UCD CENTRE FOR ECONOMIC RESEARCH

WORKING PAPER SERIES

2014

Bridging the Gaps: Inequalities in Childrens' Educational Outcomes in Ireland

David Madden, University College Dublin

WP14/20

November 2014

UCD SCHOOL OF ECONOMICS
UNIVERSITY COLLEGE DUBLIN
BELFIELD DUBLIN 4

Bridging the Gaps: Inequalities in Childrens' Educational Outcomes in Ireland

David Madden

(University College Dublin)

July 2014

Abstract: Recent developments in the inequality literature has stressed the importance of inequality of opportunity as opposed to inequality of outcome. In this paper we investigate the presence of ex post inequality of opportunity in two measures of educational achievement for a representative sample of Irish 9 year olds. Students are partitioned into four groups according to maternal education levels and gaps in outcomes are calculated between each group. Quantile decompositions of the pairwise gaps reveal that almost half of the gaps can be explained by differences in characteristics between the groups Detailed decompositions show consistently significant effects for income, number of childrens books in the home and maternal age.

Keywords: Inequality of opportunity, quantile decomposition.

JEL Codes: I24, D63, C21.

Corresponding Author: David Madden,

School of Economics,

University College Dublin,

Belfield,

Dublin 4,

Ireland.

Phone: 353-1-7168396

Fax: 353-1-2830068

E-Mail: david.madden@ucd.ie

I am grateful to Donal O Neill, Barry Reilly and participants at a Geary Institute seminar, particularly Chris Whelan, for useful comments and discussion. The usual disclaimer applies.

Inequalities in Childrens' Educational Outcomes in Ireland

1. Introduction

It does not seem controversial to suggest that education plays a pivotal role in many key outcomes in life. There is a large literature on the returns to education in the form of higher private earnings (see Ashenfelter et al, 1999), and education also appears to affect other outcomes such as health (Cutler and Lleras-Muney, 2010). Education can also provide substantial positive externalities to society in general (see the recent review and references in Dickson and Harmon, 2011). Given the undoubted benefits of education to both the individual and society, it seems important that all individuals have the opportunity to acquire education. A corollary of this is that arbitrary circumstances of background should not act as an impediment to the acquisition of education. A further corollary of this position is that if two people from different backgrounds have access to the same level of educational resources, their ability to translate these resources into educational attainment should be the same (conditional upon them expending the same level of "effort"). What each individual ultimately makes of the educational opportunities presented to them in terms of effort expended may be regarded as a private concern, but from the point of view of society, it seems desirable that all citizens should have the opportunity to invest in their education and that the return to a given investment of effort should not differ by arbitrary circumstance.

Following on from this, equality of opportunity in education would seem to be a worthy policy goal. The analysis of inequality of opportunity (as opposed to equality of outcome) has enjoyed a revival in recent years and this approach has been applied to areas such as education and health as well as income (e.g. Dworkin, 1981, Gamboa and Waltenberg, 2012, Ferreira and Gignoux, 2011a, Romer, 1998, 2002, Rosa Dias and Jones, 2007). While the precise definitions and approaches to measuring equality of opportunity may differ, in all cases a clear distinction is made between what may be regarded as "fair" and "unfair" sources of inequality. In some cases the terms ethically defensible and indefensible have been used. For example, what are sometimes labelled as "circumstances" such as parental socio-economic outcomes are seen as unfair sources of inequality, whereas inequality arising from factors such as effort or lifestyles may be seen as fair. This concept can be applied in a straightforward way to education. Suppose we observe inequality in educational outcomes, then if someone has a low educational achievement owing to background circumstances over which they had no control, this is deemed ethically offensive. But if the inequality and accompanying low outcome arises because they consciously chose not to apply sufficient effort then this is regarded as ethically defensible.

A formal framework for this view of equality was established by Romer (1998, 2002). For a given outcome for an individual y_i we divide all factors which might affect this outcome into effort factors and circumstance factors, bearing in mind that some effort factors themselves may depend upon circumstances e.g. the amount of effort someone puts into their education may be affected by the educational level of their parents. The Romer model does not specify which factors could be considered as effort and which as circumstance and clearly there is considerable room for debate here. There will also be purely random factors which affect outcomes in the sense that once all effort and circumstance factors have been accounted for there will still be a residual degree of inequality in the educational outcome.

It could also be argued that key decisions regarding the level of effort to spend on education are made by a child at an age where they could not reasonably be held responsible for their decisions. As explained below, we sidestep this issue by controlling for level of effort in a particular way, but it is an important point and should be borne in mind in the analysis which follows.

With respect to circumstances, the Romer model partitions the population into different types, whereby a type consists of individuals who are exposed to the same set of circumstances and the number of types should be mutually exclusive and exhaustive. The precise number of types is left to the choice of the analyst but the types should be meaningful in the sense that each should have a sufficiently different set of circumstances so that they can be realistically regarded as providing a different opportunity set for each type. Given the set of circumstances and types which are identified, equality of opportunity then dictates that average educational outcomes should be identical for each type, for given levels of effort. One of the most innovative aspects of the Romer approach is the identification of effort. If the outcome for each type is a monotonic function of effort, then two people from different types, but at the same quantile of outcome *within their type*, can be regarded as having exerted the same level of effort. The differences in outcomes across types (at the same within-type quantile) can then be regarded as an ex post measure of inequality of opportunity. This is known as the Romer identification assumption (RIA).

It is worth noting that there are parallels between the measurement of inequality of opportunity and other approaches which also examine differences in outcomes by type. Virtually all measures of inequality (whatever the underlying outcome measure) are a function of the gaps between people in these outcomes e.g. the Gini coefficient is the normalised double sum of all pairwise gaps in outcomes, while entropy measures are a function of the gap between the log of the outcome for each observation and the mean log. Thus measurement of the inequality of opportunity essentially involves decomposing these gaps into that part arising from inequality of circumstances (ethically indefensible inequality) and that part arising from inequality of effort (which is viewed as ethically defensible). By invoking the RIA and measuring these gaps at the same quantile, we are controlling for the level of effort.

A complementary approach to decomposing gaps in outcomes is the decomposition literature pioneered by Blinder (1973) and Oaxaca (1973), and extended in recent years by Dinardo, Fortin and Lemieux (1996), Macahado and Mata (2005) and Melly (2005) amongst others.[1] In this approach a reduced form equation for the outcome under consideration is estimated. Most applications of this approach examine outcomes in labour markets and so the reduced form equation is typically a wage equation, but in our application here it would be an education production function. Since linear regressions hold exactly at the mean, Blinder-Oaxaca (B-O) showed that for a two-way partition of the population, the gap in outcomes at the mean could be decomposed exactly into that part arising from characteristics and that part arising from the return to characteristics. The former is often referred to as the "explained gap", while the latter is the "unexplained gap" and can also, depending upon the particular application be viewed as a measure of a treatment effect (Fortin et al, 2011). Subsequent extensions showed how the decomposition can be carried out at other parts of the distribution via quantile regression.

Given that the B-O approach partitions the population into types and then analyses the gaps in outcomes between these types, some form of marriage between this approach and the ex post inequality of opportunity approach may be fruitful. In particular, quantile decomposition can be applied to the gap in outcomes between two types. If we apply the RIA, then the gap at each quantile has controlled for effort, and this gap is a reflection of ex post inequality of opportunity. The gap can then be further decomposed into that part arising from differences

[1] For a recent survey, see Fortin et al (2011).

in characteristics between types, and differences in the return to these characteristics. A detailed decomposition can then identify precisely which particular characteristics are most relevant in terms of explaining inequality of opportunity.

This is the approach we take in this paper. As with the traditional inequality of opportunity approach, we partition the population into different types (in our application we have four types, defined by maternal education level). For each of these types we then estimate what could be regarded as an education production function. The "outputs" are the scores in mathematics and reading tests taken at age nine, and the inputs are factors which are unique to the nine-year old (but clearly outside of their control) such as their birthweight, parental health and income and also various school measures such as class size and other school characteristics etc. Given four different types we have six (n(n-1)/2) different pairwise comparisons of scores in these tests, each with an associated "gap". Each pairwise gap in scores could be regarded as a bilateral measure of inequality of opportunity and an overall measure of inequality of opportunity could be obtained by some aggregation of the gaps. We do not go down the route of investigating what form that aggregation should take. Instead we concentrate upon the decomposition of the gaps, which can reveal what factors lie behind the gaps. The decomposition of the gaps could be evaluated at the mean (as in the traditional B-O approach) or at different quantiles of the distribution, the advantage of the latter being that by invoking the RIA, we are controlling for the level of effort applied within each group..

The application of the B-O and quantile decomposition approach enables a deeper exploration of the factors lying behind inequality of opportunity. In our particular application we can decompose inequality of opportunity in education into two components: the first of these is perhaps most closely related to "standard" inequality of opportunity measures and reflects inequality which arises owing to differences in observable characteristics (the inputs to the production function), whereby different types have different characteristics. This is the "explained" component of the gap, with a further attractive feature of this decomposition being the possibility of breaking down the explained component into the part arising from individual characteristics, such as maternal age, class-size etc.

The second component is the "unexplained" component of the gap and may reflect differences in unobserved characteristics which affect the gap between types and/or different returns (by type) to individual characteristics.[2] Thus even if the average child in type 1 has exactly the same characteristics as the average child in type 2, there may still be a difference in outcomes, as one of the types obtains a better return from a given set of characteristics than the other. In the early Blinder-Oaxaca literature, this was sometimes referred to as "discrimination". However, it could be argued that it should be regarded as a manifestation of a particular type of inequality of opportunity and indeed seems to be close to inequality of opportunity as discussed in Breen and Goldthorpe (1999, 2001).

The decomposition of inequality of opportunity into characteristics and returns may be very useful from a policy perspective. If we observe that a given gap in educational outcomes between types arises primarily from characteristics (such as school facilities or teacher training) then the obvious policy response is to provide such characteristics to the disadvantaged group. However, if the gap primarily arises owing to differences in the returns to such characteristics, then it may indicate deeper, structural issues, as well as perhaps a difference in the endowment of unobserved characteristics, either of which may require a different policy response.

Note that in order to invoke the RIA, and hence control for the level of effort being expended within each type, it is necessary to employ quantile decomposition. Decompositions evaluated at the mean run the risk that the mean may fall at a different quantile for each type, and so part of the gap could be viewed as arising from differential effort. Quantile decomposition ensures that the gap is being evaluated at the same quantile and hence, if the RIA holds, is being evaluated at the same level of effort.

The remainder of the paper is laid out as follows: in section 2 we describe the model of inequality of opportunity in more detail and explain the reasons behind our chosen approach. Section 3 describes our data, while section 4 presents results with section 5 offering concluding comments.

2. Inequality of Opportunity and Decomposition

[2] More specifically, in the regression equation which "explains" outcomes, the differences in the constant term between types reflects differences in unobservables, while differences in the coefficients of the regressors reflects different "returns" to characteristics.

As outlined above, the recent literature on inequality of opportunity regards inequality in outcomes as having both fair and unfair sources. Differences in outcomes arising from circumstances which are beyond the control of an individual and for which they could not be held responsible may be regarded as an unfair source of inequality. Correspondingly a difference in outcome arising from deliberate choices regarding factors such as effort and lifestyle are viewed as “fair” sources of inequality. The key issue then becomes identification of circumstances and effort.

In all approaches to measuring inequality of opportunity the population is divided into types whereby each type represents a particular combination of circumstances. Following this, there are a variety of approaches which can be taken to measuring inequality of opportunity and a recent comprehensive survey can be found in Ramos and Van de gaer (2012). What they term the direct way of measuring Inequality of Opportunity is to estimate the degree of inequality in a counterfactual distribution where inequalities due to effort have been removed and what remains is simply inequality arising from circumstances. This has been labelled the *ex ante* approach (see Ramos and Van de gaer, 2012) and is an issue we plan to pursue in future research. [3]

In this paper we employ what is known as the *ex post* approach to identifying inequality of opportunity. It is not entirely accurate to state that we will be measuring *overall* inequality of opportunity, since our approach will be to examine pairwise gaps i.e. inequality of opportunity between two groups or “types”. An overall measure of inequality of opportunity would require some form of summation of the pairwise gaps. It is not entirely clear what form of summation that would entail and we leave that for further research (for a possible approach, see Checchi and Peragine, 2010).

Our approach relies upon the Romer Identification Assumption in order to identify levels of effort. Following the notation in Romer (2013) suppose that the population is divided into T mutually exclusive and exhaustive types, indicated by $t=1,...,T$, where types are defined by circumstances. In our case the particular circumstance will be the education level of the mother. Let the outcome in question (in this case test scores) be denoted by y, then the average outcome for type t will depend upon the application of effort, e. It is assumed that the outcome is montonically increasing in effort, e and thus $y^t=y^t(e)$.

[3] For a recent discussion of *ex ante* and *ex post* approaches to measuring inequality of opportunity see Fleurbaey and Peragine (2013).

For each type t there will be a distribution of effort, which can be denoted as $G^t(e)$. The Romer Identification Assumption then identifies levels of effort by the rank in the distribution of effort $G^t(e)$. We then have the function $v^t(\theta)=y^t((G^t)^{-1}(\theta))$ which gives the average value of y for people at the θth quantile of the distribution of effort of their type.

However, it is not necessary to observe the distribution of effort for each type. If y is montonically increasing in effort for each type, then rank by effort (for each type) will correspond exactly to rank by outcome and we can simply observe $v^t(\theta)$ directly as the level of y for type t at the θth quantile of the distribution of y for that type.

Thus in order to confirm the existence of ex post inequality of opportunity, we can examine the cumulative distribution functions (cdf) for the different types in question. Take for example, figure 1, where we show the cdf for two types (1 and 2) for the outcome variable, y. The cdf on the vertical axis can be used to infer ex post inequality of outcome. If effort is monotonic in outcome, then any particular quantile on the vertical axis can be viewed as representing the same level of effort. We can then read across to find the associated level of outcome for that quantile for each type. Thus we see that for the median level of effort for both type (θ=0.5), the outcome for type 1, $y^1(0.5)$ is less than that for type 2, $y^2(0.5)$, and thus ex post inequality of opportunity is present at that level of effort.

If first order stochastic dominance is observed i.e. the cdf for type 2 lies below that of type 1 for all values of y, then we know that regardless of the level of effort chosen, there will always be inequality of opportunity between the two types. If the cdfs cross, then we have inequality of opportunity in one direction at one level of effort and inequality of opportunity in the other direction at a different level of effort. As mentioned above, in that case, some form of summary measure across the distributions will be required. Thus comparison of cdfs for different types provide a very useful check for the presence of inequality of opportunity.

To summarise, the RIA permits us to detect the presence of inequality of opportunity by examining outcomes for each type for the same quantile of outcome (thus controlling for effort). Quantile decomposition complements this approach, since it enables a more thorough exploration of the differences in outcomes (the gaps) at given quantiles. In particular it allows for a decomposition into characteristics and returns to characteristics, thus providing a richer description of inequality of opportunity. In the next section we describe our data and also the decomposition methodology we employ.

