I Z A Institute of Labor Economics
Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 12459

Good Schools or Good Students? The Importance of Selectivity for School Rankings

Aedín Doris
Donal O'Neill
Olive Sweetman

JULY 2019

I Z A Institute of Labor Economics

Initiated by Deutsche Post Foundation

DISCUSSION PAPER SERIES

IZA DP No. 12459

Good Schools or Good Students? The Importance of Selectivity for School Rankings

Aedín Doris
Maynooth University

Donal O'Neill
Maynooth University and IZA

Olive Sweetman
Maynooth University

JULY 2019

ISSN: 2365-9793

IZA – Institute of Labor Economics

Schaumburg-Lippe-Straße 5–9
53113 Bonn, Germany

Phone: +49-228-3894-0
Email: publications@iza.org

www.iza.org

ABSTRACT

Good Schools or Good Students? The Importance of Selectivity for School Rankings

This paper uses a rich set of student background characteristics, including early measures of cognitive and non-cognitive skills, to estimate the value added of second-level schools in Ireland. Although there are high performing schools in both raw and value-added terms, there is a considerable degree of reranking of schools when we move to value added. In many cases the best performing schools in raw terms are not the best in value-added terms. In addition we find that parents tend to choose schools on the basis of raw results rather than value added. We estimate that if parents chose the best value-added school from among the set of feasible schools, then this reallocation of students would increase academic achievement substantially.

JEL Classification: I210, I280
Keywords: school value added, school choice

Corresponding author:
Donal O'Neill
Rhetoric House
Maynooth University
Maynooth, Co. Kildare
Ireland
E-mail: donal.oneill@nuim.ie

1. Introduction

Choosing a good school for their child is a key decision for parents. In making their choice, parents often rely on outcomes such as the average exam performance of students in a school. However, when students non-randomly select into schools according to prior ability or other socioeconomic factors, such outcomes partly measure the prior ability or family background of the student body rather than the contribution of a given school. In some countries, governments have moved towards providing information on the value added of schools, which takes account of compositional differences between schools. However, many others do not. For example, the Irish government provides no information on school rankings, either in terms of raw examination results or value added. In the absence of other information, newspapers produce ad hoc league tables based on progression to university. Despite their acknowledged shortcomings, these league tables are believed to affect parents' choices. In this paper, we provide estimates of the value added of Irish second-level schools based on the results of a state examination taken by all students at age 15 and examine the implications of this for school choice.

Unlike other studies that tend to use administrative data, we use longitudinal survey data that include detailed background information on the children and their families. As well as prior cognitive achievement measures, we also have information on non-cognitive skills, family income, parental education and family structure. We show that these characteristics have a large impact on academic achievement and also vary substantially across schools. Controlling for selection, we find that the variance of value-added scores is substantially lower than the variance of raw scores, implying that schools are more alike than suggested by raw scores. Moreover, the ranking produced by the value-added approach differs substantially from that produced using raw examination scores. Having obtained estimates of value added for each school, we then look at the factors determining schools' rank in raw scores and value added. We find that although school type is important in determining raw ranks, it is unimportant for value-added rank.

We conclude the paper by examining the link between school quality and school choice. We first show that schools that have high raw ranks are more likely to be oversubscribed, whereas this is not true of schools that have high value added. This suggests that parents are not sending their children to the 'best' schools. When we simulate the effect of all children attending their best available school, we find that the average score increases by 0.28 standard deviations.

As noted by Eyles et al. (2016) there are a number of approaches to estimating the effectiveness of schools. One approach relies on experimental or quasi-experimental variation that uses school reforms, school lotteries or boundary discontinuities generated by admission policies to identify the effects of school quality (Abdulkadiroglu et al. (2014), Deming (2014), Beuermann et al. (2018)). In keeping with quasi-experimental research in other areas of economics, the clean identification sources provided by these approaches has the potential to generate unbiased estimates of the causal effects of schools on outcomes, without the need for detailed information on the composition of schools. A problem with the lottery-based approach is that it typically relies on schools that are oversubscribed to identify the causal effects. If the oversubscribed schools differ from other schools then this raises questions about the extent to which the findings generalise. An alternative approach to estimating school effectiveness relies on using a regression to control for differences in observed characteristics across schools (Ladd and Walsh (2002), Dearden et al. (2011), Dearden et al. (2011), Cunha and Miller (2014), Ehlert et al. (2014)). However, the results using this approach will be misleading if researchers are unable to adequately control for background variables (Dearden et al. (2011), Ehlert et al. (2014), Beuermann et al. (2018), Nicoletti and Rabe (2018)). Angrist et al. (2017) empirically examine whether the results from these conventional value-added models accurately predict the achievement consequences of random assignment to specific schools. They find that educational policies that reallocate students based on value-added models can boost student achievement, despite moderate biases in the approach. Deming (2014) reaches a similar conclusion. Chetty et al. (2014) report similar findings in value-added evaluations of teacher impacts on student achievement.

