Sorting and Inequality in Canadian Schools*

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Abstract

Researchers and educators often argue that a student's peers strongly influence his or her educational outcomes. If so, an unequal distribution of advantaged and disadvantaged students across schools in a community will leave many students doubly disadvantaged and amplify existing inequalities. We explore the relationship between the degree of sorting by socioeconomic characteristics, ethnicity and language across schools within a community and inequality as measured by the variance of standardized high school exam scores within the community. Simple cross-sectional estimates suggest a direct relationship between sorting by ethnicity and the variance of test scores, but no direct relationship between sorting by income or primary parent's education and the variance of test scores. We then implement a fixed effects estimator to control for endogeneity in the extent of sorting: the results indicate that sorting by ethnicity does not affect the variance of test scores, but that sorting by home language and primary parent's education does.

1 Introduction

Since the publication of James Coleman's *Equality of Educational Opportunity* in 1966, social scientists and policymakers have been concerned with the interaction of peer effects and segregation or sorting in maintaining or worsening economic inequality. A number of recent studies (Boozer and Cacciola 2001, Hanushek, Kain, Markman and Rivkin 2003, Hoxby 2000) provide evidence that student achievement as measured by performance on standardized tests is positively affected by the achievement level of classmates and/or schoolmates. If this is the case, then an unequal distribution of high-resource (e.g., high income, high parental education, etc.) students across schools leaves most low-resource students doubly disadvantaged: such students will have both lower private resource levels and a lower quality peer group. As this difference in human capital leads to differences in income, initial disparities in resources may be maintained and even amplified over generations despite the best efforts of

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policymakers to provide equal opportunity (Durlauf 1996, Fernandez and Rogerson 1996). Although empirical researchers have made some progress on establishing the existence and magnitude of school peer effects, much remains to be learned. The magnitude of the effect of school sorting on inequality in educational outcomes likewise is not yet well understood.

This paper uses data from the Canadian province of Alberta to evaluate the hypothesis that sorting into schools exacerbates inequality in student outcomes. Our research design is similar in spirit to Cutler and Glaeser's (1997) and Card and Rothstein's (2004) work on the consequences of racial segregation in US cities. We use a simple regression framework to determine the empirical relationship between community-level measures of segregation across schools by income, ethnicity, and other characteristics and the community's variance in standardized test scores at the Grade 9 level. By using aggregate data, our approach avoids a number of the identification problems that arise in using individual-level data to estimate peer effects (Manski 1993). In particular, our research design does not require the assumption of random or exogenous selection into schools, nor does it require the absence of aggregate idiosyncratic factors. Furthermore, by focusing directly on the relationship between sorting and inequality, we are able to directly quantify the potential for policy to reduce inequality by reducing segregation.

Our research makes a number of unique and constructive contributions to the literature on peer effects, sorting and inequality. First, we explore sorting on a wider variety of dimensions than previous studies, including ethnicity, family income, primary parent's education, and the language spoken at home. Second, we are able to link exam results in different grades and years, and thus to construct a fixed effects estimator that is robust when the degree of sorting within communities is endogenous. This is important because if greater unobserved heterogeneity among students within a community *causes* sorting, simple estimators based on aggregates in a cross-section of communities will be biased in favour of finding a large effect of sorting on inequality. Third, our data include students from both public and private schools. Comparable data sets from the United States generally include students from public schools only, which may introduce challenging selection issues.

Our cross-sectional results suggest that sorting by ethnicity increases the inequality (variance) of test scores. Although the racial composition of our sample is very different, this finding is similar in nature to the results in Card and Rothstein (2004). We are further able to show that this result persists even after controlling for sorting by several other household characteristics: wage and salary income, transfer income (a proxy variable for low-income status), home language, and primary parent's education. Our cross-sectional estimates therefore suggest that it is sorting by ethnicity *per se*, rather than one of these other variables, that leads to the increase in inequality. However, this pattern is not robust to controlling for unobserved heterogeneity within communities, suggesting that the cross-sectional results are picking up the effects of unobserved community heterogeneity that is correlated with sorting by ethnicity. Instead, the fixed effects results suggest that sorting by parental education and language spoken in the home increases the variance of test scores. The negative results we obtain are also interesting. In particular, neither the cross-section nor fixed effects estimators produce any evidence consistent with a peer effect arising from either family wage and salary income or our proxy measure for low-income status.

Finally, we use our estimates to explore the magnitudes of potential effects from different types of desegregation policies. The results suggest that fully integrating the schools of the typical multiple school community will have little effect on inequality in that community, but integrating the schools in some particularly segregated communities may have a large effect.

1.1 Related literature

This paper is not directly a study of peer effects, however, it shares with that literature both motivation and many econometric issues. The key concern in most recent empirical work dealing with peer effects is to avoid the identification problems noted by Manski (1993). Early research on peer effects simply included the average of either behavior or background characteristics among the survey respondent's peer group as a supposedly exogenous explanatory variable in a simple regression for the respondent's behavior. The coefficient on the average peer variable would then be interpreted as a measure of the peer effect. Manski notes four major problems with this methodology. The first problem ("sorting") is that self-selection into groups may lead to positive within-group correlation in many characteristics that are relevant to the outcome, and some of these relevant characteristics may be unobserved. For example, low-income students who attend private schools or public schools in high income neighborhoods may have parents which particularly value education. The second problem ("common shocks") is that there may be unobserved aggregate influences on a particular group; for example one school may have a particularly effective or ineffective principal, which will tend to raise or lower all scores in a given school. The third problem ("simultaneity") is that the respondent influences his or her peers in the same way the peers influence the respondent. Each of these three problems implies that average peer behavior and/or characteristics will fail to be exogenous, and leads the reduced form coefficient to be an upwardly biased estimate of the true peer effect. The fourth problem in this approach, also noted by Manski, is that even in the absence of the first three problems, there is no obvious way to distinguish empirically between the influence of peer characteristics ("contextual peer effects") and the influence of peer behavior ("endogenous peer effects") without imposing strong functional form assumptions on the econometric model.

Although a thorough survey of the empirical literature on peer effects is beyond the scope of this paper (see Moffitt 2001 for such a discussion), several recent studies have specifically aimed to estimate the influence of peers on a student's educational outcomes as measured by test scores, and thus speak to some of the same questions as our work. These studies are characterized by the use of experimental and other sources of credibly exogenous variation in peer group composition. Hoxby (2000) uses idiosyncratic variation in gender and racial composition between different cohorts at the same school to identify peer effects in test scores for Texas grade 3-6 students. Hanushek, et al. (2003) use a matched panel of Texas grade 3-8 students and schools to estimate peer effects while allowing for student and school-grade fixed effects. Boozer and Cacciola (2001) exploit exogenous variation in grades 1-3 classroom composition due to Tennessee's "Project STAR" class size experiment. These three studies find nontrivial and statistically significant peer effects.

While informative about some issues related to peer effects, sorting, and inequality, these microeconomic studies have two important limitations. First, those group characteristics for which there is exogenous variation are not necessarily those that are targeted by a given policy. A number of costly policies to reduce sorting, for example the Moving To Opportunity program (Katz, Kling and Liebman 2001), are aimed specifically at reducing sorting by income. However, none of the studies referenced above speaks directly to the effect of peer family income on academic outcomes, simply because their data lack credibly exogenous sources of variation in peer family income.

The second limitation of this literature is that estimates of peer effects by themselves tell us little about the relationship between sorting and inequality. If there are school-level peer effects, there will be a positive relationship between at least some types of sorting across schools and inequality in student outcomes. However, without further quantitative analysis it is difficult to say whether sorting explains a large or small proportion of the variation in test scores across students. This depends not only on the magnitude of peer effects, but on both the degree of sorting actually observed and whether the characteristics that are sorted on are the characteristics that are associated with substantial peer effects. Because inequality is generated by the interaction of sorting and peer effects, it is possible that what might be described as substantial sorting and substantial peer effects do not actually generate substantial inequality in combination. For example, Kremer (1997) develops a calibration methodology to estimate the long-run impact on inequality of what had been previously described as a large increase in marital and residential sorting. Despite calibrating the model with relatively large social interaction effects, Kremer finds that the long run impact of the increased sorting on inequality is minimal. This finding suggests that there is a clear need for direct quantitative evidence on the relationship between sorting and inequality.