3. Data, Summary Statistics and Decomposition

Data and Summary Statistics

Our data come from the Growing Up in Ireland (GUI) Survey 9 year old cohort which tracked the development of a cohort of children born in Ireland in the period November 1997-October 1998 (see Williams et al, 2009). The sampling frame of the data was the national primary school system, with 910 randomly selected schools participating in the study. Part of the survey consisted of the children undertaking tests in mathematics and reading. These tests are known in Ireland as the Drumcondra tests and have been a feature of the Irish educational system for a number of years and are linked to the national curriculum. The particular tests for the GUI survey had not been seen in advance by schools, teachers or pupils in advance of their use in GUI. The particular cohort of nine year olds in the GUI survey were spread over three different school grades (2^{nd}, 3^{rd} and 4^{th} class) and three different levels of the test were administered, with the majority of the children in 3^{rd} class (roughly equivalent to grade 3 in the US).

The educational outcome which we use in this paper is the results from these tests in maths and reading. As the tests were administered at three different levels it was necessary to standardise the results, hence the data we use are the logit scores which were obtained from the original raw data using the principles of Item Response Theory (see Lord, 1980). Results from tests at this age (and earlier) have been shown to have predictive power for subsequent later-life outcomes in areas such as education and health (Feinstein, 2003 and Batty et al, 2007).

In total there are 8568 children in the GUI survey. As our definition of "type" we use the education level of the principal carer. We drop observations where the Drumcondra test results were missing (222 observations). We also drop observations where the principal carer is not the biological mother of the child (210 observations). In carrying out our decompositions we employ a wide range of variables which might influence the test scores. These include data on the study child's principal carer, family and school circumstances. Where this data is missing, we drop those observations (see the appendix for a detailed list of variables employed). This gives us a sample for analysis of 7536 of which 3663 are boys and 3873 are girls. In all cases sampling weights are applied. [4]

We break down principal carer's education into four categories. The first category is those who have completed no further than lower secondary school education, indicating that they left formal schooling on or before the age of 16. The next category is those who completed secondary schooling, thus leaving formal education at around 18. The third category is those who have taken a post-school, but non-degree, qualification. The final category is those with at least a primary degree. While a finer breakdown by education was available, we chose to limit ourselves to four types, as a higher number of types would have reduced cell size and would also have added to the number of pairwise decompositions. Table 1 summarises educational qualifications for principal carer.

Table 2 provides the average logit scores for maths and reading by gender. Girls show higher average scores for reading, while boys show higher average scores for maths (the differential achievement by gender for maths is explored in more detail in Doris et al, 2013).

The last summary table we present before moving on to the analysis of inequality of opportunity is table 3. These show the mean results for maths and reading scores by type. In all cases average scores in maths and reading are higher for those children whose mothers' have higher levels of education. At the limit, the gap between the most advantaged and least advantaged types approaches one standard deviation of score. In terms of comparison it should be noted that such gaps are larger than the gaps observed between ethnic groups in the US (e.g. the Black-White or Hispanic-White gaps) for similar tests for similar age groups (see, for example, Clotfelter et al, 2009, who analyse gaps between grades 3 and 8 in the US). The importance of such gaps in cognitive/educational outcomes in terms of future adult outcomes has been explored by Hanushek (1986) and Haveman and Wolfe (1993). Low achievement in childhood tends to persist and significantly worse life outcomes as adults may result.

Figures 2a and 2b also show the kernel densities by education (increasing in level from 1 to 4) for maths and reading. As reflected in table 3, the densities for higher levels of education show greater weight towards the right.

[4] The variable with the greatest number of missing observations was family income. To address this we replaced these missing observations via conditional mean imputation. The inclusion/non-inclusion of these observations made little qualitative difference to the results.

Figures 3a and 3b essentially show the same information as 2a and 2b except this time it is in the form of cumulative density functions (cdfs). The cdf for education type 4 is well to the right and below those of the other types. That for type 1 is well to the left and above, while the cdfs for types 2 and 3 are quite close together. This indicates a reasonable degree of ex post inequality of opportunity between type 1 and the other types, and also between type 4 and the other types. The horizontal gap between the cdfs for each education type reflects the gap in scores at that quantile. We now propose to investigate these gaps in more detail via quantile decomposition.

Decomposition

We now explain the decomposition methodology. We first of all run through the BO decomposition at the mean, and we then describe how the decomposition can be carried out at different quantiles of the distribution.

Suppose that the outcome (e.g. the Drumcondra score test for maths or reading) for students in type t (t=1,2), y_t is a linear function of K variables (characteristics, where t indicates maternal education level. We wish to obtain a decomposition of the difference in outcomes between the two types. Thus we have

$$y_t = X_t\beta_t + v_{t,}. \quad E(v_t) = 0, t \in \{1,2\}$$

where X is a vector of characteristics and β is a vector of returns to characteristics (or slope parameters of the relationship, including the intercept). Since $E(v_t) = 0, t \in \{1,2\}$, the total difference in average educational outcome $\Delta_y^\mu = \bar{y}_1 - \bar{y}_2$ can be decomposed as follows:

$$\Delta_y^\mu = E(y_1) - E(y_2) = E(X_1)\beta_1 - E(X_1)\beta_2 + E(X_1)\beta_2 - E(X_2)\beta_2 .$$

where $E(X_1)\beta_2$ is the unconditional counterfactual mean outcome i.e. what type 1 would have achieved on average if they had the returns on type 2. This expression can be arranged as follows:

$$\Delta_y^\mu = (E(X_1)[\beta_1 - \beta_2]) + ([E(X_1) - E(X_2)]\beta_2) .$$

The second term on the right hand side above, $([E(X_1)-E(X_2)]\beta_2)$, shows that part of the gap which arises owing to differences in the characteristics of the two groups and is usually referred to as the "explained" portion of the gap. The first term on the right hand side, $(E(X_1)[\beta_1-\beta_2])$, is that part of the gap which arises owing to differences in the returns to characteristics, and is often referred to as the "unexplained" portion of the gap. As mentioned earlier, it is also possible to further decompose both the explained and unexplained portions of the gap to obtain the contribution of each covariate. This is sometimes called the "detailed decomposition".[5]

However, we may also be interested in gaps and decompositions at parts of the distribution other than the mean, and of course, given that we are looking at inequality of opportunity using the Romer Identification Assumption then we will wish to examine gaps at different quantiles and not just at the mean. Unfortunately, the simple BO decomposition holds exactly only at the mean, and so we need an alternative approach in order to carry out regression based decompositions in the spirit of BO at different quantiles.

A number of approaches to this issue have been proposed (see the review by Fortin et al, 2011). The key issue is that the law of iterated expectations does not hold in the case of quantiles. Given our outcome, y, the conditional quantile function is assumed to be linear of the form

$$Q_\theta(y|X)=X_i'\beta_\theta \text{ for each } \theta\in(0,1)$$

where X_i represents the set of covariates for individual i and β_θ is the coefficient vector for the θ^{th} quantile. The quantile coefficients can be seen as capturing the return of each covariate across the distribution of y. Given the assumption of linearity, it is possible to estimate the conditional quantile of y by linear quantile regression for each $\theta\in(0,1)$. The conditional quantiles for types 1 and 2 are then $Q_{1\theta}(y_1|X_1)=X_{1i}'\beta_{1\theta}$ and $Q_{2\theta}(y_2|X_2)=X_{2i}'\beta_{2\theta}$ respectively.

Can we reconstruct the counterfactual unconditional distribution of outcomes $Q_\theta^C=X_{1i}'\beta_{2\theta}$ using estimates from the conditional quantile regressions? This is straightforward when

[5] Detailed decompositions of the unexplained portion can also be sensitive to the choice of omitted category for categorical variables. See Fortin et al (2011).

dealing with the mean, since the law of iterated expectations tells us that $E(y) = E_X(E(y|X))$. Thus the OLS estimate for covariate X_i provides the effect of the covariate on either the conditional or unconditional mean of y. However, this does not hold in the case of quantiles. Thus $Q_\theta(y) \neq E_X[Q_\theta(y|X)]$ where $Q_\theta(y)$ is the θ^{th} quantile of the unconditional distribution and $E_X[Q_\theta(y|X)]$ is the corresponding conditional quantile. And so, in terms of a decomposition, the differences in unconditional quantiles will not be the same as the difference in conditional quantiles.

Is it possible to move between conditional and unconditional quantiles, so that we can use estimtates from conditional quantile regressions to investigate decompositions of the unconditional distribution at various quantiles? Machado and Mata (2005) and later Melly (2005) suggested related approaches, both based upon the estimation of a large number of quantile regressions. The Machado/Mata approach involves taking a random sample of size *m* from a uniform distribution U[0, 1]. For each of the types they estimate *m* different quantile regression coefficients $\beta_{1\theta}$ and $\beta_{2\theta}$. They then generate a random sample of size *m* with replacement from the empirical distribution of the covariates for each group $X_{1,i}$ and $X_{2,i}$. The counterfactuals are then generated by multiplying different combinations of quantile coefficients and characteristic distributions after repeating the random sample generation *m* times.

Melly (2005) suggested a modification of this approach which avoids its computational intensity. The counterfactual distribution is obtained by estimating the quantile coefficients $\hat{\beta}_{2\theta}$ for a grid of values of θ and then drawing random samples only for the covariates $X_{1,i}$ from the empirical distribution. 100 observations are drawn (with replacement) from each of the sub-samples for types 1 and 2. Each observation is then ranked and it represents a percentile, θ, of the outcome distribution. This can be carried out *m* times thus giving a sample of size *m* for each θ^{th} quantile, which are then used to construct the counterfactual. In addition, it is also possible to provide a further decomposition whereby the effects of coefficients can be separated from those of residuals.

There are two major drawbacks associated with these approaches. First, they are both, particularly Machado/Mata, very computationally intensive, since they involve the estimation of a large number of conditional quantile regressions and in addition bootstrapping is needed to obtain sampling variances. Secondly, carrying out a detailed decomposition is also not possible for the explained portion of the gap and the decomposition of the unexplained potion will be path dependent.

An alternative approach to estimating unconditional quantile regressions is that of Firpo, Fortin and Lemieux (henceforth FFL, 2009). They suggest an OLS-based regression method which estimates the impact of changes in an explanatory variable on the unconditional quantile of the outcome variable, via the regression of a transformation of the outcome variable on a set of explanatory variables. The transformation in question is based on the influence function (IF), which provides the influence of an individual observation on the distributional statistic of interest. Thus if *F(y)* is the cumulative distribution of the outcome variable and if *T(.)* is the distributional statistic in question e.g. a quantile, or perhaps the Gini coefficient, then the influence function is the directional derivative of *T(F)* at *F* (Essama-Nssah and Lambert, 2011). By adding the IF to the original distributional statistic, we obtain the recentered influence function (RIF) and it is this which is regressed against the covariates in the *X* vector.

For the case of a specific quantile, Q_θ, the IF is defined as

$$IF(y;Q_\theta) = \frac{(\theta - I(y \le Q_\theta)}{f_y(Q_\theta)}$$

where θ is the quantile in question, *I(.)* is an indicator function taking on the value of 1 if the expression in parentheses is satisfied, $Q_\theta(y)$ is the θ^{th} quantile of the unconditional distribution of the outcome variable and $f_y Q_\theta(y)$ is the density of the marginal distribution of y evaluated at Q_θ. The RIF is then

$$RIF(y;Q_\theta) = Q_\theta + \frac{(\theta - I(y \le Q_\theta)}{f_y(Q_\theta)}$$

It is worth noting that in the expression above, apart from the constant terms, $Q_\theta(y)$ and $f_y Q_\theta(y)$, the RIF is an indicator function for whether the outcome variable is smaller than or equal to the quantile value. This can be estimated via a linear probability model for say type 1, and counterfactual proportions for type 2 could then be constructed using type 1's coefficients. The counterfactual proportions can then be inverted back to the counterfactual outcome quantiles and standard decomposition analysis can be applied, including a detailed decomposition (though the omitted category issue remains). As we are specifically interested in the detailed decomposition for the explained part of the decomposition, we choose to use the FFL approach for our quantile decompositions.

4. Results

Tables 4 and 5 show the quantile decompositions for maths and reading respectively. They are presented for all pairwise gaps, and given we have four levels of education (our four "types"), this amounts to six pairwise gaps. We present results for the gaps at the 10th, 25th, 50th , 75th and 90th quantiles and also at the mean. We show the explained gap i.e. accounted for by characteristics and also the unexplained gap, reflecting differential returns to characteristics and also unobserved factors. Given that we have six pairwise gaps for both maths and reading, in terms of the detailed decompositions it is possible that we will observe a number of variables which will be statistically significant in the decompositions, with this significance simply reflecting type I errors. Thus we only show the part of the explained gap accounted for by two specific characteristics, income and the total number of children's books in the study child's house[6] as these variables consistently show up in virtually all detailed decompositions as having statistically significant associations with both maths and reading scores.[7] We also present these results graphically in figures 3 and 4.

Dealing with maths results first, the pairwise gaps reflect the results in table 3, with substantial gaps for all pairwise comparisons (with the possible exceptions of those between types 3 and 2, which are more modest). While the gaps do tend to fall as we move to higher quantiles, in truth there is not a lot of variation across the distribution. In general, the unexplained part of the gap slightly exceeds the explained part, except around the median. The fraction of the total gap accounted for by the explained part varies between about one

[6] For international evidence on the importance of the latter factor in terms of children's educational achievements, see Evans et al (2010) and Chiu and Chow (2010).

[7] To economise on space in the main paper, we only show the full detailed decompositions in the appendix tables.

third and one half. In turn, the portion of the explained gap accounted for by income and books is around one half, though it tends to be lower for the 10^{th} quantile.

Turning now to the pairwise gaps for reading, once again the gaps tend to fall slightly with higher quantiles, with the exception of the 3/2 gap. Contrary to the case with maths, the explained portion of the gap is much closer to the unexplained portion and in the case of pairwise gaps *not* involving type 4, it tends to account for the larger fraction. The portion of the explained gap accounted for by income and books again is around a half in most cases, though somewhat larger in the case of pairwise gaps *not* involving type 4.

Overall, however, even allowing for some differences, it does not seem unfair to say that the results show a considerable degree of uniformity across maths and reading. About 30-50% of the pairwise gaps are accounted for by differences in circumstances, and within that portion accounted for by differences in circumstances, about 50% of the difference arises from differences in income and books within the house.

On the basis of these results we can indicate some policy recommendations? As outlined above, given the large number of decompositions which we carry out it is inevitable that many variables will, on occasion, show up as contributing in a statistically significant way to the explained gap. However, the three factors which show up most consistently are the age of the principal carer, equivalised household income and the number of childrens books in the house, with the latter two factors accounting for around 50% of the explained gap. As ever with decompositions of this nature it is important to be aware of issues regarding the direction of causality. Thus it is possible that having a large number of books available in a house improves a child's reading. However, it is also possible that the presence of such a large number of books reflects a child's innate interest in and/or aptitude for reading. However, given that an association has been found in other studies between the number of *adult* books in a house and child educational outcomes it seems likely that at least some of this association reflects a causal effect, in the sense that the number of books reflects what Evans et al (2010) refer to as the degree of "family scholarly culture" present in a house.[8] In the case of principal carer's age and equivalised income, reverse causality with child test

[8] It is also interesting to note that books do not appear to have a greater impact when the principal carer has a higher level of education. The inclusion of an interaction term between books and education is insignificant for maths scores and is barely significant (p value of 0.072) and with a small coefficient for reading scores.

scores at age nine seems less plausible and so the association we find here in all probability is capturing some causal effect.

Thus, probably the most implementable policy implication appears to be greater access to availability of reading material (or perhaps other educational material or dimensions of scholarly culture). This could be achieved direct provision of books, perhaps through the schooling system, or via a public library system.

