*, 33(1): 73-90.

Kao, G. and Tienda, M., (1998) Educational aspirations of minority youth, *American Journal of Education*, 106: 349-384.

Khattab, N., (2003) Explaining educational aspirations of minority students: the role of social capital and students' perceptions, *Social Psychology of Education*, 6: 283-302.

Massey, D., S. and Denton, N., A. (1988) The dimensions of residential segregation, *Social Forces*, 67: 281-315.

Modood, T. (2003) Ethnic differentials in educational performance. in Mason, D. (ed), *Explaining Ethnic Differences: Changing Patterns of Disadvantage in Britain*, Bristol: The Policy Press.

Modood, T. (2005) The educational attainments of ethnic minorities in Britain, In Loury. G. C., Modood, T., and Teles, S.M. (eds.), *Ethnicity, Social Mobility and Public Policy*, CUP: Cambridge.

Neal, D. (2005) Why has Black-White skill convergence stopped?. In Hanushek, E. and Welch, F. (eds.), vol(1).

Ouseley Report (2001) *Community pride not prejudice*. Bradford: Bradford City Council.

Phillips, M., Crouse, J. and Ralph, J. (1998) Does the Black-White test score gap widen after children enter school? in Jencks, C. and Phillips, M. (eds.), *The Black-White Test Score Gap*. Washington D.C.: The Brookings Institute.

Reber, S.J. (2007a) From separate and unequal to integrated and equal? School desegregation and school finance in Louisiana, *NBER Working Paper 13192*.

Reber, S.J. (2007b) School desegregation and educational attainment for blacks, *NBER Working Paper 13193*.

Schneider, B., Stevenson, D., (1999) *The Ambitious Generation: America's Teenagers, Motivated but Directionless*, New Haven and London: Yale University Press.

Shavit, Y. and Williams, R., A., (1985) Ability grouping and contextual determinants of educational expectations in Israel, *American Sociological Review*, 50: 62-73.

Tikly, L. (2005) The achievement of minority ethnic learners in the UK and a critical analysis of government initiatives to tackle underachievement, in Quehl, T. (ed.), *Education Policy, Multiculturalism and Equality in Europe*, pp. 35-46.

Smith, J., (2000) A critical survey of empirical methods for evaluating active labor market pPolicies, *Schweizerische Zeitschrift fr Volwirtschaft und Statistik*, 136: 1-22.

Vigdor, J. and J. Ludwig (2007) *Segregation and the Black-White test score gap*, Paper prepared for the conference 'Stalled Progress: Inequality and the Black-White Test Score Gap', Russell Sage Foundation, November 16-17, 2006. This version March 2007.

Wilson, W., J. (1987) *The Truly Disadvantaged: The Inner City, The Underclass, and Public Policy,* Chicago: University of Chicago Press.

Wilson, D., Burgess, S. and Briggs, A. (2005) The dynamics of attainment of England's ethnic minorities, *CMPO Working Paper* 05/130, CMPO, University of Bristol.

Winder, R. (2004) *Bloody Foreigners: The Story of Immigration to Britain*. Abacus, London.

Zhou, M. (2005), Ethnicity as social capital: community-based institutions and embedded networks of social relations, in Loury, G., C., Modood, T., Teles, S., M. (eds), *Ethnicity, Social Mobility, and Public Policy: Comparing the US and UK*, Cambridge: Cambridge University press, pp.131-159.

Table 1: Sample by Ethnicity

Ethnicity	Total number of	Percentage of	Mean GCSE	Percentage of	Mean IMD
· ·	pupils	sample	Points	FSM pupils	
White	1,427,027	88.06	40.94	12	21.60
Black Caribbean	23,233	1.43	33.09	28	35.44
Black African	20,674	1.28	38.02	39	35.62
Black Other	13,700	0.85	34.78	31	33.75
Indian	41,527	2.56	48.37	13	25.91
Pakistani	40,086	2.47	37.65	41	38.91
Bangladeshi	15,122	0.93	39.88	63	42.90
Chinese	5,881	0.36	54.80	13	23.23
Other	33,193	2.05	41.35	28	28.63
Total	1,620,443				

The sample combines three cohorts, taking GCSEs in 2002, 2003 and 2004.