Our research uses cross-community data on sorting of students into schools based on their family characteristics to fill this gap in the literature. It is most closely related to the work by Cutler and Glaeser (1997) and Card and Rothstein (2004) on the effects of racial segregation in US cities. Cutler and Glaeser characterize segregation by a dissimilarity index calculated across the census tracts in a city, and include both this measure of segregation and an interaction term for segregation and race in regressions for various individual outcomes. Card and Rothstein characterize segregation by the black-white gap in percentage of black schoolmates, and include this measure of segregation along with measures of black-white gaps in various socioeconomic characteristics in a regression for the black-white SAT score gap in the city. Our work uses a similar research design to these studies, while considering sorting on a wider variety of characteristics.

The essential feature of the cross-community (or cross-city) approach is that it does not require the assumption that families do not sort; indeed it exploits the fact that they do. This feature enables us to estimate the impact of sorting along a much wider and potentially more policy-relevant set of dimensions, including income, parental education, and other characteristics. A second benefit of the cross-community approach is that it will capture effects of sorting on inequality that arise through mechanisms other than peer effects. For example, suppose that political processes operate to move resources from poor schools to rich schools. In that case, a community in which schools are more strongly sorted on income may have a more unequal distribution of resources across schools, and thus a greater dispersion in student outcomes, even in the absence of peer effects. In some sense, this "contaminates" our results if the primary goal is to estimate peer effects; however, it is an advantage if the goal is to estimate the effect of sorting on inequality.

2 Theory and Methodology

The overall methodology in the paper involves estimating the parameters of a simple linear regression model using community-level data. The dependent variable is the variance in exam scores across the students in the community, and the explanatory variables include measures of the variance in background characteristics of the students' families, as well as measures of the degree of sorting across the community's schools with respect to these same characteristics. This basic regression is estimated using both a cross-sectional and fixed effects approach, and the estimated coefficients on the sorting variables are interpreted as providing information on the effect of sorting on inequality.

To motivate this approach, and discuss some of the econometric and conceptual issues, this section introduces a simple model of peer effects and sorting. Because we are working with aggregate variables at two different levels of aggregation (school and community) and potentially at different points in time, the notation is somewhat complex. Time is indexed by t, and communities are indexed by c. The number of schools in community c in period t is given by S_{ct}, and schools within that community are indexed by $s = 1, 2, , S_{ct}$.

Let x_{isct} be an arbitrary individual-level variable describing individual at school i in school s of community c in period t. Let N_{sct} be the number of students taking the exam in school s, and let $N_{ct} = \sum_{s=1}^{S_{ct}} N_{sct}$ be the total number of students taking the exam in community c. The school average of x is given by $\bar{x}_{sct} = \frac{1}{N_{sct}} \sum_{i=1}^{N_{sct}} x_{isct}$, and the school level variance is given by $\sigma^2_{sct}(x) = \frac{1}{N_{sct}} \sum_{i=1}^{N_{sct}} (x_{isct} - \bar{x}_{sct})^2$. Using this school-level data we calculate the community-level average:

$$\bar{x}_{ct} = \sum_{s=1}^{S_{ct}} \frac{N_{sct}}{N_{ct}} \bar{x}_{sct} \tag{1}$$

the community-level variance:

$$\sigma^2_{ct}(x) = \sum_{s=1}^{S_{ct}} \frac{N_{sct}}{N_{ct}} \left(\sigma^2_{sct}(x) + (\bar{x}_{sct} - \bar{x}_{ct})^2 \right) \tag{2}$$

and the community-level cross-school variance:

$$CSV_{ct}(x) = \sum_{s=1}^{S_{ct}} \frac{N_{sct}}{N_{ct}} (\bar{x}_{sct} - \bar{x}_{ct})^2 \tag{3}$$

The cross-school variance is our measure of sorting, and is the natural measure of sorting under the model described in the next section. Under perfect integration (all of the schools in community c have the same value of $\bar{x}_{sct}$), it will be the case that $CSV_{ct}(x) = 0$. Under perfect segregation (each school in community c is perfectly homogeneous) it will be the case that $CSV_{ct}(x) = \sigma^2_{sct}(x)$. The number of schools in a community may actually constrain the range of possible sorting: for example, communities with only one school will always have $CSV_{ct}(x) = 0$ by construction. Because there may be a statistical relationship between the size of a community and its level of unobserved heterogeneity, we always include the number of schools in a community as an explanatory variable to avoid mistakenly interpreting size effects as sorting effects. Note that the degree of sorting in a community as measured by the cross school variance depends on the relevant variable; for example a community may be heavily sorted on ethnicity but not on income.

2.1 A simple model of peer effects

Next we outline a simple linear model of peer effects in academic performance. Let y_{isct} be the exam score of an individual i attending school s in community c at time t, and suppose that:

$$y_{isct} = z_{isct} + \gamma \bar{y}_{sct} + \lambda \bar{z}_{sct} \tag{4}$$

where z_{isct} is the student's (unobserved) ability, $\bar{y}_{sct}$ is the average score in the student's school, and $\bar{z}_{sct}$ is the (unobserved) average ability among the student's peers. "Ability" is meant here as simply a catch-all term for any private input into student performance: it could include innate talent, prior educational experience, parental inputs, and anything other than the qualities and/or performance of the current peer group. The model above includes both endogenous peer effects (that operate through $\bar{y}_{sct}$) and contextual effects (that operate through $\bar{z}_{sct}$). The endogenous peer effect is assumed to satisfy the stability condition $\gamma < 1$; otherwise the average score implied by the model is not necessarily finite. There are a number of different mechanisms that could generate peer effects, including:

- Simple externalities/spillovers: students may learn from one another and thus learn more when in contact with high-achieving or high-ability peers.
- Provision of public goods: parents with high endowments of time, money, or skills may supply public goods to their child's classrooms.
- Scarcity of instructor's time: students with behavioral or learning problems may take instruction time or energy away from classmates.
- Political economy/resource considerations: parents with high interest or resource levels may divert resources towards their child's school.
- Specialization: homogeneous classes may facilitate efficiency through specialization or reduced discrimination.

As with most of the literature, we will not be able to distinguish between these different mechanisms, nor between endogenous and contextual effects. This model is a standard one in the literature on peer effects, and researchers have made numerous attempts to estimate this type of model using various proxy variables for student ability. However, as discussed previously, the model parameters are not identified from standard microeconomic data when schools are sorted on ability (Manski 1993), because this sorting induces positive correlation between the unobserved components of the student's ability (z_{isct}) and the observed performance or characteristics of the student's peers ($\bar{y}_{sct}$ or $\bar{z}_{sct}$). Rather than use microeconomic data to estimate peer effects we use aggregate data to directly estimate the effect of sorting on inequality.

To do this, we aggregate the model, and decompose the community-level variance in test scores into a portion that is due to community-level variance in inputs, and a portion that is due to sorting. Aggregating, the average score in school s in community c is given by:

$$\bar{y}_{sct} = \frac{1+\lambda}{1-\gamma}\bar{z}_{sct} \tag{5}$$

and the average score in the community is given by

$$\bar{y}_{ct} = \frac{1+\lambda}{1-\gamma}\bar{z}_{ct} \tag{6}$$

The score of any individual can then be rewritten as:

$$y_{isct} = z_{isct} + \frac{\gamma+\lambda}{1-\gamma}\bar{z}_{sct} \tag{7}$$

The community level variance in scores is given by:

$$\begin{aligned} \sigma^2_{ct}(y) &= E\left[(y_{isct} - \bar{y}_{ct})^2\right] \\ &= E\left[\left(\left(z_{isct} + \frac{\gamma+\lambda}{1-\gamma}\bar{z}_{sct}\right) - \left(\frac{1+\lambda}{1-\gamma}\bar{z}_{ct}\right)\right)^2\right] \end{aligned} \tag{8}$$

where the expectation is taken across individuals. Applying a few algebraic steps, we get:

$$\begin{aligned} \sigma^2_{ct}(y) &= E\left((z_{isct} - \bar{z}_{ct})^2\right) + \frac{\lambda^2 + 2\lambda + 2\gamma - \gamma^2}{(1-\gamma)^2}E\left((\bar{z}_{sct} - \bar{z}_{ct})^2\right) \\ &= \sigma^2_{ct}(z) + \frac{\lambda^2 + 2\lambda + 2\gamma - \gamma^2}{(1-\gamma)^2}CSV_{ct}(z) \end{aligned} \tag{9}$$

Equation (9) shows how the community-level variance in student outcomes (test scores) can be broken down into a portion that is explained by community level variance in inputs, and a portion that is explained by sorting. As equation (9) indicates, sorting will affect the overall variance in outcomes in the presence of peer effects, i.e., when either γ or λ is positive. In the absence of peer effects, only the variation in inputs across individuals matters for the variation in test scores.