The other two consistently significant factors, age of principal carer and income, are less directly amenable to policy intervention. A role for income may reflect an inability to acquire educational resources (apart from books) which might influence test scores. It is possible that current subsidies and grants which assist parents in purchasing educational resources may need to be reviewed.

The role of income also suggests intergenerational forces that may be at work to acerbate inequalities. If test scores are influenced by family income, then, assuming that such test scores are good predictors of income for the next generation, this will act as an impediment for children from poorer backgrounds in having high incomes later in life. Exploration of interaction between income and education also suggests that the effect of income on test scores may be greater when the principal carer has lower levels of education, suggesting that policies to reduce income inequality for this generation may have positive implications for the next generation.

Age of principal carer also has a positive effect on tests scores. This is after controlling for income, education, lone parent status and the presence of younger and older siblings, all factors which might be expected to be correlated with age. Thus this positive effect may simply reflect the fact that older parents have a greater set of parenting skills and experience. Whilst not directly open to policy intervention it suggests that there are some positive returns (in terms of childhood educational outcomes) to delaying having children. Note that while it might be expected that maternal age will be positively correlated with level of education, a general regression of the whole sample shows independent effects for both age and education.

Are there any general observations which can be made regarding the unexplained part of the gap? Unlike the case of the explained portion where variables such as income and the number of books consistently appeared as statistically significant explanatory variables, there appears to be little such pattern in the unexplained component.

5. Discussion and Conclusion

This paper has examined inequality of opportunity in education outcomes for nine-year olds in Ireland via quantile decompositions. Four “types” were identified (via the level of maternal education) and pairwise decompositions were carried out at selected quantiles. By carrying out the decompositions at quantiles it was possible to invoke the Romer identification assumption and essentially control for the level of effort. Consistent with the inequality of opportunity approach, each type reflected a circumstance which was outside the control of the nine year olds i.e. their mothers education level.

The principal advantage of approaching inequality of opportunity from this perspective is that the detailed decomposition provides some evidence of the characteristics associated with each type which appear to explain (part of) the gap in test scores. The results here suggest a consistent role for the number of books in a house, income and maternal age. While it may be difficult to directly affect the latter factor, policy initiatives to address the number of books available to a child, and indeed the resources in a household which support education in general, may be worth considering.

In our discussion of policy conclusions, we have essentially been assuming, in line with most of the inequality of opportunity literature, that type is exogenous. This is also typically the case in decomposition exercises where the population is usually partitioned along a dimension which is considered exogenous, such as race or gender. While type is clearly beyond the control of the study children, it is a choice variable to some degree for the mothers (although it is likely to be a choice made before they have children and it is arguable that the future implications for children’s education achievements may not be a major factor in education decisions which are made during teen years). Nevertheless, as a general policy it could be reasonably expected that greater equality of education level amongst mothers would lead to a reduction in inequality of opportunity.

This argument could be made for other applications in the inequality of opportunity literature where type is defined by parental education (e.g. Checci and Peragine, 2010). However, it seems reasonable that such a policy should be viewed as more long-term. Given existing differences in type, the decompositions here do provide a menu of other policies which could address inequality of education.

Table 1: Principal Carers' Education

Education Level	Principal Carer (%)
Primary/Lower Secondary	29.4
Complete Secondary	37.3
Post School, non-degree	16.2
Primary Degree	17.1
Total	**100**

Table 2: Summary Drumcondra Logit Scores by Gender (standard deviation in brackets)

	Total	Female	Male
Maths	-0.759 (0.933)	-0.822 (0.879)	-0.699 (0.979)
Reading	0.012 (0.994)	0.015 (0.965)	0.009 (1.020)

Table 3: Mean Scores by Type (SD in brackets)

	Maths	Reading
Primary/ Low Sec	-1.121 (0.913)	-0.355 (0.967)
Complete Secondary	-0.707 (0.897)	0.009 (0.948)
Non-Degree	-0.616 (0.898)	0.169 (0.970)
Primary Degree	-0.385 (0.870)	0.500 (0.907)

Table 4: Quantile Decompositions, Maths

Quantile	Total Gap	Explained	Unexplained	Income	Books
Types 4 and 3					
10	0.316371	0.121592	0.194778	0.011188	0.018769
25	0.263893	0.123772	0.140122	0.047185	0.017767
50	0.223841	0.131546	0.092295	0.043952	0.029458
75	0.219252	0.073712	0.145539	0.034666	0.019337
90	0.209648	0.075267	0.134381	0.020713	0.026487
Mean	0.230924	0.113281	0.117643	0.025697	0.024672
Types 4 and 2					
10	0.385987	0.195218	0.190769	0.018127	0.036272
25	0.358377	0.181266	0.177111	0.076453	0.034336
50	0.308087	0.200023	0.108064	0.071391	0.056709
75	0.323783	0.102023	0.22176	0.056168	0.037371
90	0.308424	0.08301	0.225415	0.033561	0.051189
Mean	0.321671	0.16148	0.160191	0.038769	0.046799
Types 4 and 1					
10	0.801942	0.417852	0.38409	0.031209	0.071257
25	0.765347	0.351643	0.413704	0.131627	0.067454
50	0.717626	0.393431	0.324195	0.122912	0.111406
75	0.725712	0.208648	0.517064	0.096704	0.073415
90	0.646481	0.215002	0.431479	0.057781	0.100561
Mean	0.736536	0.360536	0.376	0.073321	0.102906

Table 4: Quantile Decompositions, Maths (contd)

Quantile	Total Gap	Explained	Unexplained	Income	Books
Types 3 and 2					
10	0.069616	0.060214	0.009402	0.034274	0.021818
25	0.094484	0.034984	0.059499	0.019946	0.013805
50	0.084246	0.063952	0.020294	0.029507	0.022284
75	0.104532	0.044435	0.060096	0.025029	0.012648
90	0.098777	0.039798	0.058979	0.02631	0.013289
Mean	0.090747	0.029998	0.060749	0.018391	0.013485
Types 3 and 1					
10	0.485571	0.215034	0.270537	0.098887	0.065427
25	0.501453	0.146611	0.354843	0.057549	0.041398
50	0.493785	0.221803	0.271982	0.085134	0.066824
75	0.506461	0.208637	0.297824	0.072214	0.037929
90	0.436833	0.194179	0.242654	0.07591	0.03985
Mean	0.505612	0.173576	0.332035	0.067002	0.04768
Types 2 and 1					
10	0.415955	0.128277	0.287679	0.015287	0.026154
25	0.40697	0.145039	0.261931	0.041215	0.036542
50	0.409539	0.15383	0.255709	0.046599	0.030256
75	0.401929	0.149464	0.252465	0.068675	0.015715
90	0.338056	0.166827	0.171229	0.041274	0.020935
Mean	0.414865	0.161981	0.252884	0.045702	0.0325

Table 5: Quantile Decompositions, Reading

Quantile	Total Gap	Explained	Unexplained	Income	Books
Types 4 and 3					
10	0.349558	0.21985	0.129708	0.054855	0.050832
25	0.390982	0.169928	0.221055	0.03771	0.044337
50	0.401365	0.164161	0.237204	0.030105	0.038193
75	0.317506	0.119641	0.197865	0.035343	0.029342
90	0.222055	0.103567	0.118487	0.040919	0.023744
Mean	0.331401	0.136642	0.194759	0.028593	0.036185
Types 4 and 2					
10	0.484671	0.329977	0.154695	0.088879	0.098237
25	0.51089	0.259682	0.251208	0.0611	0.085685
50	0.539758	0.245354	0.294404	0.04868	0.073933
75	0.470829	0.186957	0.283873	0.057265	0.056706
90	0.377118	0.166004	0.211114	0.0663	0.045887
Mean	0.490733	0.197498	0.293235	0.043138	0.068636
Types 4 and 1					
10	0.797999	0.630695	0.167304	0.153022	0.192989
25	0.898675	0.484331	0.414344	0.105194	0.16833
50	0.905551	0.446244	0.459307	0.083811	0.145242
75	0.784948	0.331619	0.453328	0.098592	0.111401
90	0.657412	0.28553	0.371882	0.114148	0.090146
Mean	0.855762	0.391523	0.464239	0.081586	0.150922

Table 5: Quantile Decompositions, Reading (contd)

Quantile	Total Gap	Explained	Unexplained	Income	Books
Types 3 and 2					
10	0.135113	0.083168	0.051946	0.052648	0.036751
25	0.119907	0.081375	0.038532	0.031456	0.036345
50	0.138393	0.070994	0.067399	0.022152	0.037156
75	0.153323	0.061289	0.092034	0.017709	0.042286
90	0.155064	0.038311	0.116753	0.007734	0.029995
Mean	0.159332	0.064959	0.094373	0.014177	0.037645
Types 3 and 1					
10	0.448441	0.301258	0.147183	0.151899	0.110206
25	0.507693	0.318503	0.189189	0.090757	0.108991
50	0.504186	0.293933	0.210253	0.063912	0.111422
75	0.467441	0.254072	0.213369	0.051095	0.126805
90	0.435357	0.156405	0.278953	0.022314	0.089948
Mean	0.524361	0.276863	0.247498	0.051651	0.1331
Types 2 and 1					
10	0.313328	0.146747	0.166581	0.061808	0.038402
25	0.387785	0.168397	0.219389	0.080917	0.043775
50	0.365793	0.215713	0.15008	0.082465	0.056728
75	0.314118	0.221066	0.093052	0.076889	0.072926
90	0.280293	0.176646	0.103647	0.038596	0.050403
Mean	0.365029	0.208767	0.156262	0.072417	0.059149