FSM is eligibility for Free School Meals, referring to the GCSE year

IMD is a measure of neighbourhood deprivation, referring to the GCSE year

Table 2: Number of LAs included in analysis sample and minimum number of pupils in one of those LAs

Group		2% Cut-off		1% Cut-off
	Number of	Minimum	Number of	Minimum
	observations*	number	observations*	number
Black Caribbean	9	84	22	64
Black African	6	66	11	66
Black Other	9	144	17	37
Indian	28	114	43	48
Pakistani	35	114	48	87
Bangladeshi	5	181	16	95
Chinese	0	0	1	79
Other	24	97	45	43

^{*}Sample is merged 2002, 2003 and 2004 PLASCs using old ethnicity codes and including London LAs as 1 region.

Note: Number of observations means number of LAs
Minimum number is the lowest number of pupils in an LA

Table 3a: OLS regressions of Black Caribbean-White GSCE point score gap on school and neighbourhood segregation

By LA:

	1	2	3	4	5	6
Black Caribbean-White diff in school fraction Black Caribbean	-63.924	-56.885				
Diack Caribbean-white unit in school fraction diack Caribbean	(3.84)**	(3.27)**				
Residual Black Caribbean-White diff in school fraction Black Caribbean					-65.688	-109.036
Residual Diack Caribbean-Winte uni in school fraction Diack Caribbean					(2.61)*	(4.16)**
Black Caribbean-White diff in neighbourhood fraction Black Caribbean			-47.497	-38.596	-41.935	27.762
Diack Caribbean-Winte uni in neighbourhood fraction Diack Caribbean			(2.32)*	(1.14)	(2.34)*	(0.96)
Black Caribbean-White diff in neighbourhood Income deprivation		-13.570		-6.919		-51.326
black Carlobcan-white uni in heighbourhood income deprivation		(1.23)		(0.34)		(2.82)*
LA proportion Black Caribbean	54.694	42.270	10.957	1.927	54.921	16.943
	(2.03)	(1.49)	(0.43)	(0.05)	(1.97)	(0.63)
Constant	-4.958	-3.511	-3.882	-3.387	-5.364	-2.673
	(4.88)**	(2.28)*	(2.90)**	(1.68)	(4.14)**	(1.84)
Observations	21	21	21	21	21	21
R-squared	0.50	0.54	0.30	0.30	0.50	0.66

Note:

Units are Local Education Authorities

Dependent variable is the Adjusted point score.

Residual school segregation is the residuals from a regression of school segregation on neighbourhood segregation.

By TTWA:

by ITWA.	I					
	1	2	3	4	5	6
Black Caribbean-White diff in school fraction Black Caribbean	3.362	-7.961				
	(0.13)	(0.24)				
Residual Black Caribbean-White diff in school fraction Black Caribbean					-3.536	41.205
Residual Diack Caribbean-Winte uni in school fraction Diack Caribbean					(0.08)	(0.75)
Black Caribbean-White diff in neighbourhood fraction Black Caribbean			5.114	-65.731	4.890	-110.882
			(0.24)	(0.89)	(0.22)	(1.15)
Black Caribbean-White diff in neighbourhood Income deprivation		8.426		41.267		69.090
		(0.54)		(1.01)		(1.23)
TTWA proportion Black Caribbean	-33.110	-9.240	-32.528	61.934	-28.967	84.128
	(0.71)	(0.14)	(1.10)	(0.63)	(0.55)	(0.80)
Constant	-5.785	-6.832	-5.957	-8.860	-6.021	-10.074
	(4.79)**	(2.95)*	(4.04)**	(2.74)*	(3.48)**	(2.73)*
Observations	13	13	13	13	13	13
R-squared	0.14	0.17	0.14	0.23	0.14	0.28

Note:

Units are TTWA

Dependent variable is the Adjusted point score.