Given that the quality of background variables is central to the value-added approach, an advantage of our research is the rich set of controls available in our data. Many studies using administrative data have to rely on variables such as regional income levels or entitlement to free school meals as proxies for parental socioeconomic status. In contrast, we have detailed information on family income, parental education and family structure. In addition we are able to control for early measures of both cognitive and non-cognitive ability; the importance of these for later life outcomes has been emphasised by Heckman et al. (2006).

There is some research explaining differences in academic outcomes across Irish schools (Sofroniou et al. (2000), Pfeffermann, and Landsman (2011), Cullinan et al. (2018), Weir and Kavanagh (2018)). However, measuring value added is not the focus of these papers. An exception is Smyth (1999), who estimates value added across a sample of Irish schools, controlling for background variables and a measure of prior achievement. However, the latter is measured three months prior to the Junior Certificate exam, by which stage students have already spent almost three years in the school. As noted by Smyth, to the extent that this measure is capturing some school effects, controlling for it in a value-added approach will lead to an underestimate of the effect of the school on student outcomes.

In the final section of the paper we consider the link between school quality and school choice. Abdulkadiroglu et al. (2017), Beuermann et al. (2018) and Beuermann and Jackson (2018) estimate the value added of schools in New York, Trinidad and Tobago, and Barbados respectively, and relate these estimates to preferences over schools. Abdulkadiroglu et al. (2017) find that parents prefer schools that enroll higher-achieving peers but conditional on peer quality, their choice is unrelated to causal school effectiveness. This is consistent with Beuermann and Jackson (2018) who find that while parents prefer highly selective schools, these schools are not the highest value added schools in terms of high school examination performance. In contrast Beuermann et al. (2018) find that, even conditional on peer quality, parents do value effectiveness.

Our analysis adds to the literature that cautions against using raw outcomes as indicators of school quality and shows that in a setting where parents have limited information, reallocating students to schools based on value-added measures can have a substantial impact on student outcomes.

2. Irish School System

There are approximately 720 schools in the Irish second-level education system. Although these schools are all state funded, there is no system of state allocation of children to particular schools. Parents apply to the school or schools that they wish their children to attend and depending on the admission criteria of the schools, they may or may not be accepted. These admission criteria may include whether the child lives in a particular area, whether the child attended a ‘feeder’ primary school, religious denomination, whether the child’s siblings attend the school, or whether the child’s parents (or more distant relatives) attended the school; prior academic performance may not be used as a criterion for admission. In some rural areas of the country, parents have little choice about which school their child attends, but in most towns and all cities, there is a choice, and so it is important to understand on which basis parents choose schools.

There are three main categories of schools: voluntary secondary schools; vocational schools and community colleges; and community and comprehensive schools. About 50% of schools are voluntary secondary schools and they account for almost 60% of students. These are schools that were established by religious orders and so are all denominational. Traditionally, they were single sex schools, but over the years about 40% have become mixed, often due to the amalgamation of the boys' and girls' school in an area.

About 46% of schools are vocational schools or community colleges, almost all of which are mixed. These schools, which cater for about a quarter of children, are run by area-based Education and Training Boards (ETBs) and are non-denominational. They were traditionally oriented towards technical and manual rather than academic education but that changed since the 1970s and they now provide a full range of academic as well as practical subjects (Hannan and Boyle (1987)). Nevertheless, the perception that bright and/or middle-class children attend secondary schools rather than vocational schools and community colleges persists to some extent. The remaining 2% of schools are comprehensive and community schools, which are run by boards of management that are representative of the local area. They also tend to offer a wider range of subjects than secondary schools. They are denominational and mixed.

The Irish system has the unusual feature that about 7% of schools are fee-paying. These are all secondary schools, so are all denominational. They arose because, when free second-level education was introduced in Ireland in 1967, schools were given the option of participating in the free education scheme or not. Most of the schools that chose not to participate were in upper-middle class areas of the cities – particularly south Dublin; in addition, many Protestant schools remained fee-paying. Fee-paying schools are not eligible for government capital funding, but teachers' salaries are predominantly state funded.[1] For this reason, fees are relatively low by international standards, ranging from about €3,000 to €7,000 per annum. Nevertheless, fee-paying schools are not attended by poor children, apart from a very small number of scholarship places.

While each category of school has its own management structure, individual schools have limited autonomy. For all schools, the Department of Education and Skills sets curricula, regulates the management, funding and staffing of schools, and centrally negotiates teachers' salary scales (Darmody and Smyth (2013)).

To address educational disadvantage, the government operates a scheme designed to channel additional funding towards schools with a high proportion of students from socio-economically deprived areas, the DEIS (Delivering Equality of opportunity In Schools) scheme. DEIS schools benefit from a slightly lower pupil-teacher ratio than other schools. About 27% of all second-level schools are in the DEIS scheme.