Figure 1

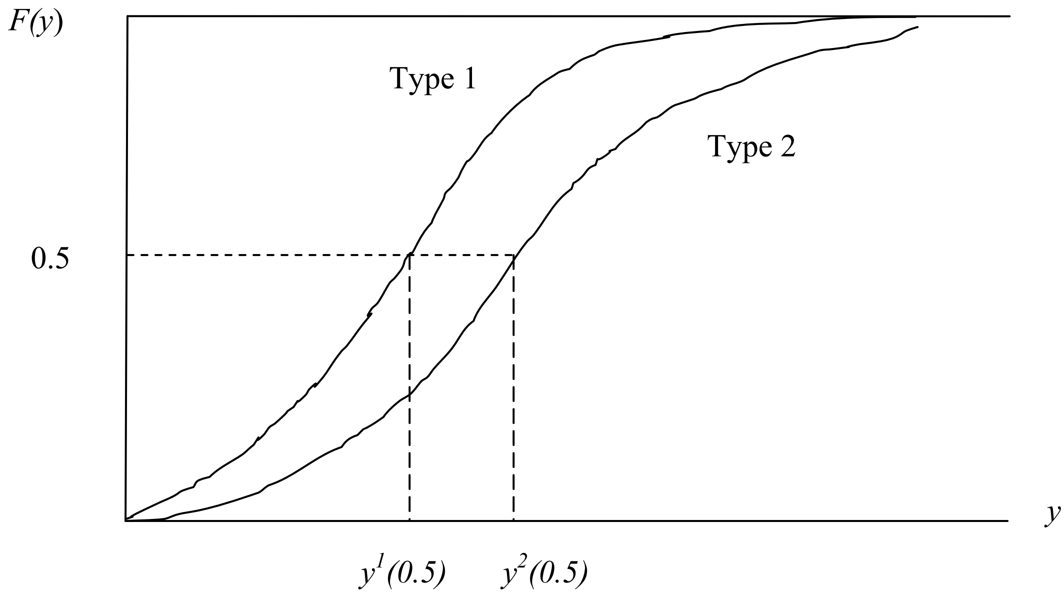


Figure 2a: Kernel Density Maths Scores by Education

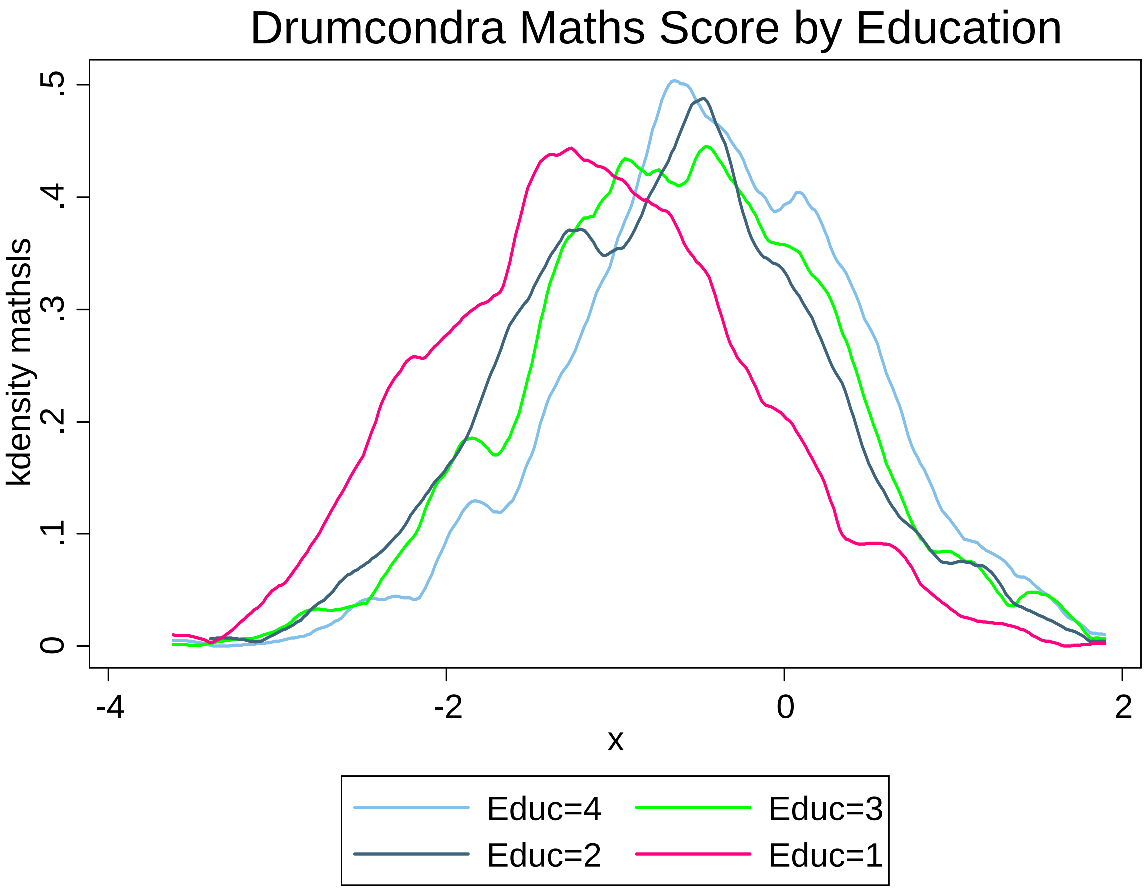


Figure 2b: Kernel Density Reading Scores by Education

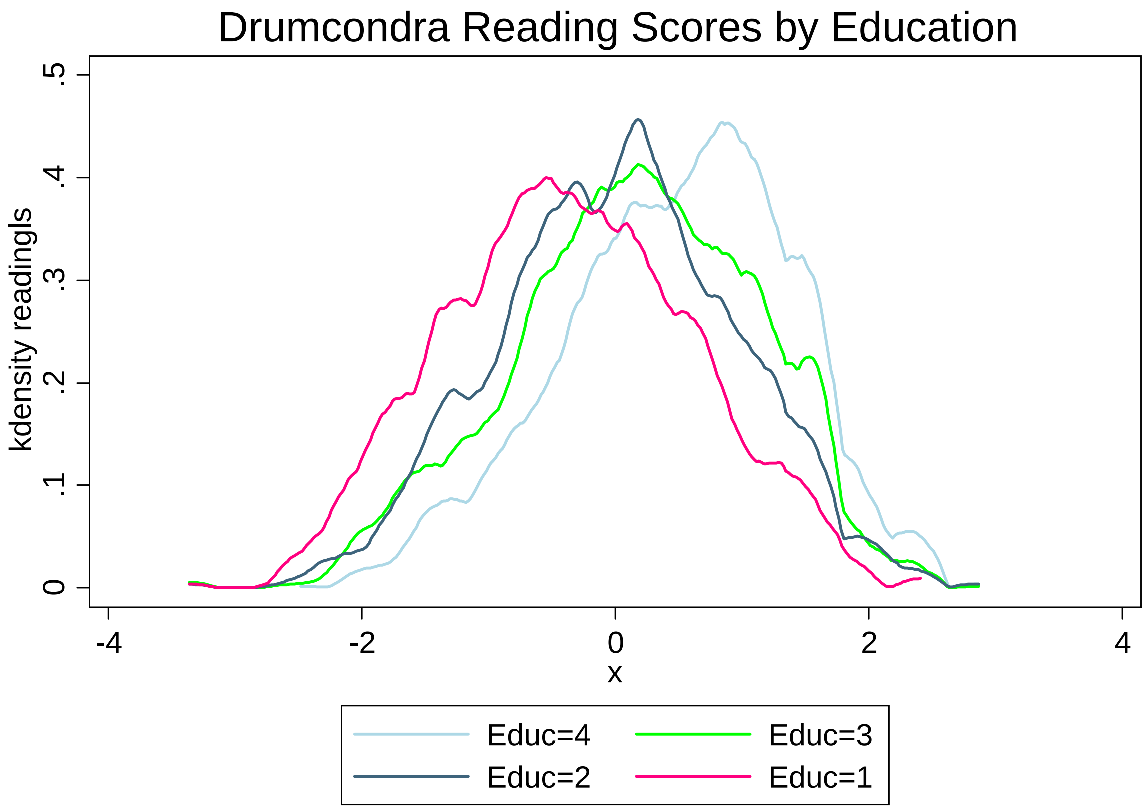


Figure 3a: CDFs Maths Scores by Education

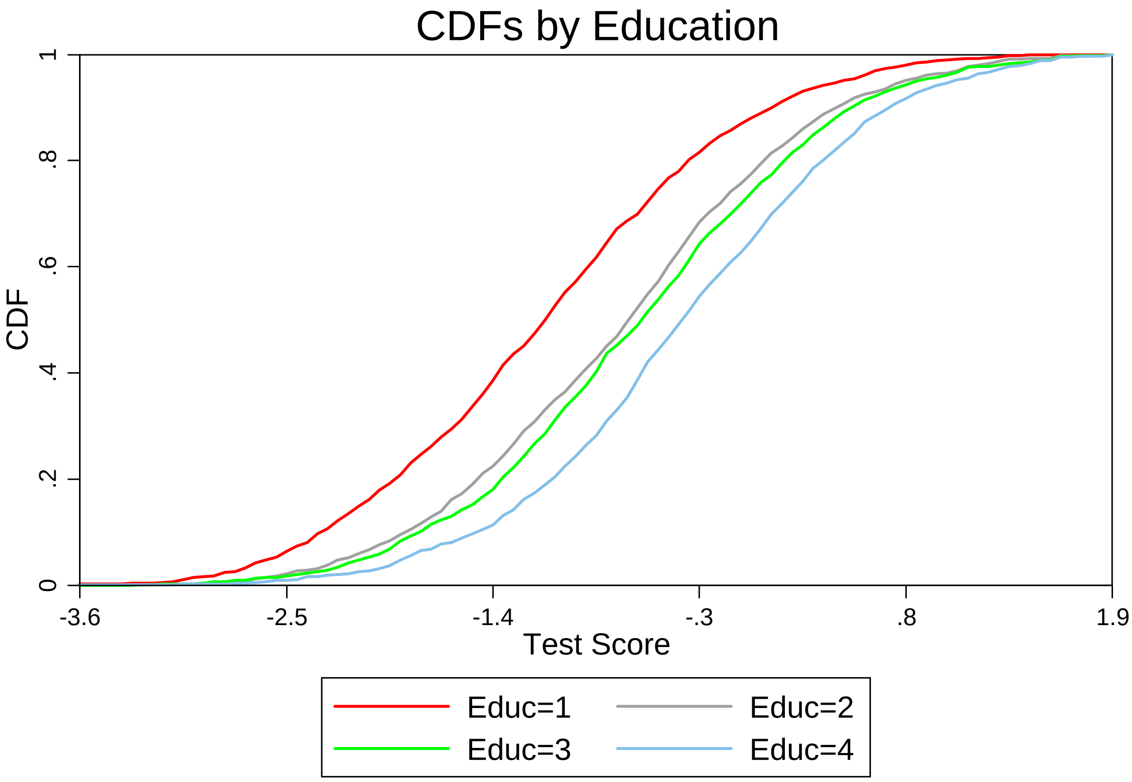


Figure 3b: CDFs Reading Scores by Education

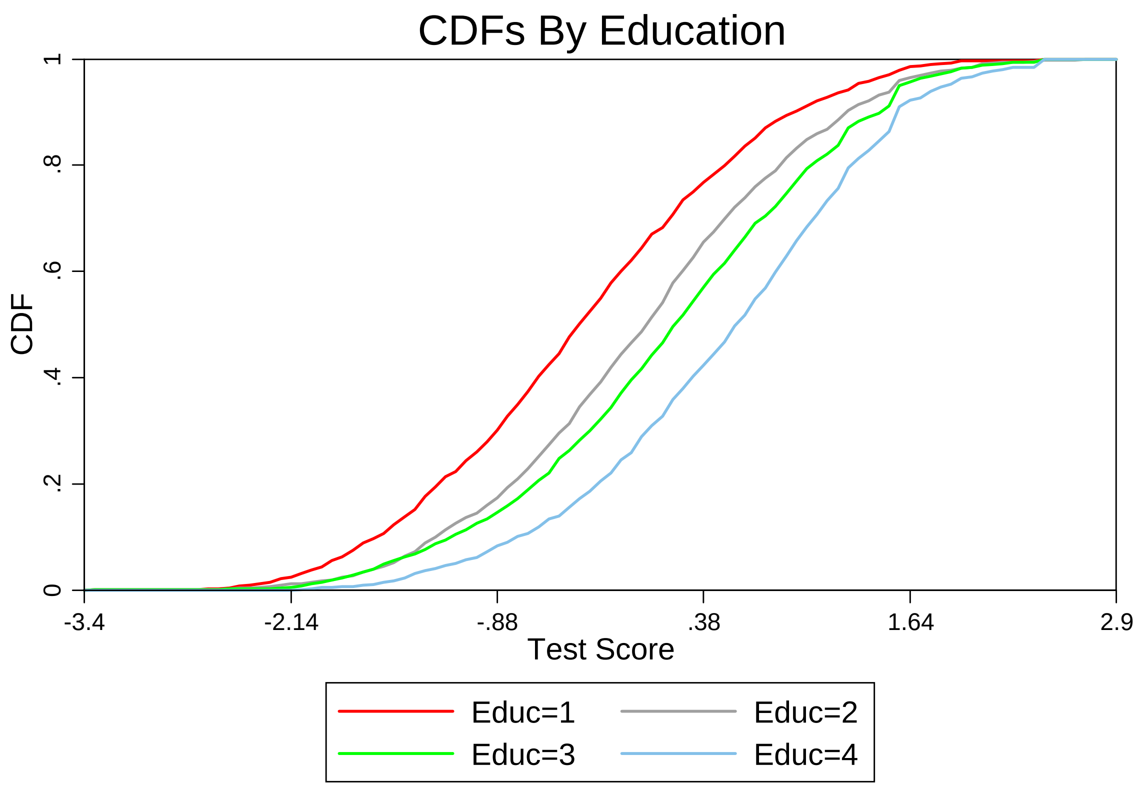


Figure 4a: Quantile Decompositions, Groups 4 and 3, Maths

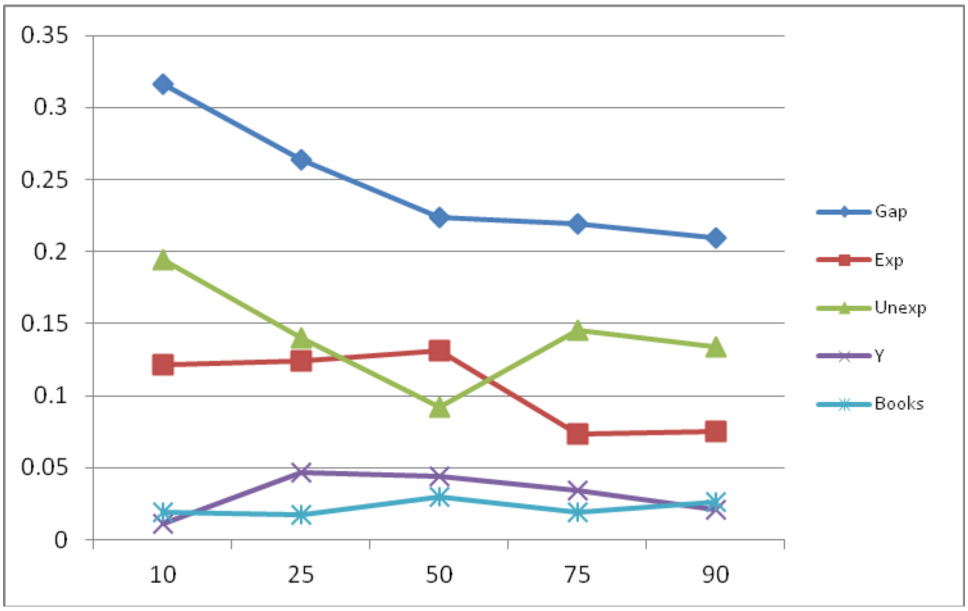


Figure 4b, Quantile Decompositions, Groups 4 and 2, Maths

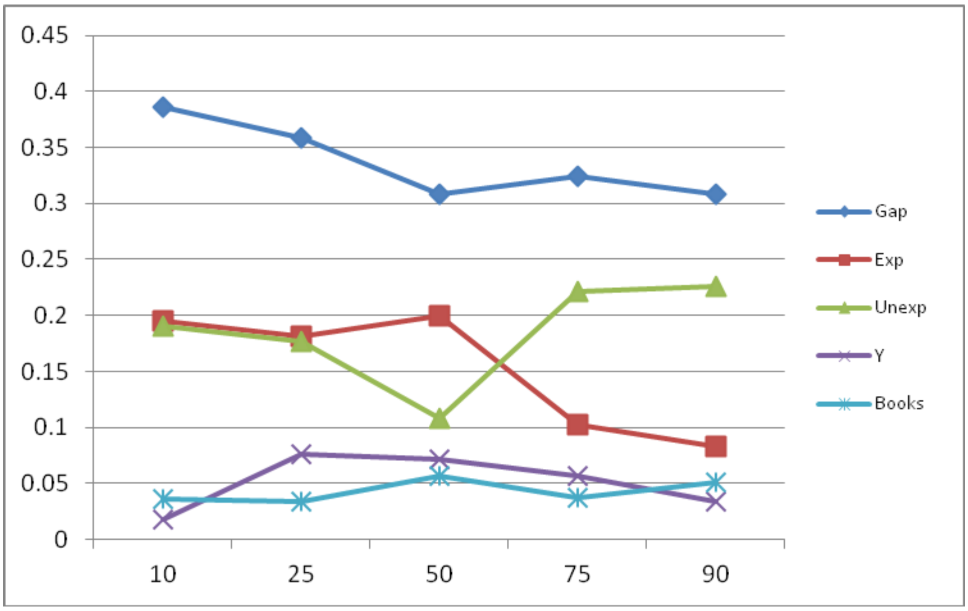


Figure 4c: Quantile Decompositions, Groups 4 and 1, Maths

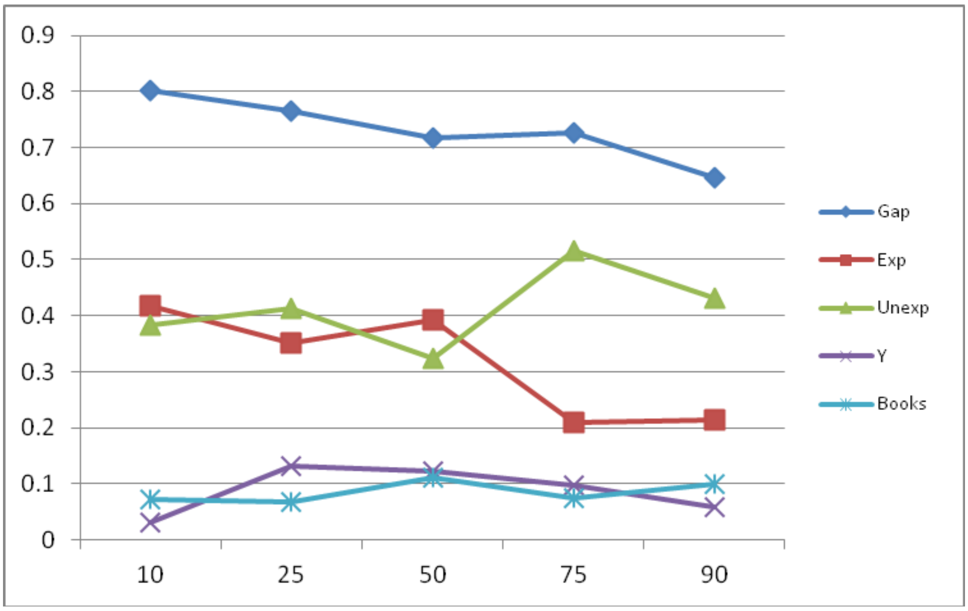


Figure 4d, Quantile Decompositions, Groups 3 and 2, Maths

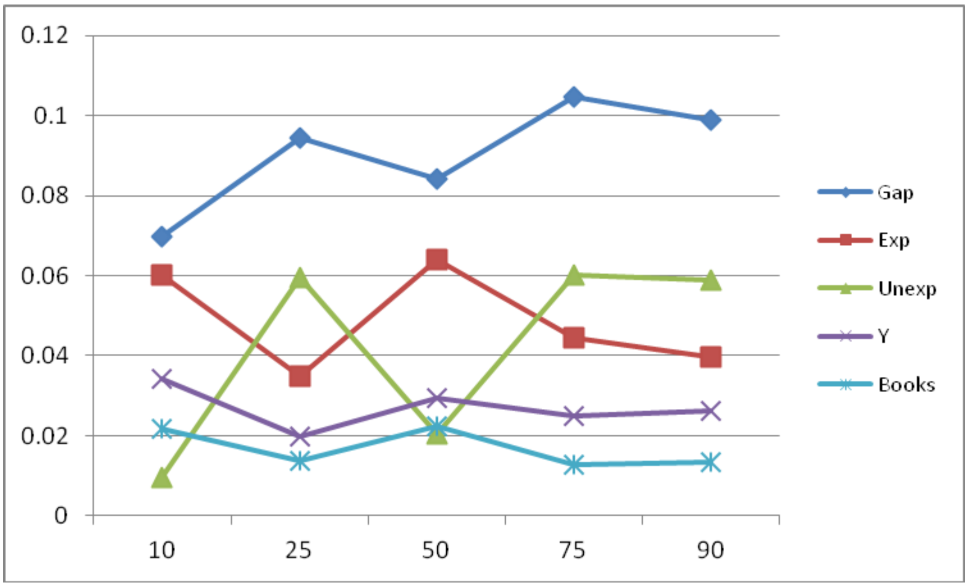


Figure 4e: Quantile Decompositions, Groups 3 and 1, Maths

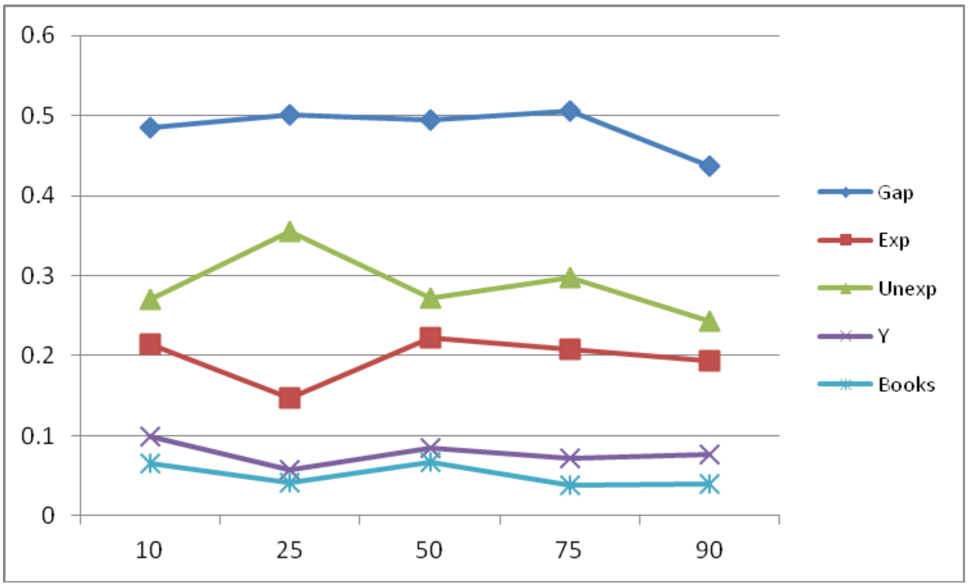