Residual school segregation is the residuals from a regression of school segregation on neighbourhood segregation.

Table 3b: OLS regressions of Indian-White GSCE point score gap on school and neighbourhood segregation

By LA:

	1	2	3	4	5	6
Indian-White diff in school fraction Indian	-12.410	-9.189				
	(2.40)*	(1.99)				
Residual Indian-White diff in school fraction Indian					-8.926	-14.127
					(0.82)	(1.47)
Indian-White diff in neighbourhood fraction Indian			-13.644	-7.962	-12.763	-6.175
			(2.26)*	(1.41)	(2.08)*	(1.08)
Indian-White diff in neighbourhood Income deprivation		-35.798		-35.149		-37.576
		(3.53)**		(3.28)**		(3.52)**
LA proportion Indian	25.932	15.486	26.272	13.822	26.767	13.745
	(3.84)**	(2.34)*	(3.68)**	(1.86)	(3.72)**	(1.88)
Constant	8.293	9.207	8.469	9.105	8.513	9.217
	(11.67)**	(13.65)**	(10.72)**	(12.46)**	(10.71)**	(12.74)**
Observations	41	41	41	41	41	41
R-squared	0.29	0.47	0.28	0.44	0.29	0.48

Note: Units are Local Education Authorities

Dependent variable is the Adjusted point score.

Residual school segregation is the residuals from a regression of school segregation on neighbourhood segregation.

By TTWA:

By 11 WA.						
	1	2	3	4	5	6
Indian-White diff in school fraction Indian	-7.091	0.721				
	(1.05)	(0.11)				
Residual Indian-White diff in school fraction Indian					7.898	5.276
					(0.71)	(0.49)
Indian-White diff in neighbourhood fraction Indian			-13.123	-2.370	-12.125	-2.005
			(1.87)	(0.28)	(1.68)	(0.24)
Indian-White diff in neighbourhood Income deprivation		-28.145		-25.629		-24.911
		(2.66)*		(2.15)*		(2.05)*
TTWA proportion Indian	14.734	0.575	23.918	6.048	20.615	4.341
	(1.04)	(0.04)	(1.79)	(0.40)	(1.45)	(0.28)
Constant	7.230	7.987	7.730	8.076	7.601	7.980
	(11.51)**	(12.40)**	(11.25)**	(12.01)**	(10.61)**	(11.28)**
Observations	36	36	36	36	36	36
R-squared	0.03	0.21	0.10	0.21	0.11	0.22

Note: Units are TTWE

Dependent variable is the Adjusted point score.

Residual school segregation is the residuals from a regression of school segregation on neighbourhood segregation.

Table 3c: OLS regressions of Pakistani-White GSCE point score gap on school and neighbourhood segregation

By LA:

	1	2	3	4	5	6
Pakistani-White diff in school fraction Pakistani	-23.772	-4.638				
	(2.74)**	(0.47)				
Residual Pakistani-White diff in school fraction Pakistani					-13.442	-7.125
					(1.17)	(0.66)
Pakistani-White diff in neighbourhood fraction Pakistani			-15.463	2.546	-20.623	-0.955
			(2.84)**	(0.34)	(2.95)**	(0.10)
Pakistani-White diff in neighbourhood Income deprivation		-36.360		-42.943		-41.115
		(3.28)**		(3.17)**		(2.96)**
LA proportion Pakistani	42.762	23.259	22.309	13.438	38.865	22.591
	(2.41)*	(1.36)	(2.04)*	(1.30)	(2.18)*	(1.30)
Constant	0.048	1.099	0.521	0.910	0.957	1.125
	(0.05)	(1.18)	(0.50)	(0.95)	(0.86)	(1.10)
Observations	47	47	47	47	47	47
R-squared	0.15	0.32	0.16	0.32	0.18	0.32

Note:

Units are Local Education Authorities

Dependent variable is the Adjusted point score.

Residual school segregation is the residuals from a regression of school segregation on neighbourhood segregation.