2.2 Econometric Implementation

Because the model presented above is highly stylized and revolves around an unobserved input, equation (9) is not estimated directly but rather used to motivate a simple econometric exercise. We assume that for a vector of observable community-level variables X_{ct} and vector of unknown parameters α that

$$\sigma^2_{ct}(z) = X_{ct}\alpha + u_{ct} \tag{10}$$

and that for a different vector of observable community-level variables W_{ct} and vector of unknown parameters δ:

$$CSV_{ct}(z) = W_{ct}\delta + v_{ct} \tag{11}$$

In the application, the X variables primarily include measures of the variability in inputs across families in the community, in particular the variance in wage and salary income, primary parent's education, etc. It will also include a few variables that may be associated with the variance in unobserved inputs, in particular the number of schools in the community and the average number of students writing the exam. The W variables include measures of the variability across schools in the community, in particular the cross-school variance in wage and salary income, primary parent's education, etc.

Combining equations (9), (10), and (11), we get the reduced form:

$$\begin{aligned} \sigma^2_{ct}(y) &= X_{ct}\alpha + W_{ct}\delta\frac{\lambda^2 + 2\lambda + 2\gamma - \gamma^2}{(1-\gamma)^2} + u_{ct} + v_{ct}\frac{\lambda^2 + 2\lambda + 2\gamma - \gamma^2}{(1-\gamma)^2} \\ &= X_{ct}\alpha + W_{ct}\beta + \epsilon_{ct} \end{aligned} \tag{12}$$

Interpretation of the reduced form coefficients is straightforward: the marginal impact of sorting on inequality is given by β. When there is no peer effect ($\gamma = \lambda = 0$), the true value of the reduced form coefficient is $\beta = 0$. As in much of the literature we will not be able to separately identify endogenous effects (γ) and contextual effects (λ). However, our approach can identify β without assuming exogenous selection into schools.

We pursue two strategies for estimating the coefficients in (12). The baseline regression uses OLS on the cross-sectional Grade 9 data, and will generate consistent estimates of β if:

$$E(\epsilon_{ct}|X_t, W_t) = 0 \tag{13}$$

In order for this assumption to be satisfied, we need two sets of conditions to hold. First, either sorting on unobserved dimensions is unrelated to sorting on observed dimensions

$$E(v_{ct}|X_t, W_t) = 0 \tag{14}$$

or there is no peer effect

$$\gamma = \lambda = 0 \tag{15}$$

However, because we are not interested in interpreting our estimates in a narrow structural sense, we are not overly concerned if there is correlation between observed and unobserved sorting in the absence of peer effects. Assumption (14) therefore is relatively innocuous for our purposes.

Second, we will need the unobserved variation in heterogeneity across communities to be unrelated to both observed heterogeneity and the degree of sorting:

$$E(u_{ct}|X_{ct}, W_{ct}) = 0 \tag{16}$$

Again, because we are not going to push a strict structural interpretation of our coefficients, we are not concerned about the first of these assumptions. The second assumption is a more serious concern, since it is not difficult to imagine greater unobserved heterogeneity within a community leading affluent families to take greater steps to segregate from disadvantaged families. We are interested in identifying heterogeneity that is caused by sorting, rather than the reverse. In order to do so, we use our linked Grade 9/Grade 6 data to develop a fixed effects estimator. In this case, we allow unobserved community and/or cohort specific factors which affect the variance in outcomes and are correlated with observables. Specifically, we replace (13) with the much weaker assumption:

$$E(\Delta\epsilon_{ct}|\Delta X_{ct}, \Delta W_{ct}) = 0 \tag{17}$$

and estimate the regression

$$\Delta\sigma^2_{ct}(y) = \Delta X_{ct}\alpha + \Delta W_{ct}\beta + \Delta\epsilon_{ct} \tag{18}$$

The specification (18) allows for there to be a community-specific fixed effect which affects the variance in test scores and is correlated with the degree of sorting.

3 Data

3.1 An overview of Alberta's Provincial examination program

Alberta is a large province in western Canada with an economy based on agriculture and natural resource extraction. The population is concentrated in two large metropolitan areas (Calgary and Edmonton), several smaller cities and a large number of small agricultural or resource industry towns.

Approximately 547,000 students attended Alberta's kindergarten to Grade 12 public school system in the 2000-2001 school year (Interprovincial Education Statistics Project 2002). Although it is administered mostly by local school boards, education is funded by the province and therefore per pupil funding formulas are the same in all public schools. Although a number of students attend private schools, both the size and degree of independence of the private educational sector are less than in the United States. In particular, 92 percent of the 192 private schools in 2001 were classified as "accredited" and therefore received provincial funding and were subject to provincial standards and curriculum requirements. The remaining private schools were classified as "registered" and did not receive provincial funding. Alberta reports that 4% of its students attended private schools in 2001, and such schools received per-student funding at approximately 60% of the per-student public school funding (Alberta Learning 2002a, Sections 8.2 and 8.4).

The Achievement Tests are conducted in Grades 3, 6, and 9. The exams are in the core academic subjects of Language Arts, Mathematics, Science, and Social Studies, and are intended to be taken by all students. Both accredited and registered private schools participate in these exams, as do public schools. Our research explores the effects of sorting on the community-level variance of Grade 9 test scores in Language Arts and Mathematics. We also use linked Grade 6 and Grade 9 data to construct a fixed effects estimator of our model. Because the exams are in principle mandatory, and because there are almost no dropouts at this level, the selection issues involved in this estimation are relatively minor. However, a small fraction of students do not take the exams. Approximately 4% to 7% of Grade 9 students are absent from school on the exam day and fail to take a make-up exam. In addition, a student may be excused from the exam if his or her principal judges that he or she is "incapable of responding to the exam," or if "participation will be harmful to the student." Approximately 3% to 6% of students are exempted in this manner (Alberta Learning 2002b).

3.2 Data structure and links with data on family characteristics

The data set was originally assembled by Cowley and Easton (2002) in conjunction with Statistics Canada and the Alberta provincial government. The primary unit of observation in the Cowley and Easton data set is the school. For each exam and each school, the data set provides the mean and variance of exam scores for the school, as well as the average number of students taking the exam and other school-level variables. If five or fewer students at a given school take a given exam in a given year, results are suppressed.

In addition, the Cowley and Easton data set features detailed Census data on the family characteristics of the school population. Statistics Canada has provided a custom 1996 Census data set describing the population of households with one or more children of secondary school age, organized by Enumeration Area (EA). This data set includes means and variances of a wide variety of background characteristics, including family income from various sources, ethnicity, language spoken at home, and primary parent's education. The Alberta provincial government has provided a breakdown of each school's population of enrolled students by EA of residence. The Census EA-level data are then aggregated to the school level using weights based on the number of students in each EA. The resulting data set thus approximates the characteristics of the families who have children attending each school.