As well as the fee income received by fee-paying schools, other schools are allowed to solicit 'voluntary contributions' from students' parents, with varying amounts requested and varying degrees of persuasion applied. These voluntary contributions are particularly prevalent in voluntary secondary schools. This does imply that there are differences in the resources available to schools, since schools with better off students can request – and are more likely to receive – greater voluntary contributions.

All schools follow the same programme. Students typically enter second-level education at age 12 and begin the three-year Junior Cycle. All students must study English, Irish,

[1] Until 2009, teachers at fee-paying schools were funded at the same pupil-teacher ratio as other schools, but since then, the pupil-teacher ratio at fee-paying schools has been reduced so that it is about 20% lower.

Mathematics and CSPE (Civic, Social & Political Education).[2] Most students also take a foreign language, History, Geography and Science, and typically at least two other optional subjects, including everything from Ancient Greek to Woodwork. At the end of the Junior Cycle, at about age 15, they sit the Junior Certificate, which entails a written state-wide examination in each of the 10-13 subjects studied.[3] Apart from CSPE, all subjects can be taken at either Higher or Ordinary level, with an additional Foundation level available for Irish and Maths. They then enter the Senior Cycle, which takes a further two or three years, depending on whether the student undertakes the optional 'Transition Year'. At the end of the Senior Cycle, students sit the Leaving Certificate, usually in seven subjects. The grades obtained in the Leaving Certificate determine whether a student can progress to higher education and the programme to which they are admitted. As such, the Leaving Certificate is a very high stakes exam. The Junior Certificate, on the other hand, is a low-stakes exam, but one that many students and parents take quite seriously as it is regarded as providing practice for the Leaving Certificate. Furthermore, Smyth (1999), finds that performance in the Junior Certificate is highly predictive of performance in the Leaving Certificate, with a correlation of 0.8 between the two.

3. Methodology

To measure the value added of a school it is necessary to control for compositional differences across schools. One way to do this is to estimate the following regression

[2] In limited circumstances students can be exempted from studying Irish, for example if they moved to Ireland in late childhood.

[3] As well as examination subjects, students also take Physical Education, SPHE (Social, Personal and Health Education) and, depending on the school, Religion. Religious Studies may also be taken as an exam subject. Note that the Junior Cycle is currently undergoing reform; the system described is as it pertained in 2012/13, which are the years relevant to the study children.

$$Y_{is} = \beta_0 + \beta_1 YL_{is} + \beta_2 X_{is} + \mu_s + \varepsilon_{is}$$

where Y_{is} is the outcome of student *i* in school s, YL_{is} is prior achievement, X_{is} is a vector of socioeconomic, family and other student characteristics that are important in determining student outcomes and μ_s is a school effect. μ_s therefore measures the individual contribution of the school after background factors and prior achievement have been taken into account. Ehlert et al. (2016) refer to this approach as the one-step value-added model.

The school effect, μ_s, could be interpreted as the value-added score but because this will not be on the same scale as the raw score, researchers often use a predicted score $\widehat{Y_s}$ (Meyer, R. 1997), where $\widehat{Y_s}$ is the predicted score for a given school s with values of YL_{is} and X_{is} set to some benchmark level, such as the mean of all students $\overline{YL_s}$ and $\overline{X_s}$.

$$\widehat{Y_s} = b_0 + b_1 \overline{YL_s} + b_2 \overline{X_{\iota s}} + \widehat{\mu_s}$$

An alternative way to measure value added is to first run the following regression, omitting the fixed effects

$$Y_{is} = \gamma_0 + \gamma_1 YL_{is} + \gamma_2 X_{is} + \epsilon_{is}$$

and then estimate the value added of a school by regressing the residuals from the above regression on a set of school dummies

$$\epsilon_{is} = \mu_s + \eta_{is}$$

Ehlert et al. (2016) refer to this approach as the two-step value-added method. The residual is estimated for every person and the school effect is then calculated as the mean residual across individuals within a school.

Ehlert et al. (2016) and Ladd and Walsh (2002) discuss the relative merits of the one-step and two-step value-added approaches. If, as seems likely, good schools select students on the basis of ability (YL_{is}) or background characteristics (X_{is}) then omitting the school fixed effects in the first stage of the two-step approach will lead to the estimates of γ_1 and γ_2 being biased upwards because they are identified using both within and between school variation. Consequently, the first stage regression will remove too much of the variation in test scores, resulting in value-added estimates that are biased against advantaged schools. Thus, if higher ability students tend to go to schools that are more effective, omitting the fixed effects will rank schools with mostly high (low) ability students too low (high). On the other hand, if prior achievement is measured with error, parameter estimates will be biased towards zero, resulting in value-added estimates that are biased against disadvantaged schools. Including fixed effects and relying solely on within-school variation will exacerbate this bias. In the extreme case where the estimates are driven to zero, the resulting value-added estimates will revert to school means in unadjusted test scores.