By TTWA:

2, 11.11.1	1	2	3	4	5	6
Pakistani-White diff in school fraction Pakistani	-3.408	3.284				
	(0.66)	(0.47)				
Residual Pakistani-White diff in school fraction Pakistani					1.536	3.189
					(0.20)	(0.41)
Pakistani-White diff in neighbourhood fraction Pakistani			-6.571	2.328	-6.621	2.953
			(1.10)	(0.22)	(1.09)	(0.27)
Pakistani-White diff in neighbourhood Income deprivation		-20.021		-18.848		-20.392
		(1.42)		(1.03)		(1.07)
TTWA proportion Pakistani	8.279	5.030	13.808	6.215	13.398	4.742
	(0.68)	(0.41)	(1.05)	(0.41)	(0.99)	(0.30)
Constant	-1.462	-0.377	-0.870	-0.441	-0.899	-0.464
	(1.43)	(0.30)	(0.72)	(0.34)	(0.73)	(0.36)
Observations	37	37	37	37	37	37
R-squared	0.01	0.07	0.04	0.07	0.04	0.07

Note:

Units are TTWA

Dependent variable is the Adjusted point score.
Residual school segregation is the residuals from a regression of school segregation on neighbourhood segregation.

Table 4a. OLS regressions on total GCSE points for Black Caribbean Pupils

	1	2	3	4
School segregation	1.46	1.67	3.27	0.28
	(4.44)**	(5.26)**	(3.15)**	(0.30)
Pupil controls?	N	Y	Y	Y
City Controls?	N	N	Y	Y
Local controls:				
In come Density of in Index				19.20
Income Deprivation Index				-18.29 (-7.18)**
Employment Deprivation Index				1.32
Employment Deprivation fidex				(0.30)
Median neighbourhood household				0.01
income				(0.51)
School Quality				1.08
School Quanty				(36.25)**
				(30.23)
Constant	31.87	33.71	64.33	79.26
	(108.49)**	(44.58)**	(10.89)**	(11.05)**
	, ,	` ′	` ,	` '
Observations	19993	19993	19993	19847
R-squared	0.00	0.07	0.07	0.15

t-statistics in parenthesis. **significant at 1%, *significant at 5%

Notes: 1. Controls for pupil characteristics: FSM, language, gender, month of birth, year of study

^{2.} Controls for LA level characteristics: proportion of lone parents, LA Black Caribbean Unemployment rate (gender specific), LA quality (Ofsted Inspection), LA mean Income Deprivation Index, LA proportion of Black Caribbeans, LA Black Caribbean proportion with 'lower level' and 'higher level' qualifications, LA Black Caribbean proportion of working in managerial and professional occupations, LA Black Caribbean proportion of born outside UK

^{3.} School quality is the value-added computed for white pupils in that school

Table 4b. OLS regressions on total GCSE points for Indian Pupils

	1	2	3	4
School segregation	0.35	0.83	2.93	0.19
	(1.72)	(4.18)**	(7.50)**	(0.56)
Pupil controls?	N	Y	Y	Y
City Controls?	N	N	Y	Y
Local controls:				
				15.05
Income Deprivation Index				-15.87
				(-7.52)**
Employment Deprivation Index				8.20
				(2.04)*
Median neighbourhood household				0.21
income				(11.30)**
School Quality				0.95
				(0.02)**
Constant	47.97	47.96	54.45	49.44
Constant	(293.16)**	(121.32)**	(12.15)**	(12.98)**
	(273.10)	(121.32)	(12.13)	(12.70)
Observations	38188	38188	38188	38023
R-squared	0.00	0.06	0.07	0.14

t-statistic in parenthesis. **significant at 1%, *significant at 5%

Notes: 1. Controls for pupil characteristics: FSM, language, gender, month of birth, year of study

^{2.} Controls for LA level characteristics: proportion of lone parents, LA Indian Unemployment rate (gender specific), LA quality (Ofsted Inspection), LA mean Income Deprivation Index, LA proportion of Indians, LA Indian proportion with 'lower level' and 'higher level' qualifications, LA Indian proportion of working in managerial and professional occupations, LA Indian proportion of born outside UK