3.3 Aggregation to community level

Although the Cowley and Easton data set is at the school level, the relevant unit of observation in this study is the group of schools in a community. For the purposes of this study, a community is defined as a collection of one or more municipalities that form an integrated labor market and host at least one school offering Grade 9. Two municipalities are considered to be part of the same community if they are fewer than 30 minutes driving time apart and at least one municipality has a population over 10,000. This definition implies that, for example, the major city Calgary and its suburbs are treated as part of the same community, but two farming towns nearby to one another are treated as two distinct communities. We distinguish between small and large municipalities in this way because many of Alberta's small municipalities are agricultural centres, where people's residential choices are dictated by the location of farmland, rather than residential amenities such as schools. Driving distance is calculated by using the quickest route provided by Microsoft's Expedia (`http://www.expedia.ca`) web site. Once communities are defined, the original school level data are aggregated to the community level using weights based on the number of students taking the exam in each school.

This method for defining communities generates 205 distinct communities in Alberta that had at least one school offering Grade 9 in 2001. For each community, the 2001 Grade 9 data is also linked to the community's Grade 6 results from the year (1998) when most of the 2001 Grade 9 class would have been in Grade 6. The assignment of Grade 6 schools to Grade 9 communities is slightly complicated by some cases where a very small municipality has a local elementary school but sends its students to a high school in another municipality. For example, Grade 6 students attending Dunstable School in the town of Busby generally attend Barrhead Composite in Barrhead for Grade 9, and so are assigned in our data to the community of Barrhead. For each such Grade 6 school, we contacted the school directly to identify the high school 1998 Grade 6 students were expected to attend in 2001.

4 Results

4.1 Descriptive Statistics

Table 1 describes the number of schools at each grade level in the 205 communities in our sample. The majority of these communities are small, where all of the Grade 6 students attend a single elementary or middle school and all of the Grade 9 students attend a single junior high or high school. A substantial number of communities have two schools at one or both grade levels. The two large metropolitan areas of Calgary and Edmonton have over 200 schools offering Grade 6 and over 100 schools offering Grade 9.

Table 2 characterizes the sample in terms of the difference between the number of Grade 6 and Grade 9 schools within communities. In Alberta, Grade 6 students generally attend an elementary (Grade 1-7 or 1-6) school, while Grade 9 students attend high schools (Grade 8-12) or junior high schools (Grade 7-9). Elementary schools are generally smaller than high schools so multiple elementary schools will often "feed" a given high school. This reallocation can in principle generate large changes in sorting. The number of Grade 6 schools in the community is equal to the number of Grade 9 schools in 155 of these communities, and the number of Grade 6 schools is higher in 47 communities. In 21 of these 47 communities, students attending two or more schools for Grade 6 are merged into a single Grade 9 school. Three communities had more schools offering Grade 9 than schools offering Grade 6 in three communities, a pattern that can be explained by the greater availability of private school alternatives to the public school system at the Grade 9 level.

Community-level summary statistics for both exam scores and family characteristics are reported for the 205 communities in the sample in Tables 3 and 4.[1] Table 3 shows that the communities in our sample exhibit substantial variation in the average exam performance of their students. The average community-level mean score on the Language Arts exam was 68.5, and ranged from 40.6 to 79.5. The average community-level mean score on the Math exam was 29.8, and ranged from 10.9 to 39.3. Table 3 also shows that some communities have considerably greater heterogeneity in Grade 9 test scores than others. The community-level variance of the Language Arts scores ranges from 35.5 in the most homogeneous (with respect to Language Arts test scores) community in the sample to 563.1 in the most heterogeneous. The community-level variance of the Math scores ranges from 9.4 to 184.9. In both cases, the cross-school variation in test scores is a small proportion of the overall within-community variation in test scores. Although there is variation in student performance across schools within most

[1] Note that the mean of community-level means is distinct from the provincial mean for a variable because it weighs small and large communities equally.

communities, there is much more variation within schools.

Our model includes as explanatory variables the community-level variances and cross-school variances of two groups of variables derived from the Canadian Census, as well as measures of the average number of students writing the exam in each school and the number of schools. The first group of Census variables describes ethnicity and language spoken at home, and the second group includes measures of socioeconomic status, including income. Table 4 presents descriptive statistics for these variables.

The question of whether sorting by race and ethnicity affects inequality has been of particular interest in the US literature, and so our regression analysis begins by exploring whether sorting by race and ethnicity affects inequality in the Alberta context. Clearly, the ethnic composition of our sample of families with school-age children in Alberta is very different from the composition of samples used in the related US literature, and the historical context in Canada is different in several important respects. The largest minority group in Alberta, who self-report as Aboriginal, make up seven percent of our sample. The self-reported ethnicity of a further three percent of the sample places them in the category of "Visible Minority". For Census purposes, those who self-identify as Aboriginal are not counted as visible minorities.

The historic relationship between aboriginal people in Canada and the school system has frequently been unhappy, and unsuccessful. The challenges that aboriginal students in Canada face in the public school system are well-known, and are the focus of much concern among community leaders and policy-makers.[2] Understanding the effect of sorting by aboriginal status on inequality of educational outcomes therefore is of direct policy interest. Although only 7 percent of the overall sample is Aboriginal, many small communities include substantial numbers of aboriginal people: the proportion of families with school age children that are headed by self-reported aboriginal people in communities in our sample ranges from 0 to 98 percent.

Visible minority status may be correlated with cultural factors that affect learning outcomes, or may subject students to discrimination or cultural stereotyping that affects their school performance. Although they make up only three percent of heads of families with school-age children in our sample, visible minorities are also concentrated in particular communities: the proportion of visible minority families in our communities ranges from zero to over 44 percent. Over one-third of those with visible minority status in our sample report their ethnicity as Chinese. Other ethnic groups do not make up a significant proportion of the overall school-age population in Alberta, but because of their concentration

[2] See for example, BC Ministry of Education (2002) and discussion on the Ministry's website at `http://www.bced.gov.bc.ca/abed/abed`.

in a small number of communities, do make up a significant proportion of the school-age population in those communities. People of Japanese ancestry, for example, form only .23 percent of the overall number of heads of families with school-age population, but make up over 31 percent of this group in the community of Banff, where the economy relies heavily on Japanese tourism. Other groups that make up substantial portions of the school-age family heads in one or more Alberta communities include Filipinos, Arabs/West Asians and Latin Americans.

Unlike the literature on black-white differentials in the US, interpreting the effect of ethnicity in our study is complicated by the fact that minority families are more likely than non-minority families to speak the language of instruction as a second language.[3] We therefore include variance measures based on the proportion of students who do not hear either English or French spoken at home on a regular basis. Overall, three percent of students in our sample live in such homes: the proportion of homes with school-age children where neither official language is spoken ranges from 0 to 64 percent across communities.

We focus on three indicators of socioeconomic status: family wage and salary income, family government transfer income, and the level of education of the primary parent. Income may affect learning directly if parents with greater financial means are able to provide more resources in support of their child's learning, such as tutoring services. More generally, income may affect health and self-esteem, which in turn influence both learning and behavior. However, it is not obvious that we would expect the relationship between family income and student learning to conform to the linear functional form that underlies our empirical specification. As a result, we also include the level of government transfer income as a proxy for low-income status. Because there is no significant intra-provincial variation in transfer programs, the level of transfer income will be closely and positively related to low-income status.[4] Our second indicator of socioeconomic status, primary parent's education, has been shown elsewhere to be an important predictor of individual student academic performance (see, for example, Hanushek and Raymond 2004). The average community in the sample has a mean family income of just over $40,000 per year, mean transfer income of about $4,000 per year, and a mean level of primary parent's education of almost one year of post-secondary schooling. All three of these variables exhibit substantial variation across communities, as do their variances.

Finally, we include in our model both the number of schools in the community and the average

[3]Canada is an officially bilingual country, where French and English have the same legal status. Although Alberta has a very small francophone population, federal funds are available to support programs and schools where French is the language of instruction.

[4]Government transfer income includes all transfer payments received from federal, provincial or municipal governments. This variable is the sum of the amounts reported as Old Age Security and Guaranteed Income Supplements, Canada Pension Plan, Employment Insurance, Canada Child Tax benefits, and "other income from government sources."

number of students writing the exam in each school. Including the number of schools in the community is a way to control for the potential for group heterogeneity associated with such factors as variation in teacher and principal quality across schools. School size may affect the variance of outcomes both because school-level averages will tend to be more variable when the schools are small, simply because the averages are taken over fewer observations (Graham 2004), and because school size itself has been shown to affect student performance (Bedard, Jr. and Helland 2001, e.g.).