Ehlert et al. (2016) argue that if the policy objective is to encourage schools to improve performance, it is better to base value-added measures on the two-step approach, since this approach compares equally circumstanced schools. If, on the other hand, the objective is to identify the most effective schools so that parents can make optimal choices, then we argue that the one-step approach is preferable. Parents care about the overall effectiveness of schools, not just how well a particular school is doing compared to similar schools. Since the focus of this paper is on parental choice, we present the results from the one-step approach. However, as a robustness check, we also examine the sensitivity of our findings when using the alternative two-step approach.

In addition to the choice of appropriate value-added model, it may be necessary to consider ceiling effects when considering school effectiveness. Ceiling effects arise because test scores are bounded. This may bias school effectiveness measures against advantaged schools; the best these schools can hope to achieve is to move students from one test ceiling to another, resulting in an average value-added score. However, this is only true in models where the coefficient on lagged test scores is restricted to be equal to one. To perform well in the general value-added model, it is not necessary that average test scores in a school must improve over time. What matters in this model is the performance of a school relative to its average predicted score given its students' prior test scores and other characteristics. Resch and Isenberg (2018) show that schools or teachers with high-performing students can still have high value-added estimates. In related work, Koedel and Betts (2010) show that over a wide range of test-score-ceiling severity, value-added estimates (of teachers) are only negligibly influenced by ceiling effects. They find correlations between ceiling-restricted value-added estimates and unrestricted estimates of approximately 0.92, even in situations where 25% of students are affected by the ceiling. Only when over half of students are affected by the ceiling do they find significant biases in value-added estimates. We examine the relevance of ceiling effects for our analysis in Sections 4 and 5.

4. Data

The data used in this paper are drawn from the Growing Up in Ireland (GUI) study, which tracks the development of a cohort of children born between November 1997 and October 1998. So far, data from the first three waves are available; these were taken when the children were aged 9, 13 and 17/18. We use data from all three waves in this research. The initial survey sample was generated through the national primary school system, with children from 910 (of about 3,300) randomly selected schools participating in the study. The sample of children and their families was randomly generated from within these schools. The response rate at the family level was 57 per cent, yielding information on a total of 8,568 study children. In the first wave, information was collected from the children, their parents, their teachers and school principals.

The study children then moved into various second-level schools according to their parents' choices and the schools available to them. As a result of the relatively free school choice, 627 schools are included in the second wave, which comprises about 87% of all schools in the state.

The second and third wave questionnaires again collected information from the children, their parents and the principals of their second-level schools. In the second wave, various ability tests were administered to the children, but no curriculum-based test was given. However, by the time of the third wave, the children had all sat their Junior Certificate examinations, so their results in each subject were collected, together with the level (Higher, Ordinary or Foundation) at which they had taken each subject.

To measure academic achievement, we use self-reported scores[4] from the Junior Certificate as the dependent variable. Following Sofroniou et al. (2000), we convert the grades for each subject from the Junior Certificate into a numerical value. Using this conversion, the maximum score a student can get in any subject is 12 and the minimum positive score is 1 (see Appendix for more detail). To construct our overall performance scale (OPS) we add the scores

[4] We have compared these to the scores based on administrative data given in Weir and Kavanagh (2018) and our averages scores are slightly higher which may be due to sample selection issues or the self-reported nature of our exam scores.

from each student's seven best subjects. As a robustness check we also discuss findings using the best ten scores.

The GUI data have detailed background information on both the student and their parents which is important for our value-added approach. As part of the first survey (age 9) each child took reading and maths tests, which were administered by GUI fieldworkers at the child's school. These curriculum based tests, known nationally as 'Drumcondra' tests, have been used for many years in Irish schools to track student performance. We use these to measure prior academic achievement.

Heckman et al. (2006) argue that for many outcomes, the effect of non-cognitive skills is comparable to or greater than the effect of cognitive skills. The GUI has several measures of non-cognitive skills of the child, measured by both the parent and their teacher. A set of questions called the Strengths and Difficulties Questionnaire (SDQ) is used to collect information on the child's socio-emotional development and behaviour. It comprises 25 items that assess emotional problems, conduct problems, hyperactivity/inattention and peer relationships. Evaluations of the SDQ test indicate that it has good psychometric properties (Stone et al. (2010)); typically children in the highest decile of the SDQ 'total difficulties' score are likely to be at a significantly higher risk of socio-emotional problems.[5] We use SDQ scores in estimating our value-added models. We are unware of any previous study that has controlled for prior measures of both cognitive and non-cognitive skills when measuring the value added of schools.