^{3.} School quality is the value-added computed for white pupils in that school

Table 4c. OLS regressions on total GCSE points for Pakistani Pupils

	1	2	3	4
School segregation	-1.88	-1.09	1.24	0.99
	(8.76)**	(5.21)**	(2.54)*	(2.04)*
Pupil controls?	N	Y	Y	Y
City controls?	N	N	Y	Y
Local controls:				
Income Deprivation Index				-10.03
income Deprivation index				(-5.21)**
Employment Deprivation Index				7.44
Employment Deprivation fidex				(2.31)*
Median neighbourhood household				0.28
income				(11.19)**
School Quality				0.48
School Quanty				(24.06)**
				(24.00)
Constant	38.08	40.38	4.65	6.91
	(308.35)**	(104.55)**	(1.08)	(1.63)
	(= = = = 3)	()	(, , , , ,	(100)
Observations	37871	37871	37871	37404
R-squared	0.00	0.06	0.08	0.11

t-statistics in parenthesis. **significant at 1%, *significant at 5%

Notes: 1. Controls for pupil characteristics: FSM, language, gender, month of birth, year of study

^{2.} Controls for LA level characteristics: proportion of lone parents, LA Pakistani Unemployment rate (gender specific), LA quality (Ofsted Inspection), LA mean Income Deprivation Index, LA proportion of Pakistani, LA Pakistani proportion with 'lower level' and 'higher level' qualifications, LA Pakistani proportion of working in managerial and professional occupations, LA Pakistani proportion of born outside UK

^{3.} School quality is the value-added computed for white pupils in that school

Table 5a. OLS results for post matching regressions for Black Caribbeans. Matching on pupil level characteristics.

	Unconditional	LA-level	Neighbourhood	LA-level & KS2	Neighbourhood
	ATT		level	scores	level & KS2 scores
	1	2	3	4	5
Treatment effect	1.80	5.66	1.82	4.43	0.70
	(12.17)**	(3.21)**	(1.18)**	(2.86)**	(0.52)
[Bootstrap]	[5.16]**	[1.27]	[0.46]	[1.19]	[0.21]
City Controls?	N	Y	Y	Y	Y
Local Controls:					
Income Deprivation Index			-23.25		-18.51
•			(7.90)**		(7.44)**
Employment Deprivation Index			6.36		7.17
			(1.22)		(1.63)
Median neighbourhood household			-0.03		-0.08
income			(0.99)		(3.40)**
School Quality			1.06		0.87
			(32.15)**		(31.12)**
KS2 English score				1.22	1.19
				(33.16)**	(33.58)**
KS2 Maths score				0.94	0.89
				(25.46)**	(25.01)**
KS2 Science score				0.47	0.46
				(12.13)**	(12.38)**
Observations ¹	15652	15652	15511	13438	13329
R-squared	0.00	0.00	0.08	0.37	0.43

t statistics in parenthesis

*Significant at 5%

**Significant at 1%

Notes: 1. Controls for LA level characteristics: proportion of lone parents, LA Black Caribbean Unemployment rate (gender specific), LA quality (Ofsted Inspection), LA mean Income Deprivation Index, LA proportion of Black Caribbeans, LA Black Caribbean proportion with 'lower level' and 'higher level' qualifications, LA Black Caribbean proportion of working in managerial and professional occupations, LA Black Caribbean proportion of born outside UK

2. Neighbourhood level and Neighbourhood level & KS2 scores post matching regressions do not control for LA mean Income Deprivation Index

¹Number of treated with at least one match from untreated sample

Table 5b. OLS results for post matching regressions for Indians. Matching on pupil level characteristics.