4.2 Cross-Section Regression Results

The first set of results, presented in Table 5, shows estimates from a variety of specifications of the cross-sectional model (12) for the community-level variance in both the Language Arts and Math exams. All specifications include a basic set of variables that includes the average number of students writing the exam in each school, a quadratic term in the number of schools in the community, and the community-level variances of the six household characteristics of interest: visible minority status, aboriginal status, home language, wage and salary income, government transfer income, and education of the primary parent.

The first specification includes only these variables and no sorting variables. The results, presented in the first columns of each of the Language Arts and Math panels, show that the variances of both the Math and Language Arts test scores are increasing in the average number of students writing the exams in each school, and are increasing at a decreasing rate in the number of schools. This evidence with respect to group heterogeneity suggests that school level inputs such as teacher quality may play a significant role in determining test score results in the case of Math, but not in the case of Language Arts. The point estimates of the effect on the variance of test scores of the variance of visible minority status and education are positive for both Math and Language Arts, as one might expect, but the other variance terms are sometimes or always negative. Most of these coefficients are statistically insignificant.

The remainder of Table 5 presents results of various specifications that include sorting by ethnicity and language. Because the sorting variables are highly collinear, we estimate specifications including each sorting variable separately, as well as a specification including all three together. When we add the sorting variables one at a time we find that sorting by visible minority status and by home language has a positive and statistically significant association with the community-level variances of both the Math and Language Arts results. Sorting by aboriginal status also has a positive and statistically significant association with the Math results, but is insignificant in the Language Arts results. When these three sorting variables are included together, sorting by visible minority status knocks out any independent effect of sorting by home language in both cases.

Table 6 presents specifications that include variables describing sorting on socioeconomic characteristics. We find that sorting by wage and salary income and by educational status is not statistically significant in either Math or Language Arts, but that sorting by transfer income is. The statistical significance of sorting by transfer income remains when all three socioeconomic variables are included in the model.

When all six sorting variables are included in the model, shown in Table 7, only sorting by visible minority status remains statistically significant in both exams, and sorting by aboriginal status remains statistically significant in the Math results. The statistical significance of sorting by government transfer income disappears when sorting by aboriginal status is included in the model. Overall, these results give the impression that there is some sort of peer effect associated with minority status that is distinct from an effect of income or primary parent's education. Surprisingly, income and primary parent's education do not appear to be associated with a peer or sorting effect at all.

The spillover effects associated with the sorting variables in these regressions are identified from cross-community variation in sorting, and can be given causal interpretation only if sorting is not correlated with unobserved community-level effects that play a role in determining the overall variance of test scores. It is easy to imagine that the sorting process may be endogenous, whereby greater unobserved heterogeneity within a community's population may cause both increased sorting and increased variance in test scores. This type of endogenous sorting mechanism would lead us to overestimate the effect of sorting if not accounted for. The pattern of results in Tables 5 through 7, for example, is consistent with a world in which a greater degree of unobserved diversity within the community in characteristics that affect test scores leads to increased sorting by visible minority status, aboriginal status, and home language, but little or even reduced sorting directly by income and education. We therefore pursue an alternative identification strategy that exploits a more credibly exogenous source of variation in the degree of sorting within communities.

4.3 First-Difference Regression Results

As described earlier, we have linked the 2001 Grade 9 test results to the 1998 Grade 6 test results from the same communities. We are then able to create first difference measures of the community-level variance in test scores, the community-level variance in characteristics, and the cross-school variance in characteristics. This first differencing procedure has the effect of eliminating any community-specific factors which affect the variance of exam scores across students and which might be correlated with the observed degree of sorting.

Table 2 showed that in 155 of the 205 communities in the sample, the number of Grade 6 schools and the number of Grade 9 schools is the same. In these communities, first-differencing the sorting variables will generate variation only from migration into and out of the communities that alters the geographical distribution of characteristics. In the remaining 50 communities, the change in the cross-school variance of the sorting variables will come primarily from differences between the elementary and high school catchment boundaries. On average for this group of communities, the value of measured sorting by all six characteristics considered is smaller at the Grade 9 level than at the Grade 6 level, and the change is orders of magnitude greater compared to communities where the numbers of schools is the same at both grade levels.

Because first differencing substantially reduces variation in some of the explanatory variables, the specification of the fixed effects model is simplified somewhat. Both the Grade 6 and Grade 9 family characteristic measures are derived from the same 1996 Census data, so that any changes in the *community level* variance of the background variables will only be due to changes in the distribution of students across Census EA's. As a result, this variation will be noisy and close to zero. We therefore do not include changes in the variances of characteristics in our first difference specifications. In contrast, variation in the *cross-school* variance will be generated in part by changes in school catchment boundaries.

Tables 8 and 9 show that when the sorting variables are included one at a time, primary parent's education is statistically significant in the regressions for both exams, and home language is statistically significant in the Language Arts case. Table 10 shows that the same results obtain when all sorting variables are included in the model. None of the other sorting variables is statistically significant.

It is interesting to compare these results to the cross-section estimates. Some results are qualitatively similar: wage and salary income is not statistically significant in either the fixed effects or cross-section results for either the Language Arts or Math exams, and aboriginal status is not statistically significant in either the fixed effects or cross-section results for Language Arts. Of the results that do differ, their differences may reflect several factors: point estimates may differ because social interactions have a different effect at different grade levels or because of the treatment of unobserved heterogeneity; statistical significance may differ because variables exhibit greater independent variation in the cross-section or the first-differenced data. Although we can't sort out these possibilities definitively, we offer our preferred interpretation of each result. We find that visible minority status and transfer income are statistically significant for both exams in the cross-section results, but not for either in the fixed effects results. We think it is more likely that sorting by visible minority status and low income is correlated with unobserved heterogeneity across communities in the variance of unobserved factors that affect test scores than that their role in the production function of the variance of test scores is different at the different grade levels. We think the reverse is likely to be true for primary parent's education, which is statistically significant in the fixed effects estimates for both exams but not in the cross-section estimates for either. It seems plausible that communities would be more likely to sort themselves by visible minority and low income status than by primary parent's education, since the former characteristics are more easily observed. The strength of the effect of sorting by home language in the fixed effects Language Arts results may reflect either the increased importance of this variable at higher grade levels, or greater independent variation in sorting by home language in the first-differenced data.

4.4 How Big Are the Estimated Sorting Effects?

We next assess the magnitudes of effects of sorting according to characteristics that appear to matter, using the estimates from models that include a single sorting variable. Table 11 presents the predicted change in the variance of test scores (based on the cross-section results) that would result from complete desegregation of multi-school communities along a single dimension. For example, the cross-section estimates generate the prediction that fully integrating visible minority students in the average (with respect to sorting by visible minority status) multi-school community would reduce the average variance of Language Arts test scores by 4.5 percent, and would reduce the average variance of Math test scores by 2.5 percent. Fully integrating aboriginal students in the average (with respect to sorting by aboriginal status) multi-school community is predicted to reduce the average variance of Language Arts test scores by .4 percent and Math test scores by 1.7 percent. Integrating by home language in the average (with respect to sorting by home language) multi-school community is predicted to reduce the average variance of Language Arts scores by 3.3 percent and Math scores by 4.3 percent. Finally, integrating by government transfer income the average (with respect to sorting by transfer income) multi-school community is predicted to reduce the average variance of Language Arts test scores by 2.5 percent and Math test scores by 3.3 percent.

Table 12 presents predictions based on the fixed effects estimates for the variables that were important in these results. Eliminating segregation by home language in Grade 9 schools in the average (with respect to home language) multi-school community is predicted to reduce the average variance of Grade 9 Language Arts test scores by 2.6 percent and the average variance of Grade 9 Math scores by .3 percent. Eliminating segregation by parental education in Grade 9 schools in the average (with respect to primary parent's education) multi-school community is predicted to reduce the average variance of Grade 9 Language Arts test scores by 1.2 percent and the variance of the Grade 9 Math test scores by 2.7 percent.