The GUI also has a very rich set of family background variables which allows us to control for family income, parental education and family structure. Since girls mature earlier than boys,

[5] See for example http://www.sdqinfo.com/a0.html

we also include the gender of the child in the model. This may be especially important when considering value added in single-sex schools. These controls provide for a much richer specification than is typically possible when using administrative data to estimate school value added models.

We use information on the second-level school attended in the wave two. In order to balance the precision of the value added estimates against the number of schools included in the analysis, we exclude schools with fewer than five study children. Although the minimum is five, the average number of sampled students in a school in our analysis is 15 and the maximum is 48.[6] We also exclude schools that solely cater for students with special needs and a very small number that did not provide a valid school type code. Once all restrictions are in place we are left with a working sample of 4,577 students across 388 second-level schools, corresponding to approximately 54% of all second-level schools in Ireland.

The mean Junior Certificate overall score for these students is 73.25 with a variance of 55.25. The minimum score is 35.5 and the maximum is 84, with 4.84% of students achieving this maximum. Looking across schools we find that the average percentage of students scoring the maximum within a school is 5.17%, with no school having more than 40% getting the maximum.

If we assign to each student the school average test score, the variance falls from 55.25 to 12.84. Therefore 23.3% of the total variance in overall Junior Certificate scores is accounted for by between-school variation.[7] Smyth (1999) obtains a similar result (22%) in an Irish data set with fewer schools but more observations within each school. This is also consistent with previous

[6] An approximate calculation indicates that on average our sampled students correspond to about 14% of the relevant school class.
[7] The proportion of overall variance accounted for by between-school variation using the best 10 subject scores is 22.49%.

international research that typically finds within-school variation accounting for the majority of the variance in test scores (OECD (2004)).

Table 1 provides summary statistics for the variables used in our analysis. The 4,577 students are spread across 388 schools and so value added measures are calculated for all these schools. However, when reporting summary statistics across schools we restrict the sample to the 338 schools that provide the information used when examining the determinants of value-added in Section 5.2. In our analysis we distinguish between four school types; fee-paying, non-DEIS secondary, non-DEIS vocational/community and DEIS. Looking at the distribution of school types we see that about 9% of schools are fee-paying and 27% are non-DEIS vocational/community, both figures that are consistent with the national distribution. However, at 13%, DEIS schools are substantially underrepresented in our sample, given that they account for 27% of all schools nationally. This is because these schools are typically smaller and therefore less likely to satisfy our inclusion criteria. By the same reasoning, non-fee paying non-deis secondary schools are overrepresented in our sample because they tend to be larger.

5. Results

5.1 Measuring Value Added

As a preliminary analysis, we rank schools according to the average Junior Certificate score in each school. This is in keeping with the league tables based on raw outcomes available to parents in Ireland. Information on our rankings is presented in Figure 1, which graphs the average Junior Certificate score in each school, ranked from lowest to highest, together with 95% confidence intervals. Although it is difficult to distinguish between schools in the middle of the rankings, we can to some extent distinguish between high and low performing schools. In particular the bottom

15% of schools, whose upper bound is typically less than or equal to 74, can be identified as low performing, when compared to those in the top 15%, whose lower bound generally exceeds 74.

However, if children with higher prior achievement or from a higher socioeconomic background cluster in particular schools, then it is difficult to distinguish good schools from schools with good students. To examine selectivity across schools, we plot the prior maths and reading achievement scores, household income and non-cognitive skill scores by quartile of raw Junior Certificate scores. These are given in Figures 2-5. For both maths and reading, the distributions for schools in the top quartile of Junior Certificate scores are furthest to the right, followed in order by each of the other quartiles. The ranking by parental income is similar. It is also apparent that children attending schools in the lowest quartile have poorer non-cognitive skills. The same pattern applies to parental education and family structure. The proportion of parents with a university education is 33% overall, but 48% for students attending schools in the top quartile and 21% for those in the bottom quartile. Likewise, the proportion of students living in households without their father is 23% overall, but 17% for students in schools in the top quartile and 31% for students in the bottom. These clear differences across schools illustrate the importance of the controlling for compositional differences when assessing school effectiveness.