Figure 4f: Quantile Decompositions, Groups 2 and 1, Maths

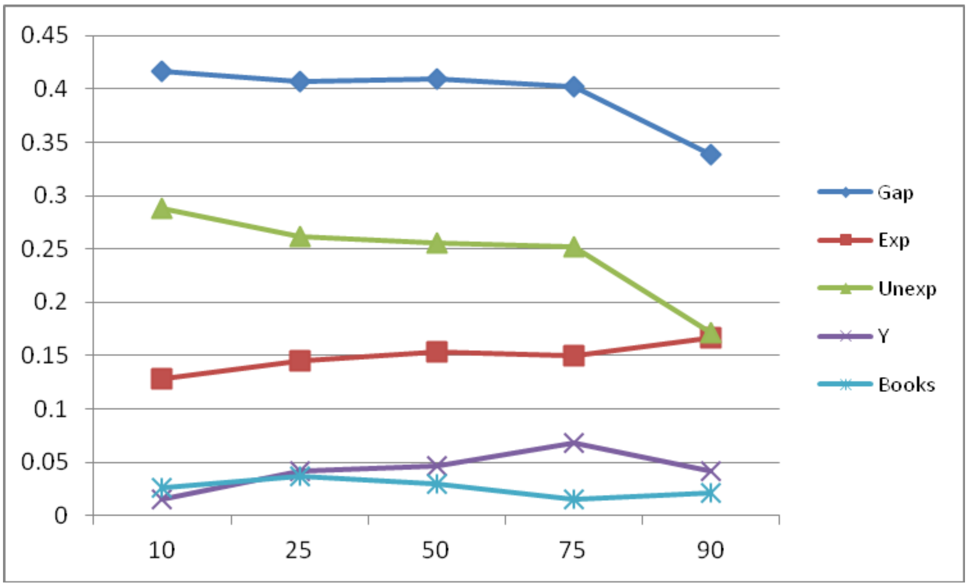


Figure 5a: Quantile Decompositions, Groups 4 and 3, Reading

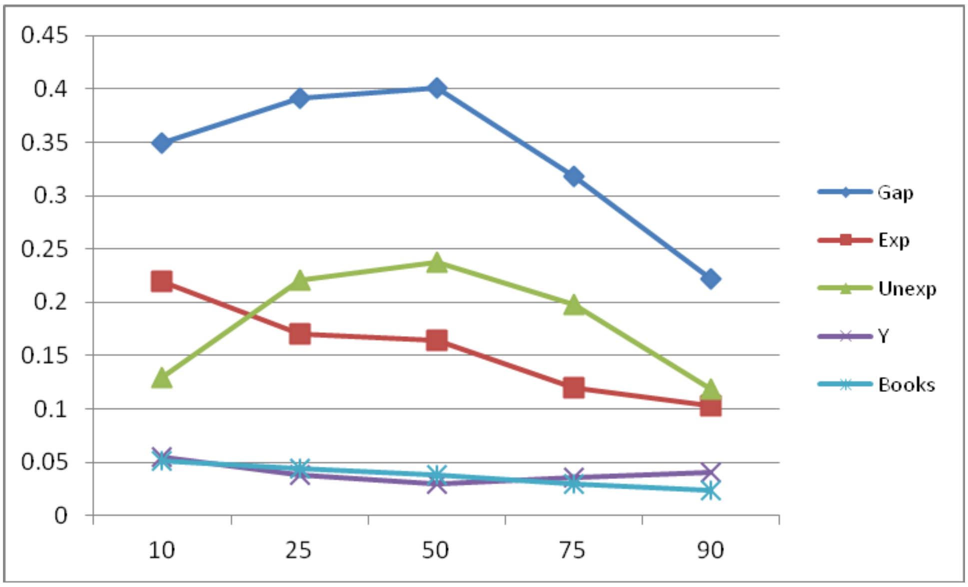


Figure 5b, Quantile Decompositions, Groups 4 and 2, Reading

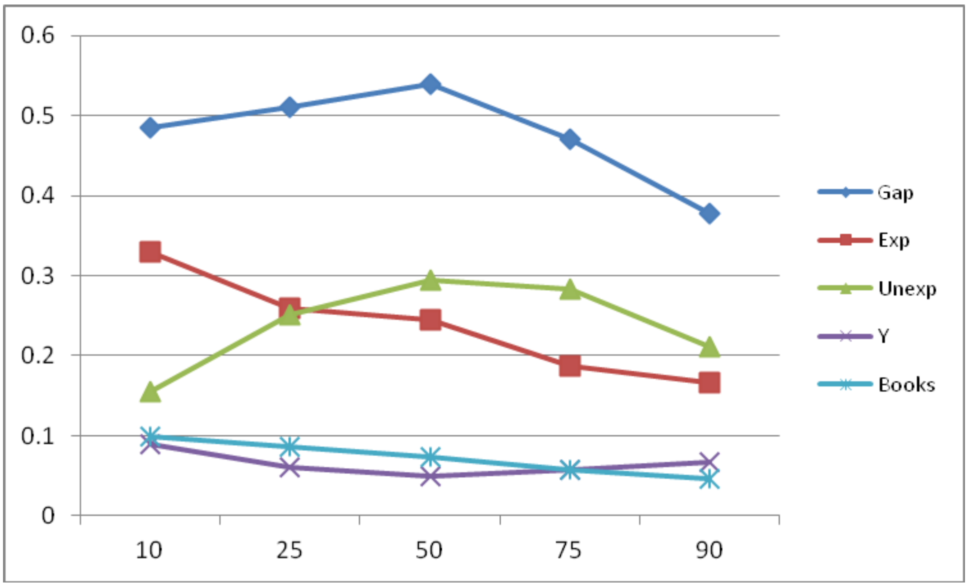


Figure 5c: Quantile Decompositions, Groups 4 and 1, Reading

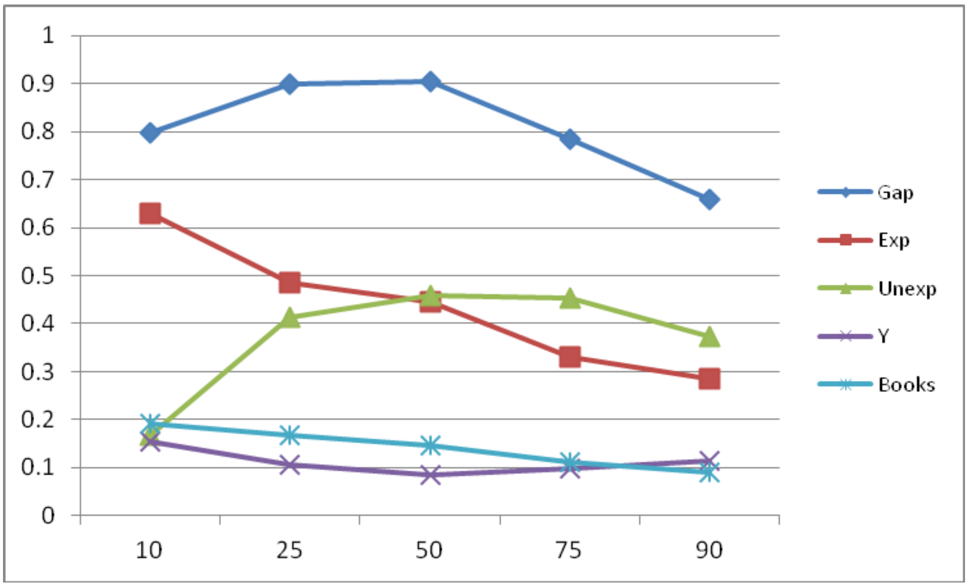


Figure 5d, Quantile Decompositions, Groups 3 and 2, Reading

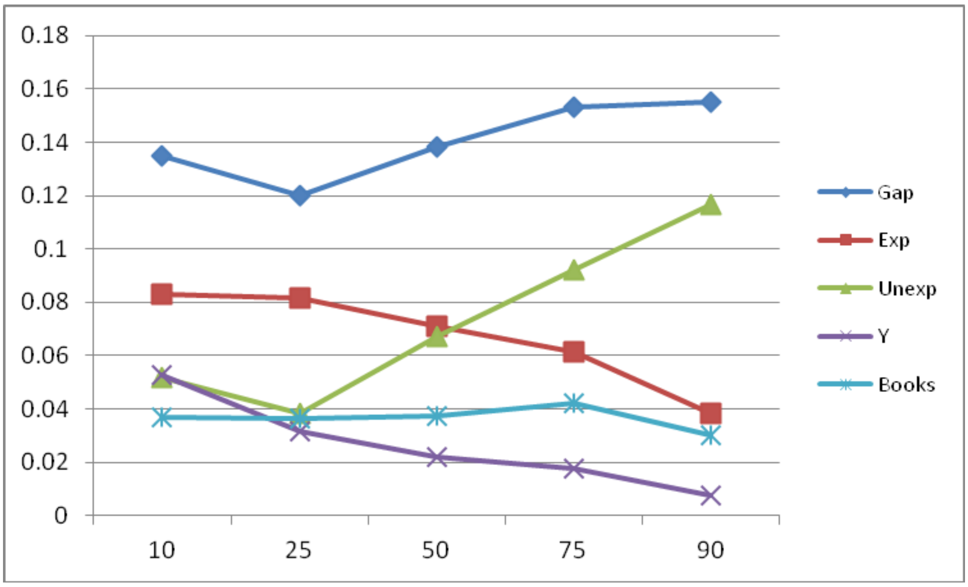


Figure 5e: Quantile Decompositions, Groups 3 and 1, Reading

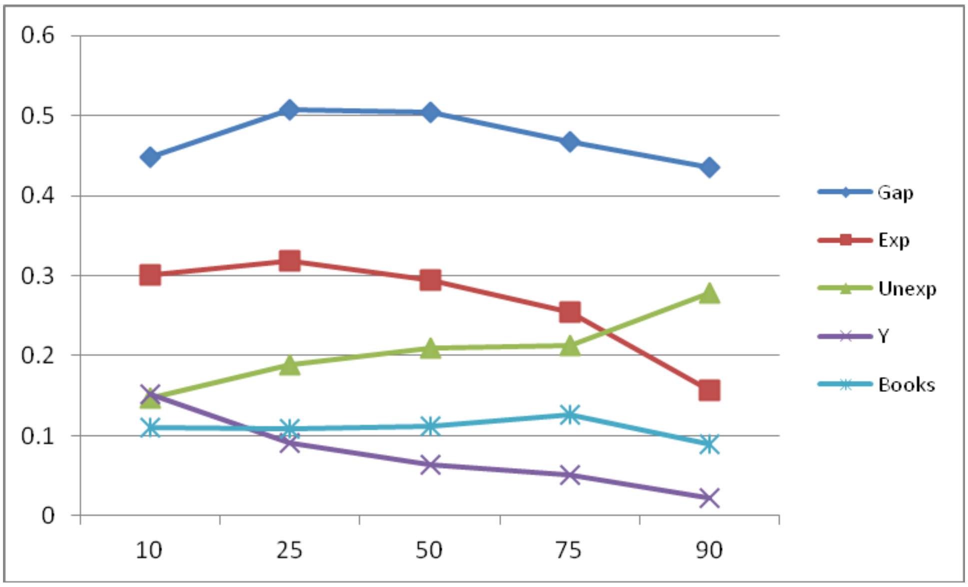
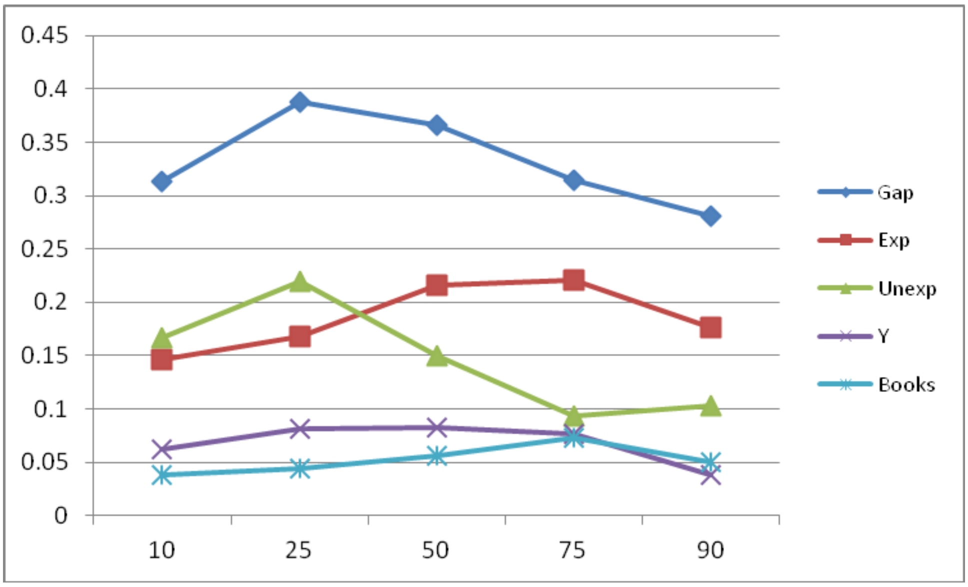


Figure 5f: Quantile Decompositions, Groups 2 and 1, Reading



References

Ashenfelter, O., C. Harmon and H, Oosterbeek (1999): "A Review of Estimates of the Schooling-Earning Relationship, with Tests for Publication Bias", *Labour Economics*, Vol. 6, pp. 453-470.