	Unconditional	LA-level	Neighbourhood	LA-level & KS2	Neighbourhood
	ATT		level	scores	level & KS2 scores
	1	2	3	4	5
Treatment effect	0.88	-0.46	-2.23	2.27	-0.80
	(7.34)**	(0.44)	(4.49)**	(2.83)**	(2.10)*
[Bootstrap]	[4.36]**	[0.27]	[3.29]**	[1.65]	[1.51]
City Controls?	N	Y	Y	Y	Y
Local Controls:					
Income Deprivation Index			-11.61		-2.40
•			(4.16)**		(1.12)
Employment Deprivation Index			-8.92		-14.63
			(1.65)		(3.53)**
Median neighbourhood household			0.19		0.04
income			(7.72)**		(2.27)*
School Quality			0.83		0.56
			(31.65)**		(27.38)**
KS2 English score				1.15	
				(40.72)**	
KS2 Maths score				1.23	
				(45.45)**	
KS2 Science score				0.56	
1				(18.98)**	
Observations ¹	24556	24556	24398	22342	22240
R-squared	0.00	0.02	0.08	0.46	0.48

t statistics in parenthesis

*Significant at 5%

**Significant at 1%

Notes: 1. Controls for LA level characteristics: proportion of lone parents, LA Indian Unemployment rate (gender specific), LA quality (Ofsted Inspection), LA mean Income Deprivation Index, LA proportion of Indians, LA Indian proportion with 'lower level' and 'higher level' qualifications, LA Indian proportion of working in managerial and professional occupations, LA Indian proportion of born outside UK

2. Neighbourhood level and Neighbourhood level & KS2 scores post matching regressions do not control for LA mean Income Deprivation Index

¹Number of treated with at least one match from untreated sample

Table 5c. OLS results for post matching regressions for Pakistanis. Matching on pupil level characteristics.

•	Unconditional	LA-level	Neighbourhood	LA-level & KS2	Neighbourhood
	ATT		level	scores	level & KS2 scores
	1	2	3	4	5
Treatment effect	-1.14	-2.49	-1.86	-2.60	-1.42
	(6.48)**	(1.26)	(1.07)	(1.70)	(1.05)
[Bootstrap]	[5.31]**	[1.07]	[0.91]	[1.36]	[0.85]
City Controls?	N	Y	Y	Y	Y
Local Controls:					
Income Deprivation Index			-2.09		1.14
moone 2 op. 1 wood moon			(0.56)		(0.39)
Employment Deprivation Index			-8.80		-14.68
I do la			(1.48)		(3.14)**
Median neighbourhood household			0.42		0.09
income			(5.99)**		(1.58)
School Quality			0.37		0.27
•			(13.41)**		(12.31)**
KS2 English score				1.32	1.29
				(31.17)**	(30.21)**
KS2 Maths score				1.07	1.04
				(25.27)**	(24.30)**
KS2 Science score				0.58	0.61
				(13.17)**	(13.77)**
Observations ¹	12550	12550	12147	10993	10634
R-squared	0.00	0.02	0.05	0.46	0.47

t statistics in parenthesis

*Significant at 5%

**Significant at 1%

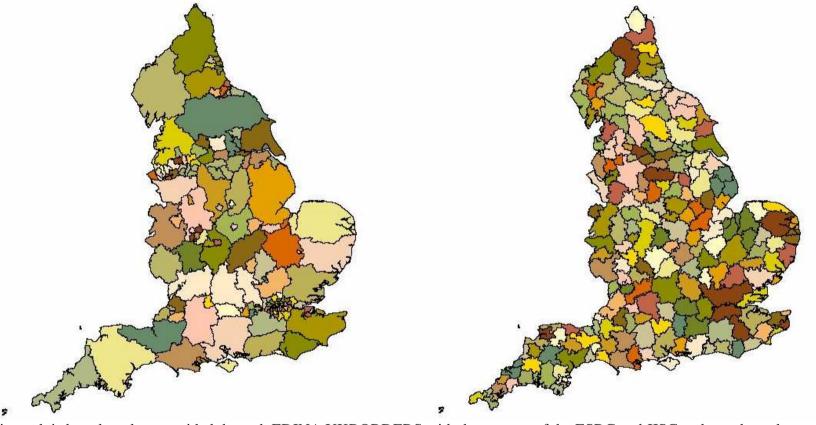
Notes: 1. Controls for LA level characteristics: proportion of lone parents, LA Pakistani Unemployment rate (gender specific), LA quality (Ofsted Inspection), LA mean Income Deprivation Index, LA proportion of Pakistani, LA Pakistani proportion with 'lower level' and 'higher level' qualifications, LA Pakistani proportion of working in managerial and professional occupations, LA Pakistani proportion of born outside UK