The results from the one-step value added model are given in Table 2. Although the coefficients on the school fixed effects are what are used to measure value added, it is also informative to examine the coefficients on the prior achievement and background variables. All the estimates are statistically significant with the expected signs. When interpreting the magnitude of these coefficients, it is useful to recall that the standard deviation of Junior Certificate scores in our sample is approximately 7.4. The point estimates on prior cognitive achievement indicate that a one unit (one standard deviation) increase in a student's prior reading score is associated with a

0.28 standard deviation increase in their Junior Certificate score, while a one unit increase in the prior maths score increases the Junior Certificate score by 0.20 standard deviations. Looking at the results on non-cognitive achievement, taking into account that moving a child from the bottom quartile of the SDQ distribution to the median entails a two unit increase in SDQ score, the regression results imply that this would decrease the Junior Certificate score by 0.07 standard deviations. In addition, students with the lowest level of persistence/attention span as reported by teacher have Junior Certificate scores that are 0.35 standard deviations lower than those in the highest category. Girls' Junior Certificate scores are approximately 0.06 standard deviations higher than boys'. Students who have a parent with a university degree have Junior Certificate scores that are 0.22 standard deviations higher. Students from wealthier backgrounds are also more likely to have higher scores; a €10,000 increase in equivalised income is associated with a 0.07 standard deviation increase in Junior Certificate scores. Finally the father being absent from the household is associated with a Junior Certificate score that is 0.18 standard deviation lower, while having a main caregiver who is Irish is associated with a Junior Certificate score that is 0.08 standard deviations lower.

We use these estimates to calculate the one-step value added measure $\widehat{Y_s}$. In particular we estimate $\widehat{Y_s}$ for boys with average values for prior test scores, equivalised income and SDQ scores, with a high level of persistence and whose parents are Irish, have a university degree and are both present in the household.

Figure 6 shows the average value-added score in each school, ranked from lowest to highest.[8] The graph in Figure 6 is notably flatter than that given for raw scores in Figure 1. To

[8] We have also estimated value-added using the two step value added model. The rank correlation in value added between the one-step and two step models is 0.99.

verify this we estimated a non-parametric kernel based local-linear regression through the data given in Figures 1 and 6. The average estimated derivative in Figure 6 is half of that in Figure 1, with the difference in slopes particularly pronounced at the lower end. This reduction in slope translates into a 28% reduction in the standard deviation of value-added scores across schools relative to raw Junior Certificate scores (2.80 compared to 3.89).

However, despite the reduced variance there is still evidence in Figure 6 of high and low value-added schools. As with raw scores, we can distinguish between the bottom and top 15% of schools, based on a value-added threshold of approximately 75. However, there is nothing in the analysis thus far that requires that the schools that perform well in raw Junior Certificate scores (Figure 1) are the same schools that perform well in value-added terms (Figure 6). To examine this, we plot a school's value-added score against its ranking in raw scores. These are given by the triangles in Figure 7, which can be compared to the dark dots indicating raw performance. For the most part, schools that have the lowest raw scores perform much less poorly in value-added terms and the strong performance of the top ranking schools in raw terms is less evident. To illustrate this we also present a non-parametric regression of value-added on raw rank, given by the light dashed line. The average derivative of this line is 0.019, confirming the weak relationship between raw ranks and value-added performance over much of the range.

These results imply a substantial reranking of schools when we switch from raw scores to value-added scores; the top performing schools in value-added are not necessarily the top performing schools in raw Junior Certificate scores. Figure 8 illustrates this reranking using a scatterplot of the raw and value added ranks. Schools above the 45 degree line improve their ranking when selection is accounted for, while those below disimprove. The rank correlation between raw and value-added scores is 0.72. Jenkins and van Kerm (2006) provide a decomposition technique that quantifies the importance of re-ranking in distributional analysis. Using this decomposition we find that, had ranks remained fixed, the reduction in inequality would have been 36% larger than was actually observed. The standard practice of looking at reductions in variances across schools when moving from raw to value-added measures therefore tends to understate (overstate) the value-added performance of schools that are ranked low (high) in raw terms.

As noted earlier, second-level schools in Ireland are classified by school type, distinguishing between fee-paying, secondary, community/vocational and DEIS schools. Anecdotal evidence suggests that school choice is often based on this classification and indeed information on school type is one of the relatively few characteristics of schools provided to parents by the Department of Education and Skills.[9] To examine the extent to which student characteristics vary by school type, we plot the prior maths and reading achievement scores, household income and non-cognitive scores by school type. These are given in Figures 9-12, which show clear differences across school types in terms of student intake. In order to consider whether the reranking discussed above depends on school type, Figure 13 reproduces Figure 8, including identifiers for school type. As fee-paying schools are predominantly located below the diagonal line and the DEIS schools above, it is apparent that the reranking of schools is not independent of school type. However, it is also evident that there is a lot of variation in value-added performance within each school type. In the next section we examine the determinants of value-added in more detail.

[9] https://www.education.ie/en/Publications/Statistics/Data-on-Individual-Schools/

5.2 Determinants of School Value Added

In this section, we consider the factors that are important in determining school value-added. The results are presented in Table 3, which includes an analysis of raw Junior Certificate scores for comparison. These estimates are based on the 338 schools that have complete information on all variables. The first column and third columns present results for raw and value-added measures respectively, including only school level information that can be obtained by parents from publically available sources. These include the school type, whether the school is single sex, and the size and religious ethos of the school. In the second and fourth columns we add variables that are not readily available to parents but are available in the GUI data. These include indicators for the sex of the principal and whether the school uses class tutors, operates a student mentoring system, offers study skills classes and streams students according to ability. We also include information provided by the principal on the incidence of numeracy, literacy and emotional problems amongst student in the school and average daily attendance, which we think might capture school peer effects. Finally, we control for the average local area unemployment rates, which is included to capture peer effects from the student's residential area.