Batty, G.D., I. Deary, I. Schoon and C. Gale (2007): "Mental Ability Across Childhood in Relation to Risk Factors for Premature Mortality in Adult Life: the 1970s British Cohort Study", *Journal of Epidemiology and Community Health*, Vol. 61, pp. 997-1003.

Blinder, A. (1973). "Wage Discrimination: Reduced Form and Structural Estimates." *Journal of Human Resources*. 8: 436-455.

Breen, R., and J. Goldthorpe (1999): "Class Inequality and Meritocracy: a Critique of Saunders and an Alternative Analysis", *British Journal of Sociology*, Vol. 50, pp. 1-27.

------------., and ---------------- (2001): "Class, Mobility and Merit: the Experience of Two British Birth Cohorts", *European Sociological Review*, Vol. 17, pp. 81-101.

Checci, D., and V. Peragine (2010): "Inequality of Opportunity in Italy", *Journal of Economic Inequality*, Vol. 8, pp. 429-450.

Chiu, M., and B. Chow (2010): "Culture, Motivation and Reading Achievement: High School Students in 41 Countries", *Learning and Individual Differences*, Vol. 20, pp. 579-592.

Clotfelter, C., H. Ladd and J. Vigdor (2009): "The Academic Achievement Gap in Grades 3 to 8", *Review of Economics and Statistics*, Vol. 91, pp. 398-419.

Cutler, D. and A. Lleras-Muney (2010): "Understanding Differences in Health Behaviours by Education", *Journal of Health Economics,* Vol. 29, pp. 1-28.

Dickson, M., and C. Harmon (2011): "Economic Returns to Education: What We Know, What We Don't Know and Where Are We Going – Some Brief Pointers", *Economics of Education Review*, Vol. 30, pp. 1118-1122.

DiNardo, J., N. Fortin and T. Lemieux. (1996) Labour Market Institutions and the Distribution of Wages, 1973-1992: A Semiparametric Approach. *Econometrica*, 64, 1001-1044.

Doris, A., D. O Neill and O. Sweetman (2013): "Gender, Single Sex Schooling and Maths Achievement", *Economics of Education Review*, Vol. 35, pp. 104-119.

Dworkin, R., (1981) What is Inequality? Part 2: Equality of Resources. *Philosophy and Public Affairs*, 10, 283-345.

Essama-Nssah, B., and P. Lambert (2011): "Influence Functions for Distributional Statistics", Society for the Study of Economic Inequality Working Paper, ECINEQ WP 2011-236.

Evans, M., J. Kelley, J. Sikora and D. Treiman (2010): "Family Scholarly Culture and Educational Success: Books and Schooling in 27 Nations", *Research in Social Stratification and Mobility*, Vol. 28, pp. 171-197.

Feinstein, L., (2003): "Inequality in the Early Cognitive Development of British Children in the 1970 Cohort", *Economica*, Vol. 70, pp. 73-97.

Ferreira, F., and J. Gignoux (2011a): "The Measurement of Educational Inequality: Achievement and Opportunity", IZA Working Papers, DP 6161.

--------------- and ------------------(2011b): "The Measurement of Inequality of Opportunity: Theory and an Application to Latin America", *Review of Income and Wealth*, Vol. 57, pp. 622-657.

Firpo, S., N. Fortin and T. Lemieux (2009): "Unconditional Quantile Regressions", *Econometrica*, Vol. 77, No. 3, pp. 953-973.

Fleurbaey, M., and V. Peragine (2013): "*Ex Ante* versus *Ex Post* Inequality of Opportunity", *Economica*, Vol. 80, pp. 118-130.

Fortin, N., T. Lemieux and S. Firpo (2011) in O. Ashenfelter & D. Card (ed.), 2011. *Handbook of Labor Economics*, Elsevier, edition 1, volume 4, number 4.

Gamboa, L., and F. Waltenberg (2012): "Inequality of Opportunity for Educational Achievement in Latin America: Evdience from PISA, 2006-2009", *Economics of Education Review*, Vol. 31, pp. 694-708.

Hanushek, E., (1986): "The Economics of Schooling: Production and Efficiency in Public Schools", *Journal of Economic Literature*, Vol. 23, pp. 1141-1177.

Haveman, R., and B. Wolfe (1993): "Children's Prospects and Children's Policy", *Journal of Economic Perspectives*, Vol. 7, pp. 153-174.

Lefranc, A., N. Pistolesi and A. Trannoy (2009): "Equality of Opportunity and Luck: Definitions and Testable Conditions, with an Application to Income in France", *Journal of Public Economics*, Vol. 93, pp. 1189-1207.

Lord, F. M. (1980): *Applications of Item Response Theory to Practical Testing Problems*. Hillsdale, NJ: Lawrence Erlbaum.

Machado, J., and J. Mata (2005): "Counterfactual Decomposition of Changes in Wage Distributions Using Quantile Regression", *Journal of Applied Econometrics*, Vol. 20, pp. 445-465.

Melly, B., (2005): "Decomposition of Differences in Distributions Using Quantile Regression", *Labour Economics*, Vol. 12, pp. 577-590.

Oaxaca, R. (1973). "Male-Female Wage Differentials in Urban Labour Markets." *International Economic Review*. 14: 693-709.

Ramos, X., and D. Van de gaer (2012) Empirical Approaches to Inequality of Opportunity: Principles, Measures and Evidence. IZA Discussion paper 6672.

Rosa Dias, P. (2009): "Inequality of Opportunity in Health: Evidence from a UK Cohort Study", *Health Economics*, Vol. 18, pp. 1057-1074.

Rosa Dias, P. and A, Jones (2007) Giving Equality of Opportunity a Fair Innings, *Health Economics*, 16, 109-112.

Romer, J (1998) *Equality of Opportunity*. Harvard University Press, Harvard.

Romer, J (2002) Equality of Opportunity: A Progress Report. *Social Choice and Welfare*, 19, 455-471.

Romer, J (2013) Economic Development as Opportunity Equalisation. *World Bank Policy Research Working Paper 6530.*

Thomas, D., (1994): "Like Father, Like Son; Like Mother, Like Daughter", *Journal of Human Resources*, Vol. 29, pp. 950-988.

Williams, J., S. Greene, E. Doyle et al (2009): *The Lives of 9 Year Olds: Growing Up in Ireland, National Longitudinal Study of Children* (Report 1 of the Child Cohort). Dublin; The Stationery Office.

Appendix Table 1 – Definition of Variables

Variable	**Definition**
Age	Age of principal carer of study child
Birthweight	Study child's birthweight in kg
Earlybirth	0/1 variable, takes value of 1 if study child born at 32 weeks or earlier.
Smoker	0/1 variable, takes value of 1 if principal carer is current smoker
Pregsmoker	0/1 variable, takes value of 1 if principal carer was daily smoker during pregnancy
Pregdrinker	0/1 variable, takes value of 1 if principal carer drank weekly or more during pregnancy
Breastfed	0/1 variable, takes value of 1 if study child was ever breastfed
Illness	0/1 variable, takes value of 1 if study child has ongoing chronic illness
Income Decile	Equivalised Household Annual Income Decile, value of 1 for lowest, 2 for second lowest etc
Mumhealthy	0/1 variable, takes on 1 if self-assessed health of principal carer is excellent, very good or good.
Trauma	Sum of answers to 0/1 questions relating to whether study child experienced a range of traumas including death of parent/close relative, divorce/separation of parents, serious injury of family member, drug-taking/alcoholism in immediate family etc
Books	Categorical (1-5) response to question of number of childrens books which study child has access to in home
Local 1	Sum of answers to categorical (1-5) questions regarding quality of local area in terms of litter, vandalism, drug-taking etc
Local2	Sum of answers to categorical (1-5) questions regarding how safe for children to play in area etc

Working	0/1 variable relating to whether or not principal carer is working or not
Sizeclass	Total number of children in study child's class, numeric ranging from 13 to 36
Par_teacher	0/1 variable relating to whether parent attends parent-teacher meeting
Engage	Variable reflecting teachers engagement with class in terms of monitoring progress, variable is the sum of 5 0/1 questions, with weekly monitoring taking value of 1, less frequent monitoring taking value of 0
texperience	Numeric variable, number of years teacher has been teaching at primary level
qual	Numeric variable reflecting quality of school facilities (based on response of principal) – school principal asked 17 questions regarding school quality. Variable is sum of "excellent" responses, ranging from 0 to 17
School size	Ordinal numeric variable (1-10) reflecting size of school, ranging from 1-80 pupils to >400

Table A2: Detailed Quantile Decomposition, Maths, Groups 4 and 3

	q(25)		q(50)		q(75)	
Pred (4)	-0.940***		-0.351***		0.2507***	
Pred (3)	-1.204***		-0.575***		0.0314	
Gap	0.264***		0.224***		0.2193***	
	Explained	Unexp.	Explained	Unexp.	Explained	Unexp.
age	0.0213	-0.0117	0.0291**	0.0522	0.0228*	-0.3199
birthwgt	0.0005	-0.0925	0.0004	-0.3992	0.0004	-0.1159
earlybirth	0.0010	-0.0017	0.0022	-0.0084	0.0010	-0.0021
smoker	0.0134	-0.0385	0.0064	-0.0036	0.0085	0.0051
pregsmoker	0.0016	-0.0037	0.0040	-0.0178	0.0021	0.0006
pregdrinker	0.0006	0.0043	0.0007	0.0059	0.0003	0.0056
breastfed	0.0318**	0.1375**	0.0283**	0.0935*	0.0167	0.0541
illness	0.0010	0.0097	0.0011	-0.0078	0.0007	-0.0067
logeqinc	0.0472***	0.6833	0.0441***	-0.1596	0.0347**	-0.2586
mumhealthy	0.0009	0.0787	0.0006	-0.0095	0.0002	-0.0431
trauma	-0.0008	-0.0806	-0.0007	-0.0797	-0.0011	-0.0355
books	0.0178*	0.0634	0.0293***	0.1165	0.0193**	0.1234
local1	0.0051	0.3504	0.0036	-0.0043	-0.0018	-0.0548
local2	0.0028	0.0093	0.0008	0.1886	0.0024	0.0573
working	-0.0179*	-0.0693	-0.0141*	-0.0612	-0.0264***	-0.1841***
sizeclass	-0.0056	-0.7369***	-0.0022	-0.2209	-0.0017	-0.0059
par_teacher	0.0003	-0.0126	0.0000	-0.0355	0.0018	0.0822
engage	0.0004	0.1898	0.0011	0.1528	0.0016	0.0282
texperience	-0.0015	0.0390	-0.0008	-0.0361	-0.0004	-0.0941*
qual	0.0034	0.0155	0.0025	-0.0102	-0.0001	-0.0041
schoolsize	-0.0010	-0.0062	-0.0030	-0.0031	-0.0046	0.0092
youngsib	0.0023	-0.0436	-0.0028	-0.0931*	-0.0013	-0.0007
oldsib	0.0006	0.0452	-0.0000	-0.0150	-0.0000	-0.0048
Partner	-0.0014	-0.2412	0.0005	0.0353	-0.0012	-0.1946
Constant		-0.1473		0.6130		1.1046
Total	0.124***	0.140***	0.131***	0.0927*	0.0737***	0.1455***

*** p<0.01, ** p<0.05, * p<0.1

Table A3: Detailed Quantile Decomposition, Maths, Groups 4 and 2

	q(25)		q(50)		q(75)	
Pred (4)	-0.9403^{***}		-0.3513^{***}		0.2507^{***}	
Pred (2)	-1.2987^{***}		-0.6594^{***}		-0.0731^{**}	
Gap	0.3584^{***}		0.3081^{***}		0.3238^{***}	
	Explained	Unexp.	Explained	Unexp.	Explained	Unexp.
age	0.0195	-0.2934	0.0266^{**}	-0.1522	0.0208^{*}	-0.6752
birthwgt	0.0014	0.0960	0.0011	-0.0679	0.0012	-0.0713
earlybirth	0.0011	0.0015	0.0024	-0.0035	0.0011	0.0015
smoker	0.0186	-0.0468	0.0088	-0.0181	0.0118	-0.0217
pregsmoker	0.0025	-0.0012	0.0065	-0.0120	0.0035	-0.0084
pregdrinker	0.0007	0.0051	0.0009	0.0062	0.0004	-0.0004
breastfed	0.0622^{**}	0.0736^{*}	0.0555^{**}	0.0546	0.0327	0.0112
illness	0.0012	0.0170	0.0013	0.0087	0.0008	-0.0013
logeqinc	0.0765^{***}	0.5354	0.0714^{***}	0.1888	0.0562^{**}	-1.0793
mumhealthy	0.0018	0.0683	0.0013	0.1522	0.0003	0.1299
trauma	-0.0041	-0.0294	-0.0034	-0.0186	-0.0056	-0.0077
books	0.0343^{*}	-0.0376	0.0567^{***}	0.2680	0.0374^{**}	0.2229
local1	0.0066	0.1772	0.0047	-0.0161	-0.0024	-0.3169
local2	0.0027	-0.0017	0.0007	0.0868	0.0023	0.0133
working	-0.0372^{*}	-0.0729	-0.0293^{*}	-0.0566	-0.0550^{***}	-0.0930^{*}
sizeclass	-0.0073^{*}	-0.5746^{***}	-0.0029	-0.2749	-0.0023	-0.2880
par_teacher	0.0000	-0.0068	0.0000	-0.0347	0.0002	0.2440^{*}
engage	0.0004	0.0245	0.0013	0.1020	0.0020	0.1817
texperience	-0.0040	0.0115	-0.0021	-0.0074	-0.0011	-0.0116
qual	0.0043	0.0291	0.0032	-0.0054	-0.0002	0.0217
schoolsize	0.0004	-0.0044	0.0013	0.0048	0.0020	0.0117
youngsib	0.0054	-0.0183	-0.0066	-0.0619	-0.0031	-0.0441
oldsib	-0.0047	0.0304	0.0000	0.0175	0.0002	0.0340
Partner	-0.0013	-0.1730	0.0005	-0.0331	-0.0012	-0.0032
Constant		0.3675		-0.0193		1.9718^{*}
Total	0.1813^{***}	0.1771^{***}	0.2000^{***}	0.1081^{*}	0.1020^{**}	0.2218^{***}