2. Neighbourhood level and Neighbourhood level & KS2 scores post matching regressions do not control for LA mean Income Deprivation Index

¹Number of treated with at least one match from untreated sample

Figure 1: Definition of Aggregate Areas Local Education Administration

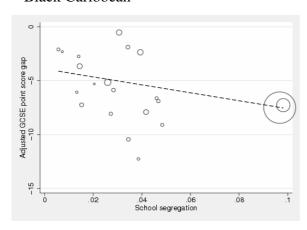
Travel-to-Work Areas

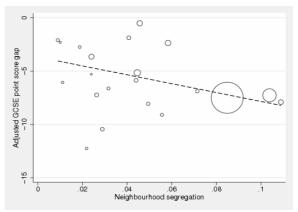


This work is based on data provided through EDINA UKBORDERS with the support of the ESRC and JISC and uses boundary material which is copyright of the Crown, the Post Office and the ED-LINE Consortium.

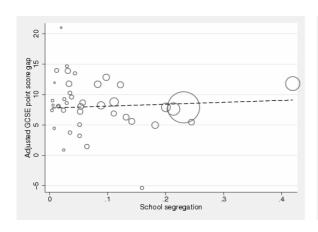
Figure 2 Score Gaps and Segregation

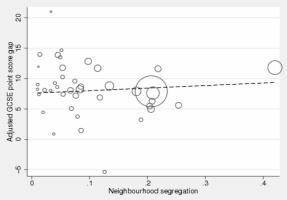
Black Caribbean



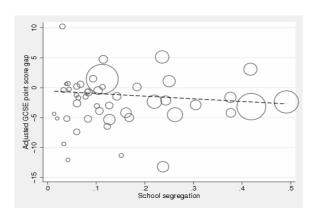


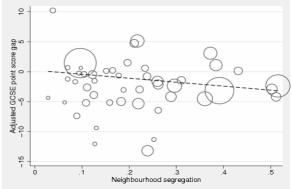
Indian





Pakistani



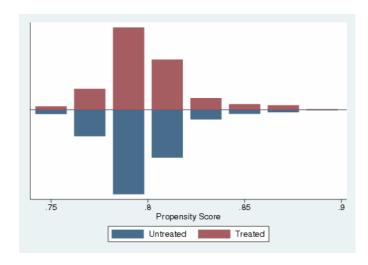


Notes:

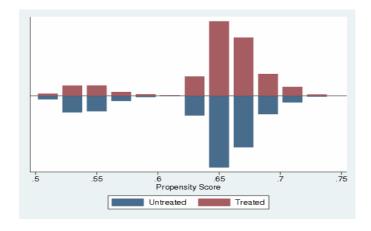
Units are the LAs, weighted by the number of respective minority pupils. Line is a regression of the point score gap on segregation, weighted by LA minority pupils.