These estimates refer to the predicted effect of desegregating communities with average degrees of sorting. How big an effect would we expect if we integrated the most segregated communities? Alberta's capital city, Edmonton, is the most highly segregated community in our sample in terms of both home language and education. While the average level of education in Edmonton is very close to the sample mean, the proportion of students who live in homes where neither French nor English are usually spoken is almost 12 percent, compared to 3.5 percent in the average community in the sample. According to the first difference estimates, fully integrating the Grade 9 schools in Edmonton according to home language would reduce the variance of Grade 9 Language Arts test scores by 41 percent, and Grade 9 Math scores by 4.8 percent. Fully integrating the Grade 9 schools in Edmonton according to primary parent's education would reduce the variance of Grade 9 Language Arts test scores by 11.1 percent, and of Grade 9 Math test scores by 39.1 percent.

5 Conclusion

The results reported in this paper suggest that certain types of sorting across schools increase the community-level variance of test scores on standardized exams in Alberta high schools. This evidence contributes to the literature on peer effects, sorting and inequality in two ways. First, it provides new evidence that sorting across school affects students' exam performance. Unlike previous studies of peer effects in schools, we are able to explore the possibility that the family income and parents' education of a student's peers may affect his or her learning, and to consider the effect of the language spoken in peers' homes as well as the ethnic and cultural composition of the peer group. Second, it allows us to gauge the magnitude of the effect of sorting on inequality of student outcomes, and conversely to quantify the potential for programs designed to integrate school communities according to a number of important characteristics, such as ethnicity and income, to reduce current levels of inequality in student outcomes.

Our cross-sectional estimates indicate a sorting effect that might be associated directly with ethnicity, rather than other characteristics that are correlated with ethnicity, including family wage and salary income, government transfer income, primary parent's education and language spoken in the home. This intriguing result suggests that factors such as differences in cultural norms or discrimination may be generating peer effects within school communities. Endogenous sorting may be contaminating these results if, as seems plausible, communities that are more diverse in unobserved ways are more likely to sort themselves along ethnic or racial lines. When we implement a procedure that differences out any relevant unobserved heterogeneity within communities, we find that sorting by visible minority status and aboriginal status is no longer statistically significant in the results for either exam. While it may be the case that ethnicity matters for learning up until Grade 6 but not beyond, we think it more likely that the cross-sectional results are picking up the effects of unobserved community heterogeneity that is correlated with sorting by ethnicity.

The fixed effects estimates do generate results consistent with social interactions, although they are not associated with ethnicity itself. Communities in which the degree of sorting by home language falls more as students move from elementary to high school exhibit a greater reduction in inequality in Language Arts test scores between Grades 6 and 9, and communities in which the degree of sorting by primary parent's education falls more exhibit a greater reduction in inequality in both Language Arts and Math test scores. These results seem intuitively plausible. Parental education may serve as a proxy for other characteristics that might affect peers, such as the degree of parental provision of public goods or political economy considerations, or it may be correlated with ability and therefore picking up simple externalities. Language spoken in the home may also serve as a proxy for public goods or political economy considerations. Furthermore, students from homes where English is not spoken may themselves have relatively weak English language skills. The presence of students in the classroom with weak language skills may alter teaching methods in ways that affect their fellow students' progress in the Language Arts.

The negative results we obtain are also interesting. In particular, neither the cross-section nor fixed effects estimates produce any evidence consistent with any social interaction effect arising directly from family wage and salary income or a proxy measure for low-income status.

A number of these sorting variables are fairly highly correlated with one another, so that policies that target desegregation according to characteristics that do not appear to be directly associated with social interactions may nevertheless reduce the inequality of test scores. The cross-section estimates indicate that integrating by ethnicity, home language or transfer income would reduce test score inequality. This last result suggests that programs that target low income families of the type implemented in the Moving to Opportunity project could be effective in the Alberta context. However, the fixed effects estimates undermine this finding, suggesting that the apparent role of ethnicity and low income may merely be picking up the effects of endogenous sorting. The fixed effects estimates suggest that desegregating communities according to language spoken in the home is most likely to effect a significant reduction in Language Arts test score inequality, and desegregating communities according to primary parent's education is most likely to effect a significant reduction in Math test score inequality.

The point estimates suggest that within the average community studied, the magnitudes of the effects of sorting on the variance of test scores are not especially large. In the small number of larger cities in the sample with their more diverse populations, however, the estimated magnitudes are very large. The significance of these results from a policy perspective would be clearer if we were able to say more about the effect of sorting on other moments of the test score distributions. In particular, it would be helpful to know whether sorting has a symmetric effect on the upper and lower tails of the distributions. While the data set used in this study does not allow us to investigate higher moments or different quantiles of the test score distributions, this would be an interesting question for future work.

This research could be extended in a number of ways. First, as both more years of data and data from more provinces are becoming available, increased sample sizes may allow for the estimation of richer models. The approach can also be applied to data from outside of Canada, although extension to US data will require addressing the selection issues with private schools. Finally, if peer effects are nonlinear, sorting may affect average student performance as well as the variance in performance. Future research may determine whether this is the case.

References

Alberta Learning, *2001-2002 Funding Manual for School Authorities*, Province of Alberta, 2002.

___ , *Achievement Test Multiyear Report 1997-2998 to 2001-2002*, Province of Alberta, 2002.

Bedard, Kelly, William O. Brown Jr., and Eric Helland, "School size and the distribution of test scores," Working Paper, University of California - Santa Barbara 2001.

Boozer, Michael A. and Stephen E. Cacciola, "Inside the 'black box' of Project STAR: Estimation of peer effects using experimental data," Working Paper, Yale University 2001.

British Columbia Ministry of Education, *How are we doing? Demographics and performance of aboriginal students in BC public schools*, Queen's Printer, 2002.

Card, David and Jesse Rothstein, "Racial segregation and the Black-White test score gap," Working Paper, Princeton University 2004.

Coleman, James S., Ernest Q. Campbell, Carol F. Hobson, James M. McPartland, Alexander M. Mood, Frederic D. Weinfeld, and Robert L. York, *Equality of Educational Opportunity*, Department of Health, Education, and Welfare, 1966.

Cowley, Peter and Stephen T. Easton, *Report Card on Alberta's Elementary Schools*, The Fraser Institute, 2002.

Cutler, David M. and Edward L. Glaeser, "Are ghettos good or bad?," *Quarterly Journal of Economics*, 1997, *112*, 827–872.

Durlauf, Steven N., "A theory of persistent income inequality," *Journal of Economic Growth*, 1996, *1*, 75–93.

Fernandez, Raquel and Richard Rogerson, "Income distribution, communities, and the quality of public education," *Quarterly Journal of Economics*, 1996, *111*, 135–164.

Graham, Bryan S., "Social interactions and excess variance contrasts: Identification, estimation, and inference with an application on the role of peer group effects in academic achievement," Working Paper, Harvard University 2004.

Hanushek, Eric A. and Margaret E. Raymond, "The effect of school accountability systems on the level and distribution of student achievement," *Journal of the European Economic Association*, 2004, *2.* (forthcoming).

__ **, John F. Kain, Jacob M. Markman, and Steven G. Rivkin**, "Does peer ability affect student achievement?," *Journal of Applied Econometrics*, 2003, *18* (5), 527–544.

Hoxby, Caroline M., "Peer effects in the classroom: Learning from gender and race variation," Working Paper 7867, NBER 2000.

Interprovincial Education Statistics Project, *Summary of school statistics from the provinces and territories*, British Columbia Ministry of Education, 2002.

Katz, Lawrence F., Jeffrey R. Kling, and Jeffrey B. Liebman, "Moving to Opportunity in Boston: Early results of a randomized mobility experiment," *Quarterly Journal of Economics*, 2001, *116* (2), 607–654.

Kremer, Michael, "How much does sorting increase inequality?," *Quarterly Journal of Economics*, 1997, *112*, 115–140.

Manski, Charles F., "Identification of endogenous social effects: The reflection problem," *Review of Economic Studies*, 1993, *60* (3), 531–542.