*** p<0.01, ** p<0.05, * p<0.1

Table A4: Detailed Quantile Decomposition, Maths, Groups 4 and 1

	q(25)		q(50)		q(75)	
Pred (4)	-0.9403***		-0.3513***		0.2507***	
Pred (1)	-1.7057***		-1.0690***		-0.4751***	
Gap	0.7653***		0.7176***		0.7257***	
	Explained	Unexp.	Explained	Unexp.	Explained	Unexp.
age	0.0311	0.2089	0.0425**	0.0448	0.0333*	-0.0302
birthwgt	0.0084	0.0017	0.0067	0.3188	0.0070	0.3222
earlybirth	0.0034	-0.0025	0.0075	-0.0069	0.0035	0.0002
smoker	0.0547	-0.1144*	0.0259	-0.0462	0.0347	-0.0505
pregsmoker	0.0079	0.0540	0.0202	0.0155	0.0108	0.0107
pregdrinker	-0.0007	-0.0014	-0.0009	0.0001	-0.0004	-0.0012
breastfed	0.0969**	0.0433	0.0864**	0.0258	0.0509	-0.0075
illness	0.0050	0.0079	0.0054	-0.0068	0.0034	0.0025
logeqinc	0.1316***	0.1998	0.1229***	0.8419	0.0967**	0.4619
mumhealthy	0.0098	0.0529	0.0071	0.0802	0.0018	0.0168
trauma	-0.0021	-0.0844	-0.0017	-0.0160	-0.0029	-0.0511
books	0.0675*	-0.1927	0.1114***	0.2795	0.0734**	0.1792
local1	0.0246	-0.0951	0.0174	0.0458	-0.0089	-0.3051
local2	0.0045	-0.1542	0.0012	-0.0633	0.0038	0.0093
working	-0.0588*	-0.0587	-0.0463*	-0.0755*	-0.0869***	-0.0715*
sizeclass	-0.0300**	-0.5553**	-0.0119	-0.3780*	-0.0094	-0.2219
par_teacher	0.0012	-0.0975	0.0001	-0.0984	0.0070	0.1398
engage	0.0003	-0.0913	0.0008	-0.0351	0.0012	0.0596
texperience	0.0018	0.0522	0.0010	0.0089	0.0005	0.0024
qual	0.0064	0.0003	0.0048	-0.0065	-0.0002	-0.0155
schoolsize	-0.0002	0.0049	-0.0006	0.0038	-0.0010	0.0098
youngsib	0.0073	0.0308	-0.0091	-0.0116	-0.0042	-0.0128
oldsib	-0.0123	0.1035	0.0001	0.0335	0.0004	0.0893
Partner	-0.0066	-0.1940	0.0026	-0.0116	-0.0058	-0.0812
Constant		1.2952		-0.6185		0.0618
Total	0.3516***	0.4137***	0.3934***	0.3242***	0.2086***	0.5171***

*** p<0.01, ** p<0.05, * p<0.1

Table A5: Detailed Quantile Decomposition, Maths, Groups 3 and 2

	q(25)		q(50)		q(75)	
Pred (3)	-1.2042***		-0.5752***		0.0314	
Pred (2)	-1.2987***		-0.6594***		-0.0731**	
Gap	0.0945**		0.0842*		0.1045*	
	Explained	Unexp.	Explained	Unexp.	Explained	Unexp.
age	-0.0018	-0.2817	-0.0023	-0.2045	-0.0030	-0.3541
birthwgt	0.0013	0.1882	0.0021	0.3299	0.0012	0.0442
earlybirth	0.0000	0.0033	-0.0001	0.0053	0.0000	0.0037
smoker	-0.0013	-0.0019	0.0018	-0.0140	0.0041	-0.0277
pregsmoker	-0.0002	0.0038	-0.0033	0.0117	0.0016	-0.0092
pregdrinker	-0.0000	0.0010	-0.0001	0.0006	-0.0002	-0.0058
breastfed	-0.0065	-0.0270	0.0020	-0.0138	0.0015	-0.0283
illness	0.0004	0.0071	0.0000	0.0167	-0.0000	0.0055
logeqinc	0.0199*	-0.1385	0.0295**	0.3463	0.0250*	-0.8243
mumhealthy	0.0003	-0.0098	0.0008	0.1616	0.0005	0.1727
trauma	0.0035	0.0444	0.0041	0.0544	-0.0015	0.0248
books	0.0138*	-0.0981	0.0223**	0.1566	0.0126	0.1049
local1	-0.0004	-0.1713	0.0011	-0.0118	-0.0002	-0.2624
local2	-0.0001	-0.0109	-0.0003	-0.1015	-0.0002	-0.0439
working	-0.0061	-0.0168	-0.0035	-0.0071	0.0067	0.0559
sizeclass	0.0015	0.1591	0.0003	-0.0550	-0.0005	-0.2821
par_teacher	-0.0004	0.0059	-0.0004	0.0012	-0.0007	0.1609
engage	-0.0004	-0.1649	-0.0001	-0.0504	0.0003	0.1536
texperience	-0.0014	-0.0285	-0.0024	0.0297	-0.0033	0.0852
qual	0.0004	0.0141	0.0009	0.0045	0.0001	0.0257
schoolsize	0.0040	-0.0008	0.0056	0.0066	0.0027	0.0064
youngsib	0.0085*	0.0199	0.0076	0.0197	-0.0017	-0.0434
oldsib	0.0001	-0.0202	-0.0018	0.0344	-0.0004	0.0394
Partner	-0.0001	0.0684	0.0000	-0.0685	-0.0001	0.1915
Constant		0.5147		-0.6323		0.8672
Total	0.0350*	0.0595	0.0640***	0.0203	0.0444*	0.0601

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table A6: Detailed Quantile Decomposition, Maths, Groups 3 and 1

	q(25)		q(50)		q(75)	
Pred (3)	-1.2042***		-0.5752***		0.0314	
Pred (1)	-1.7057***		-1.0690***		-0.4751***	
Gap	0.5015***		0.4938***		0.5065***	
	Explained	Unexp.	Explained	Unexp.	Explained	Unexp.
age	0.0101	0.2204	0.0124*	-0.0063	0.0166*	0.2836
birthwgt	0.0106*	0.0914	0.0180**	0.7063**	0.0100	0.4347
earlybirth	0.0010	0.0006	-0.0019	0.0087	0.0007	0.0042
smoker	-0.0103	-0.0244	0.0147	-0.0378	0.0330	-0.0625
pregsmoker	-0.0015	0.0656	-0.0212	0.0708	0.0100	0.0088
pregdrinker	0.0003	-0.0073	0.0007	-0.0080	0.0015	-0.0089
breastfed	-0.0139	-0.0152	0.0043	-0.0140	0.0031	-0.0305
illness	0.0086	-0.0065	0.0006	0.0047	-0.0005	0.0125
logeqinc	0.0575*	-0.4566	0.0851**	0.9953	0.0722*	0.7103
mumhealthy	0.0032	-0.0200	0.0072	0.0890	0.0048	0.0567
trauma	0.0014	-0.0064	0.0016	0.0611	-0.0006	-0.0168
books	0.0414*	-0.2478	0.0668***	0.1783	0.0379*	0.0719
local1	-0.0050	-0.4210*	0.0141	0.0498	-0.0032	-0.2541
local2	0.0019	-0.1637	0.0044	-0.2558	0.0026	-0.0492
working	-0.0128	-0.0175	-0.0074	-0.0392	0.0141	0.0379
sizeclass	0.0207**	0.1365	0.0039	-0.1707	-0.0073	-0.2164
par_teacher	0.0013	-0.0854	0.0013	-0.0641	0.0023	0.0604
engage	0.0005	-0.2817	0.0002	-0.1884	-0.0004	0.0313
texperience	0.0019	0.0146	0.0031	0.0437	0.0044	0.0931
qual	0.0014	-0.0136	0.0033	0.0026	0.0003	-0.0119
schoolsize	0.0022	0.0098	0.0031	0.0062	0.0015	0.0027
youngsib	0.0138*	0.0656	0.0124	0.0628	-0.0028	-0.0122
oldsib	0.0003	0.0450	-0.0043	0.0530	-0.0010	0.0955
Partner	0.0120	0.0299	-0.0005	-0.0443	0.0093	0.0995
Constant		1.4424		-1.2315		-1.0428
Total	0.1466***	0.3548***	0.2218***	0.2720***	0.2086***	0.2978***

*** p<0.01, ** p<0.05, * p<0.1

Table A7: Detailed Quantile Decomposition, Maths, Groups 2 and 1

	q(25)		q(50)		q(75)	
Pred (2)	-1.2987***		-0.6594***		-0.0731**	
Pred (1)	-1.7057***		-1.0690***		-0.4751***	
Gap	0.4070***		0.4095***		0.4019***	
	Explained	Unexp.	Explained	Unexp.	Explained	Unexp.
age	0.0182**	0.4957	0.0193**	0.1936	0.0275***	0.6298
birthwgt	0.0044	-0.0918	0.0073	0.3850	0.0076	0.3917
earlybirth	0.0035	-0.0053	0.0023	-0.0007	0.0035	-0.0024
smoker	-0.0109	-0.0206	-0.0011	-0.0098	0.0011	-0.0071
pregsmoker	0.0038	0.0567	-0.0023	0.0435	-0.0039	0.0304
pregdrinker	0.0008	-0.0087	0.0010	-0.0089	-0.0009	-0.0006
breastfed	0.0039	0.0005	0.0081	-0.0060	0.0135	-0.0141
illness	0.0114*	-0.0168	0.0080*	-0.0194	0.0020	0.0044
logeqinc	0.0412**	-0.3217	0.0466**	0.6580	0.0687***	1.5131
mumhealthy	0.0035	-0.0108	-0.0042	-0.0620	-0.0071	-0.1046
trauma	0.0003	-0.0533	0.0006	0.0036	0.0023	-0.0429
books	0.0365***	-0.1586	0.0303***	0.0359	0.0157	-0.0234
local1	0.0065	-0.2608	0.0138	0.0608	0.0140	-0.0087
local2	0.0018	-0.1525	0.0024	-0.1520	0.0018	-0.0043
working	-0.0023	-0.0051	-0.0020	-0.0339	-0.0073	-0.0032
sizeclass	0.0101	-0.0135	0.0068	-0.1189	0.0093	0.0496
par_teacher	0.0015	-0.0910	0.0016	-0.0653	-0.0041	-0.0933
engage	-0.0000	-0.1159	0.0000	-0.1377	0.0002	-0.1231
texperience	0.0051	0.0413	0.0036	0.0158	0.0024	0.0132
qual	-0.0001	-0.0267	0.0020	-0.0015	-0.0017	-0.0356
schoolsize	-0.0021	0.0108	-0.0004	-0.0025	0.0008	-0.0058
youngsib	0.0036	0.0475	0.0031	0.0448	0.0028	0.0274
oldsib	-0.0029	0.0684	0.0028	0.0133	0.0055	0.0501
Partner	0.0072	-0.0335	0.0044	0.0192	-0.0044	-0.0782
Constant		0.9277		-0.5992		-1.9100
Total	0.1450***	0.2619***	0.1538***	0.2557***	0.1495***	0.2525***

*** p<0.01, ** p<0.05, * p<0.1

Table A8: Detailed Quantile Decomposition, Reading, Groups 4 and 3

	q(25)		q(50)		q(75)	
Pred (4)	-0.0704*		0.6142***		1.1880***	
Pred (3)	-0.4614***		0.2128***		0.8705***	
Gap	0.3910***		0.4014***		0.3175***	
	Explained	Unexp.	Explained	Unexp.	Explained	Unexp.
age	0.0512***	-0.4336	0.0685***	0.3510	0.0436***	-0.4005
birthwgt	0.0008	-0.1874	0.0007	0.0701	0.0003	-0.1580
earlybirth	0.0005	-0.0011	0.0011	-0.0061	-0.0002	-0.0033
smoker	0.0058	-0.0264	0.0106	-0.0247	0.0020	0.0168
pregsmoker	-0.0008	0.0106	-0.0023	0.0117	0.0075	-0.0167
pregdrinker	0.0003	-0.0022	-0.0003	-0.0060	0.0004	-0.0001
breastfed	0.0288*	0.1044	0.0250*	0.0745	0.0185*	0.0989*
illness	0.0015	0.0136	0.0019	-0.0089	0.0013	0.0066
logeqinc	0.0377**	-0.5913	0.0300*	-0.2578	0.0353***	0.3088
mumhealthy	0.0004	-0.1051	-0.0005	-0.3680*	-0.0006	-0.1819
trauma	-0.0006	-0.0252	-0.0004	-0.0555	-0.0003	-0.0490
books	0.0443***	0.1147	0.0383***	-0.0339	0.0293***	-0.3420
local1	-0.0021	-0.0537	-0.0012	-0.2145	-0.0032	-0.1034
local2	0.0040	-0.0134	0.0012	0.1684	-0.0009	0.2226
working	-0.0086	-0.0547	-0.0129	-0.0531	-0.0094	-0.0173
sizeclass	0.0010	-0.0427	-0.0027	-0.3468	-0.0029	-0.3137
par_teacher	0.0029	0.1241	0.0001	-0.0599	0.0006	0.0631
engage	0.0010	0.0336	0.0006	0.0749	0.0000	-0.0685
texperience	-0.0002	-0.0395	0.0005	-0.0659	-0.0001	-0.0130
qual	0.0036	0.0173	0.0066	0.0507	0.0017	-0.0191
schoolsize	-0.0042	0.0139	-0.0043	0.0168	-0.0033	0.0033
youngsib	0.0029	-0.0203	0.0027	0.0453	0.0014	0.0512
oldsib	-0.0002	0.0650	-0.0011	0.0091	-0.0006	0.0794
Partner	-0.0003	0.0248	0.0022	0.1401	-0.0010	-0.0179
Constant		1.2958		0.7256		1.0516
Total	0.1699***	0.2211***	0.1644***	0.2370***	0.1196***	0.1979***

*** p<0.01, ** p<0.05, * p<0.1

Table A9: Detailed Quantile Decomposition, Reading, Groups 4 and 2

	q(25)		q(50)		q(75)	
Pred (4)	-0.0704*		0.6142***		1.1880***	
Pred (2)	-0.5813***		0.0744**		0.7172***	
Gap	0.5109***		0.5398***		0.4708***	
	Explained	Unexp.	Explained	Unexp.	Explained	Unexp.
age	0.0468***	0.0678	0.0627***	0.2985	0.0399***	-0.7599*
birthwgt	0.0024	0.3501	0.0020	0.3198	0.0008	-0.1999
earlybirth	0.0005	0.0052	0.0012	0.0017	-0.0002	0.0043
smoker	0.0080	0.0034	0.0146	-0.0239	0.0027	0.0077
pregsmoker	-0.0014	-0.0088	-0.0037	0.0033	0.0123	-0.0339
pregdrinker	0.0004	0.0029	-0.0003	-0.0007	0.0004	0.0020
breastfed	0.0565*	0.0616	0.0490*	0.0234	0.0362*	-0.0051
illness	0.0018	-0.0029	0.0022	-0.0043	0.0016	-0.0102
logeqinc	0.0611**	-1.4123	0.0487*	-1.8155*	0.0573***	-1.3640
mumhealthy	0.0008	0.1926	-0.0010	0.0020	-0.0013	-0.0110
trauma	-0.0029	0.0073	-0.0019	0.0139	-0.0013	-0.0115
books	0.0857***	0.4263*	0.0739***	0.1599	0.0567***	-0.1999
local1	-0.0027	-0.0015	-0.0015	-0.0701	-0.0042	-0.1333
local2	0.0039	0.0644	0.0012	0.1300	-0.0008	0.1514
working	-0.0179	-0.0152	-0.0269	-0.0380	-0.0196	-0.0100
sizeclass	0.0014	0.0784	-0.0035	-0.2954	-0.0038	-0.1672
par_teacher	0.0003	0.1713	0.0000	-0.0618	0.0001	0.0433
engage	0.0012	0.1063	0.0007	0.0527	0.0000	0.0596
texperience	-0.0006	-0.0318	0.0015	-0.0735	-0.0001	-0.0363
qual	0.0045	0.0126	0.0082*	0.0592*	0.0021	-0.0060
schoolsize	0.0018	0.0113	0.0019	0.0051	0.0015	0.0084
youngsib	0.0069	-0.0207	0.0064	-0.0107	0.0033	-0.0274
oldsib	0.0014	0.0167	0.0079	0.0192	0.0042	0.1063*
Partner	-0.0002	0.0609	0.0021	0.2293	-0.0009	0.1492
Constant		0.1053		1.3704		2.7274**
Total	0.2597***	0.2512***	0.2454***	0.2944***	0.1870***	0.2839***