Figure 3. Propensity Scores for matching on pupil characteristics

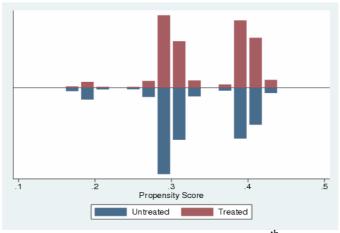
Black Caribbean



Indian



Pakistani



Note: Treatment – LA school segregation is higher than 90th percentile

	Total GCSE point score
Pupil FSM eligibility	-10.872
M.I. J.	(165.27)**
Male dummy	-4.866 (110.12)**
Born in July dummy	0.420
•	(4.29)**
Born in June dummy	0.696
Born in May dummy	(7.06)** 0.994
Dorn in May duminy	(10.14)**
Born in April dummy	1.034
D 116 11	(10.43)**
Born in March dummy	1.341 (13.63)**
Born in February dummy	1.401
· ·	(13.80)**
Born in January dummy	1.514
Born in December dummy	(15.13)** 1.718
born in December dummy	(17.03)**
Born in November dummy	2.019
P : 0 () 1	(19.88)**
Born in October dummy	2.465 (24.76)**
Born in September dummy	2.490
	(25.10)**
FSM*Black Caribbean dummy	7.224
FSM*Indian dummy	(25.33)** 4.703
1 Siv 2 minum dummiy	(16.59)**
FSM*Pakistani dummy	6.851
Mala*Dlack Caribbaan dummy	(34.20)**
Male*Black Caribbean dummy	-2.119 (7.41)**
Male *Indian dummy	-0.097
25.2.42.24.4.2	(0.47)
Male *Pakistani dummy	-1.181 (5.55)**
Born in July *Black Caribbean dummy	0.091
·	(0.15)
Born in July *Indian dummy	-0.194
Born in July *Pakistani dummy	(0.44) 0.201
Dorn in duly 1 unistum duming	(0.46)
Born in June *Black Caribbean dummy	0.243
Down in Lune *Indian dummy	(0.41) -0.347
Born in June *Indian dummy	(0.77)
Born in June *Pakistani dummy	0.673
	(1.51)
Born in May *Black Caribbean dummy	-0.196
Born in May *Indian dummy	(0.33) -0.097
	(0.22)
Born in May *Pakistani dummy	0.724
Rorn in April *Rlack Caribbaan dummy	(1.63)
Born in April *Black Caribbean dummy	-0.620

(1.04)		
(1.21) Born in April *Pakistani dummy		
Born in April *Pakistani dummy	Born in April *Indian dummy	
Co.51 Born in March *Black Caribbean dummy	Rorn in April *Dakistani dummy	
Born in March *Black Caribbean dummy	born in April "Pakistain duminy	
Born in March *Indian dummy	Born in March *Black Caribbean dummy	
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Born in March *Pakistani dummy 0.526 Born in February *Black Caribbean dummy 0.104 Born in February *Indian dummy 0.172 Born in February *Pakistani dummy 0.582 Born in January *Black Caribbean dummy 0.582 Born in January *Indian dummy 0.297 Born in January *Pakistani dummy 0.297 Born in January *Pakistani dummy 0.208 Born in December *Black Caribbean dummy 0.209 Born in December *Black Caribbean dummy 0.016 Born in December *Pakistani dummy 0.016 Born in November *Pakistani dummy 0.030 Born in November *Black Caribbean dummy 0.127 Born in November *Indian dummy 0.137 Born in November *Pakistani dummy 0.1410 Born in November *Pakistani dummy 0.1410 Born in October *Black Caribbean dummy 0.010 Born in October *Black Caribbean dummy 0.010 Born in October *Black Caribbean dummy 0.010 Born in October *Pakistani dummy 0.013 Born in September *Black Caribbean dummy 0.015 Born in September *Pakistani dummy 0.015 Born in September *Pakistani dummy 0.0564 0.081 Born in September *Pakistani dummy 0.564 0.081 Born in September *Pakistani dummy 0.564 0.081	Born in March *Indian dummy	
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Born in February *Indian dummy	dummy	(0.17)
Content Cont	Rorn in Fahruary *Indian dummy	
Born in February *Pakistani dummy	Born in February Indian duminy	
(1.26) Born in January *Black Caribbean dummy	Born in February *Pakistani dummy	
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(1.27) Constant 42.951	Down in Contambon *Poliston: Jumm-	
Constant 42.951	Dorn in September "Pakistani duminy	
	Constant	
(652.62)**		(652.62)**
Observations 919669	Observations	
R-squared 0.32	R-squared	0.32

Absolute value of t statistics in parentheses * significant at 5%; ** significant at 1%

Note: Also allows for ethnicity specific school effects