Looking at column 1, we find that on average fee-paying schools are ranked about 120 places ahead of secondary schools in raw outcomes and about 212 places above DEIS schools; school type clearly matters for raw Junior Certificate scores. None of the other regressors included in column 1 have a significant effect on raw scores. When we consider the full specification in column 2 we see that the effect of school type is still large and significant although smaller than in column 1. Schools with a female principal tend to be ranked higher (by about 28 places) and schools with students from high unemployment areas rank significantly lower.

When we look at the determinants of value added in columns 3 and 4, the results change. In contrast to the earlier results, the dominance of fee-paying schools is no longer evident in value-added terms. In fact vocational schools now outperform all other school types, with the effect being statistically significant in the full specification. These findings are in keeping with the re-reanking results reported earlier and with the work of Cullinan et al. (2018), who found that attending a fee-paying school does not affect individual exam scores when family background is controlled for. As noted earlier, while some fee-paying schools continue to rank highly on measures of value added (see Figure 9), when viewed in aggregate, fee-paying schools as a group perform no better than other second-level schools.

In keeping with the results for raw scores, if students in a school come from areas with high local unemployment then the school is ranked lower in value-added terms, perhaps indicating local peer effects. Also schools with female principals have higher value added. This may reflect differences in leadership style between male and female principals. In a recent meta-analytic study, Hallinger et al. (2016) found evidence of a gender effect on instructional leadership, with female principals showing more active instructional leadership (see also Shaked et al. (2018)). Alternatively, if only particularly able women go forward for principalships or more progressive schools hire female principals, then this could reflect a selection effect.

Despite the fact that we find differences in value added across schools, it is striking how few of the variables we include affect a school's ranking. This may indicate that the factors determining value added are related to idiosyncratic school effects such as effective management, which are difficult to measure. The Department of Education and Skills conducts Whole School Evaluations that include qualitative assessments of school leadership. Combining these evaluations with our value added measures could provide additional insight into effective management practices.

5.3 School Choice

In this section, we examine whether parents are influenced by a school's value added when choosing a school for their child and the extent to which school choice matters to a child's school performance. Unlike in other school systems where parents are asked to rank schools in order of preference, we cannot observe parents' preferences directly. Instead, we observe a binary variable denoting that the school is oversubscribed, as reported by the principal. Table 4 shows the results of a probit model in which the oversubscribed indicator is regressed on the rank of the school attended in raw and value added scores. The results show that schools with high average raw scores are significantly more likely to be oversubscribed, whereas schools with high average value added are not. An improvement of 100 ranks in raw scores is associated with a 4 percentage point increase in the probability of a school being oversubscribed. Including both raw and value added ranks indicates that conditional on average raw scores, schools with high value added are significantly *less* likely to be oversubscribed.

The result that value added scores do not raise the probability of a school's oversubscription is consistent with the results of Abdulkadiroglu et al. (2017) for New York City. They find no impact of school effectiveness on school choice once school average outcomes are conditioned on. Our results may imply that parents cannot discern a school's causal impact and so use the average raw score as a signal of its true impact. Alternatively, parents may value a broader set of outcomes that are not well measured by test scores (Beuermann and Jackson (2018)). For example, they may value the school's sports or other facilities, its extra-curricular programme, its ethos or its longer run benefits on education, employment and health.

The above results suggest that parents are not choosing the 'best' schools for their children. In order to examine the extent to which school choice matters for test scores, we carry out a counterfactual simulation, where we reassign each student to the best value-added school accessible to that student. Because there is no detailed information on a child's location in the dataset, nor on the school's, we identify the set of accessible second level schools to student *i* as the set of schools attended by any classmate of student *i* in their primary school. In some parts of the country, there is effectively no choice available to students; for 9.6% of students in our sample, all the sample children in their primary school attended the same second level school. However, for the remaining children, there was some variation in the schools they attended; from any given primary school in the first wave, children attended between one and 16 second-level schools in the second wave, with a median figure of 4. For each child, we identify the school with the highest value added score of the accessible schools. We then calculate the predicted score of each child using the child's own characteristics for both its own school and the best available school. We find that on average the effect of each child attending the best available school is to raise scores by 1.45 points or 0.28 standard deviations. This effect is substantial when placed in the context of the value-added results presented earlier. The estimated effect of school choice is equivalent to a one standard deviation increase in prior reading ability or having a parent with a university degree. Our estimate is also consistent with international research. Angrist et al. (2017) found in their analysis that closing the lowest ranked district school and sending the students to schools with average value added boosted achievement by 0.37 standard deviations.