# Schools	# communities Grade 6	# communities Grade 9
1	153	155
2	28	24
3	6	9
4	3	2
5	1	3
6	0	1
7	3	3
8	1	3
10	1	0
11	2	1
12	1	0
17	1	0
18	0	1
19	0	1
21	1	0
23	1	0
34	1	0
104	0	1
117	0	1
216	1	0
264	1	0
Total # Schools	892	573
Total # Communities	205	205

Table 1: Frequency count of communities by number of schools, Grade 6 and Grade 9

Change in # Schools (Grade 9 - Grade 6)	**# Communities**
1	3
0	155
-1	29
-2	3
-3	5
-4	1
-5	2
-6	2
-10	1
-15	1
-16	1
-113	1
-147	1
Total	205

Table 2: Frequency count of communities by difference between number of Grade 6 and Grade 9 schools in community

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Grade 9 Language Arts exam score				
Community # writing	43.2	43.3	6.0	235
Community mean	68.5	4.9	40.6	79.5
Community variance	161.0	61.8	35.5	563.1
Cross-school variance	2.3	6.0	0.0	39.1
Grade 9 Math exam score				
Community # writing	43.0	41.6	6.0	235
Community mean	29.8	4.3	10.9	39.3
Community variance	83.9	27.4	9.4	184.9
Cross-school variance	1.6	4.7	0.0	39.2

Table 3: Summary statistics for Language Arts and Math exam results

Variable	**Mean**	**Std. Dev.**	**Min**	**Max**
Visible minority				
Community mean	0.03	0.06	0.00	0.44
Community variance	0.03	0.05	0.00	0.25
Cross-school variance	0.0002	0.001	0.00	0.01
Aboriginal				
Community mean	0.07	0.16	0.00	0.98
Community variance	0.04	0.059	0.00	0.25
Cross-school variance	0.0002	0.002	0.00	0.03
Official language not usually spoken at home				
Community mean	0.03	0.08	0.00	0.64
Community variance	0.03	0.05	0.00	0.24
Cross-school variance	0.0001	0.001	0.00	0.01
Annual Family Wage and salary income ($1,000)				
Community mean	40.96	11.79	10.50	80.57
Community variance	198.20	192.35	11.75	1091.02
Cross-school variance	6.99	33.01	0.00	290.50
Annual Family Transfer Income ($1,000)				
Community mean	4.39	1.49	1.76	11.96
Community variance	3.14	3.52	0.19	28.47
Cross-school variance	0.05	0.19	0.00	1.29
Education of primary parent (years)				
Community mean	12.44	0.83	9.57	14.43
Community variance	0.96	1.02	0.04	8.63
Cross-school variance	0.02	0.09	0.00	0.82

Table 4: Summary statistics for family characteristics

	Language Arts					Mathematics				
Avg # writing	0.05	0.05	0.06	0.06	0.05	0.14	0.14	0.14	0.14	0.14
(t-stat)	0.45	0.44	0.48	0.46	0.42	3.23	3.22	3.34	3.25	3.32
(p-value)	0.651	0.659	0.632	0.645	0.678	0.001	0.002	0.001	0.001	0.001
# schools	0.98	0.26	0.95	0.59	1.45	1.01	0.77	0.97	0.69	0.79
	0.76	0.21	0.75	0.49	1.05	2.09	1.60	2.06	1.51	1.65
	0.445	0.835	0.457	0.622	0.297	0.038	0.112	0.040	0.134	0.100
(# schools)^2	-0.01	-0.01	-0.01	-0.01	-0.02	-0.01	-0.01	-0.01	-0.01	-0.01
	-0.79	-1.11	-0.77	-1.08	-1.93	-2.19	-2.60	-2.17	-2.77	-2.31
	0.430	0.268	0.442	0.280	0.055	0.030	0.010	0.031	0.006	0.022
Var(Vis. Min.)	20.52	6.44	21.94	20.56	8.32	94.34	90.05	96.84	94.73	92.78
	0.29	0.09	0.31	0.29	0.11	2.69	2.53	2.81	2.71	2.63
	0.774	0.930	0.759	0.773	0.910	0.008	0.012	0.005	0.007	0.009
Var(Aboriginal)	49.98	47.20	40.90	43.74	43.67	-5.70	-6.53	-20.96	-10.33	-21.86
	0.84	0.79	0.64	0.72	0.67	-0.20	-0.22	-0.71	-0.37	-0.72
	0.403	0.429	0.524	0.472	0.505	0.845	0.823	0.479	0.714	0.470
Var(Home Lang.)	-117.0	-111.06	-118.6	-119.99	-115.24	-144.9	-143.06	-147.84	-147.42	-145.81
	-1.77	-1.66	-1.79	-1.81	-1.71	-3.66	-3.61	-3.74	-3.69	-3.67
	0.079	0.099	0.076	0.072	0.090	0.000	0.000	0.000	0.000	0.000
Var(W/S income)	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	-0.33	-0.25	-0.37	-0.38	-0.28	-0.63	-0.56	-0.85	-0.72	-0.77
	0.742	0.801	0.711	0.706	0.779	0.530	0.578	0.397	0.471	0.441
Var(Transfer inc.)	-0.62	-0.62	-0.61	-0.65	-0.63	-0.18	-0.18	-0.17	-0.20	-0.17
	-0.73	-0.73	-0.72	-0.76	-0.72	-0.41	-0.41	-0.39	-0.45	-0.38
	0.465	0.464	0.470	0.447	0.469	0.685	0.684	0.697	0.655	0.705
Var(Par. Educ.)	6.93	6.95	7.01	7.05	7.23	1.84	1.84	1.97	1.91	1.97
	1.34	1.35	1.35	1.36	1.39	0.78	0.77	0.83	0.81	0.82
	0.181	0.179	0.180	0.176	0.166	0.438	0.441	0.408	0.420	0.413
CSV(Vis. Min.)		13111.26			13692.88		4009.49			3869.15
		2.62			2.57		2.73			2.42
		0.010			0.011		0.007			0.016
CSV(Aboriginal)			827.26		226.51			1401.93		1483.34
			1.02		0.21			3.91		3.11
			0.308		0.836			0.000		0.002
CSV(Language)				15089.21	7008.70				11287.52	-1924.1
				2.05	0.82				2.68	-0.49
				0.042	0.415				0.008	0.626
Constant	154.15	154.46	154.41	154.76	154.74	78.27	78.38	78.70	78.78	78.74
	14.55	14.58	14.51	14.56	14.49	20.04	20.08	20.10	20.17	20.04
	0.00	0.00	0.00	0.00	0.00	0.000	0.000	0.000	0.000	0.000

Table 5: Regression results: Community level variance of Grade 9 Test Scores, 2001 cross-sectional data, with sorting by ethnicity and language