*** p<0.01, ** p<0.05, * p<0.1

Table A10: Detailed Quantile Decomposition, Reading, Groups 4 and 1

	q(25)		q(50)		q(75)	
Pred (4)	-0.0704*		0.6142***		1.1880***	
Pred (1)	-0.9691***		-0.2914***		0.4030***	
Gap	0.8987***		0.9056***		0.7849***	
	Explained	Unexp.	Explained	Unexp.	Explained	Unexp.
age	0.0748***	0.1800	0.1001***	0.7247*	0.0637***	-0.1967
birthwgt	0.0137*	0.2124	0.0118*	0.0751	0.0045	-0.1640
earlybirth	0.0016	0.0016	0.0038	-0.0025	-0.0006	0.0046
smoker	0.0236	-0.0432	0.0431	-0.0446	0.0081	0.0406
pregsmoker	-0.0043	0.0346	-0.0116	0.0264	0.0384	-0.0754
pregdrinker	-0.0004	-0.0049	0.0003	-0.0039	-0.0004	-0.0012
breastfed	0.0880*	0.0430	0.0763*	0.0155	0.0563*	-0.0471
illness	0.0075	0.0182	0.0091	-0.0203	0.0066	-0.0140
logeqinc	0.1052**	0.5423	0.0838*	0.0411	0.0986***	1.1967
mumhealthy	0.0041	-0.0947	-0.0056	-0.1154	-0.0067	-0.1072
trauma	-0.0015	-0.0453	-0.0010	-0.0569	-0.0006	-0.0564
books	0.1683***	0.0548	0.1452***	0.0762	0.1114***	-0.1869
local1	-0.0100	-0.4697*	-0.0056	-0.2118	-0.0157	-0.1807
local2	0.0065	-0.1849	0.0020	-0.1675	-0.0014	-0.1224
working	-0.0283	-0.0457	-0.0425	-0.0509	-0.0310	-0.1142**
sizeclass	0.0057	0.1740	-0.0144	-0.1213	-0.0155	-0.2580
par_teacher	0.0112*	0.1754	0.0003	-0.0078	0.0023	0.1493
engage	0.0007	-0.2529	0.0004	-0.2448	0.0000	-0.1536
texperience	0.0003	0.0255	-0.0007	-0.0328	0.0001	0.0158
qual	0.0067	0.0390	0.0123*	0.0244	0.0032	-0.0037
schoolsize	-0.0009	0.0182	-0.0009	0.0257*	-0.0007	0.0095
youngsib	0.0095	0.0033	0.0087	0.0881*	0.0045	0.0587
oldsib	0.0037	0.1728*	0.0209*	0.1041	0.0111	0.2005**
Partner	-0.0012	0.0820	0.0105	-0.0182	-0.0047	-0.2345
Constant		-0.2216		0.3565		0.6935
Total	0.4843***	0.4143***	0.4462***	0.4593***	0.3316***	0.4533***

*** p<0.01, ** p<0.05, * p<0.1

Table A11: Detailed Quantile Decomposition, Reading, Groups 3 and 2

	q(25)		q(50)		q(75)	
Pred (3)	-0.4614***		0.2128***		0.8705***	
Pred (2)	-0.5813***		0.0744**		0.7172***	
Gap	0.1199**		0.1384***		0.1533***	
	Explained	Unexp.	Explained	Unexp.	Explained	Unexp.
age	-0.0058	0.5029	-0.0046	-0.0537	-0.0051	-0.3581
birthwgt	0.0022	0.5368*	0.0011	0.2500	0.0011	-0.0425
earlybirth	0.0000	0.0064	-0.0001	0.0081	-0.0001	0.0078
smoker	-0.0022	0.0343	-0.0001	0.0050	0.0036	-0.0119
pregsmoker	0.0029	-0.0229	0.0024	-0.0122	-0.0007	-0.0117
pregdrinker	0.0002	0.0050	0.0002	0.0050	0.0001	0.0021
breastfed	-0.0004	-0.0148	0.0040	-0.0311	-0.0089	-0.0775*
illness	0.0006	-0.0168	0.0001	0.0048	0.0004	-0.0170
logeqinc	0.0315**	-0.8291	0.0222*	-1.5612	0.0177	-1.6686
mumhealthy	0.0012	0.2968	0.0023	0.3672*	0.0008	0.1695
trauma	-0.0002	0.0303	0.0032	0.0647	0.0031	0.0334
books	0.0363***	0.3166	0.0372***	0.1923	0.0423***	0.1271
local1	-0.0003	0.0519	0.0008	0.1432	-0.0004	-0.0305
local2	-0.0002	0.0777	-0.0003	-0.0381	-0.0003	-0.0708
working	0.0012	0.0290	-0.0038	0.0049	-0.0069	0.0039
sizeclass	0.0005	0.1209	0.0007	0.0498	0.0005	0.1451
par_teacher	-0.0013	0.0459	-0.0007	-0.0013	0.0001	-0.0205
engage	0.0001	0.0729	-0.0001	-0.0220	0.0002	0.1280
texperience	-0.0015	0.0088	-0.0009	-0.0058	-0.0005	-0.0229
qual	0.0004	-0.0042	0.0002	0.0100	0.0010	0.0126
schoolsize	0.0002	0.0032	-0.0009	-0.0047	0.0033	0.0065
youngsib	0.0065	-0.0029	-0.0019	-0.0504	-0.0044	-0.0723
oldsib	0.0094	-0.0561	0.0101*	0.0091	0.0143*	0.0174
Partner	0.0000	0.0361	0.0000	0.0891	0.0000	0.1670
Constant		-1.1905		0.6448		1.6758
Total	0.0814***	0.0385	0.0710***	0.0674	0.0613**	0.0920*

*** p<0.01, ** p<0.05, * p<0.1

Table A12: Detailed Quantile Decomposition, Reading, Groups 3 and 1

	q(25)		q(50)		q(75)	
Pred (3)	-0.4614***		0.2128***		0.8705***	
Pred (1)	-0.9691***		-0.2914***		0.4030***	
Gap	0.5077***		0.5042***		0.4674***	
	Explained	Unexp.	Explained	Unexp.	Explained	Unexp.
age	0.0319**	0.6053	0.0250**	0.3803	0.0277**	0.1962
birthwgt	0.0184**	0.3943	0.0090	0.0071	0.0089	-0.0107
earlybirth	0.0002	0.0037	-0.0025	0.0089	-0.0033	0.0107
smoker	-0.0176	0.0187	-0.0006	0.0132	0.0285	0.0014
pregsmoker	0.0188	0.0018	0.0153	-0.0100	-0.0044	-0.0234
pregdrinker	-0.0015	-0.0018	-0.0017	0.0044	-0.0008	-0.0010
breastfed	-0.0008	-0.0014	0.0085	-0.0162	-0.0190	-0.0892**
illness	0.0124*	-0.0019	0.0030	-0.0071	0.0084	-0.0238
logeqinc	0.0908**	1.1103	0.0639*	0.2888	0.0511	0.9001
mumhealthy	0.0114	0.0027	0.0218*	0.2257	0.0072	0.0614
trauma	-0.0001	-0.0209	0.0012	-0.0033	0.0012	-0.0090
books	0.1090***	-0.0448	0.1114***	0.1057	0.1268***	0.1103
local1	-0.0042	-0.4198	0.0105	-0.0123	-0.0052	-0.0846
local2	0.0022	-0.1712	0.0043	-0.3394*	0.0041	-0.3496
working	0.0025	-0.0132	-0.0081	-0.0193	-0.0145	-0.1039*
sizeclass	0.0072	0.2141	0.0095	0.2042	0.0066	0.0365
par_teacher	0.0040	0.0556	0.0023	0.0500	-0.0004	0.0884
engage	-0.0002	-0.2866	0.0001	-0.3199*	-0.0002	-0.0849
texperience	0.0019	0.0635	0.0012	0.0307	0.0006	0.0284
qual	0.0013	0.0235	0.0005	-0.0210	0.0035	0.0135
schoolsize	0.0001	0.0075	-0.0005	0.0127	0.0018	0.0070
youngsib	0.0106	0.0196	-0.0031	0.0520	-0.0071	0.0178
oldsib	0.0229*	0.0887	0.0246*	0.0924	0.0349**	0.0978
Partner	-0.0027	0.0590	-0.0018	-0.1483	-0.0024	-0.2179
Constant		-1.5174		-0.3691	0.2541***	-0.3581
Total	0.3185***	0.1892**	0.2939***	0.2103***	0.2541***	0.2134**

*** p<0.01, ** p<0.05, * p<0.1

Table A13: Detailed Quantile Decomposition, Reading, Groups 2 and 1

	q(25)		q(50)		q(75)	
Pred (2)	-0.5813***		0.0744**		0.7172***	
Pred (1)	-0.9691***		-0.2914***		0.4030***	
Gap	0.3878***		0.3658***		0.3141***	
	Explained	Unexp.	Explained	Unexp.	Explained	Unexp.
age	0.0264***	0.1137	0.0307***	0.4329	0.0408***	0.5462
birthwgt	0.0022	-0.1286	0.0014	-0.2364	0.0089	0.0307
earlybirth	0.0052	-0.0077	0.0039	-0.0055	0.0029	-0.0031
smoker	0.0190	-0.0500	0.0045	0.0032	0.0130	0.0252
pregsmoker	-0.0148	0.0553	-0.0035	0.0187	-0.0193	0.0039
pregdrinker	0.0005	-0.0091	0.0003	-0.0029	0.0000	-0.0041
breastfed	0.0057	0.0072	0.0175*	0.0019	0.0223*	-0.0441
illness	0.0044	0.0224	0.0050	-0.0140	0.0005	0.0008
logeqinc	0.0809***	1.9178	0.0825***	1.8093	0.0769***	2.5252*
mumhealthy	-0.0094	-0.2746	-0.0047	-0.1173	-0.0047	-0.0969
trauma	0.0018	-0.0530	0.0017	-0.0716	-0.0000	-0.0442
books	0.0438***	-0.3326*	0.0567***	-0.0691	0.0729***	-0.0052
local1	-0.0072	-0.4683*	0.0004	-0.1463	-0.0029	-0.0561
local2	0.0041	-0.2507	0.0037	-0.3004*	0.0029	-0.2772
working	-0.0064	-0.0346	-0.0056	-0.0229	-0.0087	-0.1068*
sizeclass	-0.0002	0.1001	0.0060	0.1572	-0.0021	-0.1003
par_teacher	0.0032	0.0118	0.0031	0.0513	0.0004	0.1080
engage	0.0001	-0.3598*	0.0000	-0.2978*	0.0003	-0.2136
texperience	0.0029	0.0553	0.0024	0.0361	0.0025	0.0498
qual	0.0013	0.0273	-0.0004	-0.0303	0.0015	0.0019
schoolsize	0.0010	0.0032	-0.0011	0.0189*	0.0006	-0.0016
youngsib	0.0044	0.0222	0.0033	0.0979*	0.0036	0.0836
oldsib	0.0049	0.1535*	0.0159**	0.0819	0.0233**	0.0777
Partner	-0.0054	0.0254	-0.0082	-0.2309*	-0.0145	-0.3729**
Constant		-0.3269		-1.0138		-2.0338
Total	0.1684***	0.2194***	0.2157***	0.1501**	0.2211***	0.0931

*** p<0.01, ** p<0.05, * p<0.1

UCD CENTRE FOR ECONOMIC RESEARCH – RECENT WORKING PAPERS

WP13/15 David Madden: 'Winners and Losers on the Roller-Coaster: Ireland, 2003-2011' September 2013
WP13/16 Sarah Parlane and Ying-Yi Tsai: 'Optimal Contract Orders and Relationship-Specific Investments in Vertical Organizations' October 2013
WP13/17 Olivier Bargain, Eliane El Badaoui, Prudence Kwenda, Eric Strobl and Frank Walsh: 'The Formal Sector Wage Premium and Firm Size for Self-employed Workers' October 2013
WP13/18 Kevin Denny and Cormac Ó Gráda 'Irish Attitudes to Immigration During and After the Boom' December 2013
WP13/19 Cormac Ó Gráda ''Because She Never Let Them In': Irish Immigration a Century Ago and Today' December 2013
WP14/01 Matthew T Cole and Ronald B Davies: 'Foreign Bidders Going Once, Going Twice... Protection in Government Procurement Auctions' February 2014
WP14/02 Eibhlin Hudson, David Madden and Irene Mosca: 'A Formal Investigation of Inequalities in Health Behaviours after age 50 on the Island of Ireland' February 2014
WP14/03 Cormac Ó Gráda: 'Fame e Capitale Umano in Inghilterra prima della Rivoluzione Industriale (Hunger and Human Capital in England before the Industrial Revolution)' February 2014
WP14/04 Martin D O'Brien and Karl Whelan: 'Changes in Bank Leverage: Evidence from US Bank Holding Companies' March 2014
WP14/05 Sandra E Black, Paul J Devereux and Kjell G Salvanes: 'Does Grief Transfer across Generations? - In-Utero Deaths and Child Outcomes' March 2014
WP14/06 Morgan Kelly and Cormac Ó Gráda: 'Debating the Little Ice Age' March 2014
WP14/07 Alan Fernihough, Cormac Ó Gráda and Brendan M Walsh: 'Mixed Marriages in Ireland A Century Ago' March 2014
WP14/08 Doireann Fitzgerald and Stefanie Haller: 'Exporters and Shocks: Dissecting the International Elasticity Puzzle' April 2014
WP14/09 David Candon: 'The Effects of Cancer in the English Labour Market' May 2014
WP14/10 Cormac Ó Gráda and Morgan Kelly: 'Speed under Sail, 1750–1850' May 2014
WP14/11 Johannes Becker and Ronald B Davies: 'A Negotiation-Based Model of Tax-Induced Transfer Pricing' July 2014
WP14/12 Vincent Hogan, Patrick Massey and Shane Massey: 'Analysing Match Attendance in the European Rugby Cup' September 2014
WP14/13 Vincent Hogan, Patrick Massey and Shane Massey: 'Competitive Balance: Results of Two Natural Experiments from Rugby Union' September 2014
WP14/14 Cormac Ó Gráda: 'Did Science Cause the Industrial Revolution?' October 2014
WP14/15 Michael Daly, Liam Delaney, Orla Doyle, Nick Fitzpatrick and Christine O'Farrelly: 'Can Early Intervention Policies Improve Well-being? Evidence from a randomized controlled trial' October 2014
WP14/16 Thérèse McDonnell and Orla Doyle: 'Maternal Employment, Childcare and Childhood Overweight during Infancy' October 2014
WP14/17 Sarah Parlane and Ying-Yi Tsai: 'Optimal Sourcing Orders under Supply Disruptions and the Strategic Use of Buffer Suppliers' October 2014
WP14/18 Morgan Kelly and Cormac Ó Gráda: 'Ready for Revolution? The English Economy before 1800' November 2014
WP14/19 Johannes Becker, Ronald B Davies and Gitte Jakobs: 'The Economics of Advance Pricing Agreements' November 2014

UCD Centre for Economic Research Email economics@ucd.ie