	Language Arts				Mathematics			
Avg # writing	0.05	0.06	0.05	0.05	0.14	0.14	0.14	0.14
(t-stat)	0.44	0.48	0.44	0.43	3.25	3.29	3.20	3.22
(p-value)	0.660	0.635	0.662	0.667	0.001	0.001	0.002	0.002
# schools	1.13	-0.12	1.64	1.05	0.69	0.16	1.39	0.70
	0.83	-0.09	1.15	0.71	1.12	0.30	2.09	1.09
	0.405	0.930	0.250	0.479	0.266	0.761	0.038	0.278
(# schools)^2	-0.01	0.00	-0.01	-0.01	-0.01	0.00	-0.01	-0.01
	-0.85	-0.02	-1.11	-0.59	-1.40	-0.59	-2.20	-1.11
	0.399	0.983	0.267	0.557	0.163	0.555	0.029	0.269
Var(Visible Minority)	19.99	21.32	21.52	21.23	95.58	95.03	94.70	96.15
	0.28	0.30	0.30	0.29	2.73	2.75	2.70	2.77
	0.781	0.767	0.764	0.770	0.007	0.007	0.008	0.006
Var(Aboriginal)	51.43	44.13	50.92	48.63	-8.64	-10.05	-5.19	-10.32
	0.84	0.72	0.85	0.79	-0.30	-0.36	-0.18	-0.36
	0.401	0.470	0.395	0.432	0.763	0.721	0.859	0.716
Var(Home Language)	-116.56	-119.73	-118.25	-120.96	-145.84	-147.06	-145.60	-148.80
	-1.75	-1.80	-1.78	-1.81	-3.67	-3.71	-3.66	-3.71
	0.081	0.074	0.076	0.073	0.000	0.000	0.000	0.000
Var(W/S income)	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	-0.28	-0.29	-0.33	-0.17	-0.74	-0.57	-0.63	-0.57
	0.780	0.771	0.740	0.867	0.460	0.572	0.529	0.569
Var(Transfer income)	-0.62	-0.85	-0.61	-0.95	-0.17	-0.36	-0.18	-0.36
	-0.74	-0.95	-0.72	-1.03	-0.37	-0.75	-0.40	-0.74
	0.461	0.342	0.470	0.303	0.712	0.452	0.690	0.459
Var(Parent's Education)	6.89	7.08	7.03	7.14	1.92	1.96	1.89	2.08
	1.32	1.36	1.36	1.35	0.80	0.83	0.79	0.86
	0.187	0.177	0.177	0.178	0.422	0.410	0.431	0.391
CSV(W/S income)	-0.02			-0.09	0.05			0.02
	-0.23			-0.90	0.77			0.44
	0.816			0.371	0.444			0.659
CSV(Transfer income)		22.86		30.83		17.35		18.37
		2.01		2.53		3.00		3.78
		0.046		0.012		0.003		0.000
CSV(Parent's Education)			-34.71	-52.97			-19.07	-35.51
			-0.71	-1.27			-0.89	-1.98
			0.480	0.207			0.375	0.049
Constant	154.56	156.34	154.11	154.90	78.81	79.46	77.87	78.96
	14.39	14.50	14.45	14.24	19.82	20.15	19.53	19.57
	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 6: Regression results: Community level variance of Grade 9 test scores, 2001 cross-sectional data, with sorting by income and education

	Language Arts	Mathematics		Language Arts	Mathematics
Avg # writing	0.05	0.14	Var(Parent's Education)	7.15	1.98
(t-stat)	0.42	3.26		1.35	0.81
(p-value)	0.677	0.001		0.179	0.421
# schools	1.41	1.27	CSV(Visible minority)	13314.39	4487.62
	0.87	1.98		2.79	2.24
	0.384	0.049		0.006	0.026
(# schools)^2	-0.02	-0.01	CSV(Aboriginal)	794.74	1823.67
	-1.30	-1.93		0.41	2.51
	0.194	0.055		0.684	0.013
Var(Visible Minority)	7.64	91.60	CSV(Language)	-185.57	-5372.11
	0.10	2.59		-0.02	-1.24
	0.919	0.010		0.986	0.218
Var(Aboriginal)	42.65	-21.83	CSV(W/S income)	-0.12	-0.07
	0.64	-0.70		-0.76	-1.43
	0.524	0.482		0.448	0.153
Var(Home Language)	-115.00	-146.05	CSV(Transfer income)	18.55	9.18
	-1.68	-3.65		1.23	1.08
	0.094	0.000		0.220	0.282
Var(W/S income)	0.00	-0.01	CSV(Parent's Education)	-69.58	-21.03
	-0.12	-0.51		-1.28	-0.95
	0.902	0.611		0.201	0.343
Var(Transfer income)	-0.84	-0.28	Constant	153.94	78.14
	-0.88	-0.56		13.90	19.02
	0.380	0.574		0.000	0.000

Table 7: Regression results: Community level variance of Grade 9 test scores, 2001 cross-sectional data, with all sorting variables

	Language Arts				Mathematics			
Δ# schools	0.07	-0.19	0.07	-0.05	-0.04	0.07	0.07	-0.04
(t-stat)	0.76	-0.63	0.76	-0.50	-0.54	1.54	1.56	-0.60
(p-value)	0.45	0.53	0.45	0.62	0.59	0.12	0.12	0.55
ΔAvg # writing	-0.17	-0.14	-0.16	-0.15	0.18	0.15	0.17	0.17
	-1.28	-0.97	-1.17	-1.15	3.11	2.58	3.01	2.73
	0.20	0.33	0.24	0.25	0.00	0.01	0.00	0.01
ΔCSV(Visible Minority)		15954.25			7092.47			6549.97
		0.93			1.71			1.56
		0.35			0.09			0.12
ΔCSV(Aborig)			1250.38			-1407.81		-1511.93
			0.74			-1.69		-1.75
			0.46			0.09		0.08
ΔCSV(Home Language)				12073.22			772.63	1394.29
				3.87			0.57	1.33
				0.00			0.57	0.19
Constant	15.09	15.27	15.07	16.01	-10.05	-10.15	-10.09	-9.93
	2.58	2.61	2.57	2.71	-3.47	-3.52	-3.43	-3.40
	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00

Table 8: Regression results: Difference in community level variance of Grade 9 test scores in 2001 and Grade 6 test scores in 1998, with sorting by ethnicity and language

	Language Arts				Mathematics			
Δ# schools	0.00	0.05	0.04	-0.01	0.09	0.07	0.05	0.08
(t-stat)	0.02	0.57	0.46	-0.06	1.56	1.66	1.30	1.33
(p-value)	0.99	0.57	0.64	0.95	0.12	0.10	0.19	0.18
ΔAvg # writing	-0.13	-0.16	-0.16	-0.13	0.14	0.18	0.19	0.15
	-0.88	-1.17	-1.19	-0.86	1.93	3.07	3.39	2.20
	0.38	0.24	0.23	0.39	0.06	0.00	0.00	0.03
ΔCSV(W/S Income)	0.19			0.15	-0.09			-0.16
	1.15			0.79	-0.77			-1.52
	0.25			0.43	0.44			0.13
ΔCSV (Transfer Income)		6.62		0.56		2.87		3.89
		0.61		0.05		0.69		1.77
		0.54		0.96		0.49		0.08
ΔCSV (Education)			23.72	21.95			28.60	30.06
			6.10	5.22			7.84	9.54
			0.00	0.00			0.00	0.00
Constant	15.17	15.39	15.86	15.88	-10.17	-10.03	-9.32	-9.12
	2.59	2.60	2.67	2.64	-3.52	-3.40	-3.21	-3.10
	0.01	0.01	0.01	0.01	0.00	0.00	0.00	0.00

Table 9: Regression results: Difference in community level variance of Grade 9 test scores in 2001 and Grade 6 test scores in 1998, with sorting by income and education

	Language Arts	Mathematics
Δ# schools	-0.23	0.00
(t-stat)	-0.63	-0.02
(p-value)	0.53	0.98
ΔAvg # writing	-0.11	0.18
	-0.77	2.48
	0.44	0.01
ΔCSV(Visible Minority)	0.08	3.84
	0.23	1.51
	0.81	0.13
ΔCSV(Aborig)	-3.61	2836.59
	-0.29	0.62
	0.77	0.53
ΔCSV(Home Language)	22.06	-1548.93
	4.56	-1.38
	0.00	0.17
ΔCSV(W/S Income)	9486.10	1438.96
	0.48	1.30
	0.63	0.20
ΔCSV (Transfer Incomel)	53.83	-0.04
	0.02	-0.50
	0.99	0.62
ΔCSV (Education)	10741.53	28.64
	4.76	8.67
	0.00	0.00
Constant	16.59	-8.97
	2.71	-3.00
	0.01	0.00

Table 10: Regression results: Difference in community level variance of Grade 9 test scores in 2001 and Grade 6 test scores in 1998, with all sorting variables

	Language Arts	Mathematics
CSV(Visible minority)	4.5%	2.5%
CSV(Aboriginal)	.4%	1.7%
CSV(Home language)	3.3%	4.2%
CSV(Transfer Income)	2.5%	3.3%

Table 11: Predicted effect on variance of test score from desegregating average multi-school community, based on cross-sectional estimates.

	Language Arts	**Mathematics**
Average Community		
CSV(Home language)	2.6%	.3%
CSV(Parent's education)	1.2%	2.7%
Edmonton		
CSV(Home language)	41.0%	4.8%
CSV(Parent's education)	11.1%	39.1%

Table 12: Predicted effect on variance of test score from desegregating multi-school communities, based on fixed effects estimates.