While we acknowledge that parents may make decisions about schools for reasons other than academic success, our results show that providing parents with information on the value-added of schools and allowing them to choose on this basis, from among a reasonable set of feasible alternatives, can have a meaningful impact on the academic success of their children.

6. Conclusion

When students non-randomly select into schools according to prior achievement or other socioeconomic factors, it can be difficult for parents to identify good schools. This is especially true in countries, like Ireland, where the information available to parents is very limited. In this paper we use a rich data set with detailed information on cognitive skills, non-cognitive skills, family income, parental education and family structure. We show that these characteristics have a large impact on academic achievement and also vary substantially across schools. Controlling for selection substantially changes the rankings of schools.

School type is important in determining raw ranks, with fee-paying schools overrepresented among the highest performing schools in raw terms. However, this is not true once we account for compositional differences. Indeed our analysis suggests that vocational schools, which were traditionally perceived as less academic schools, outperform other school types in value-added terms. Schools with female principals rank highly in terms of both raw and value added performance. However, in general the factors determining value added appear to be related to unobserved individual school practices, rather than systematic school policies.

Finally, we show that parents base their school decisions on raw scores rather than value added, which implies that they may not be sending their children to the 'best' schools. Reallocating students to schools on the basis of value added can substantially boost student outcomes. When we simulate the effect of all children attending their best available school, we find that the average score increases by 0.28 standard deviations, which is comparable to the impact of having a parent with a university degree. Providing information on the value added of schools to parents when making their school choices has the potential to boost academic achievement without incurring substantial costs.

Figure 1: Rankings of Schools based on Raw Junior Certificate Scores

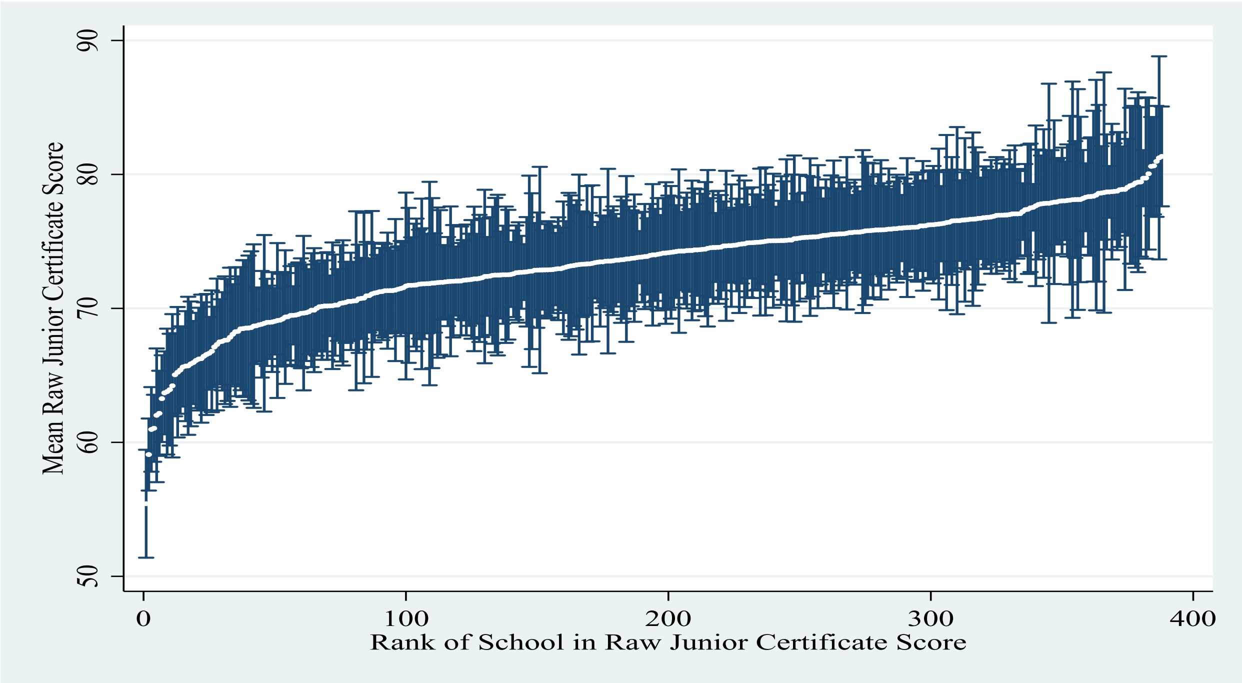

Figure 2: Distribution of Age 9 Maths Scores by School Raw Junior Certificate Ranking

Figure 3: Distribution of Age 9 Reading Scores by School Raw Junior Certificate Ranking

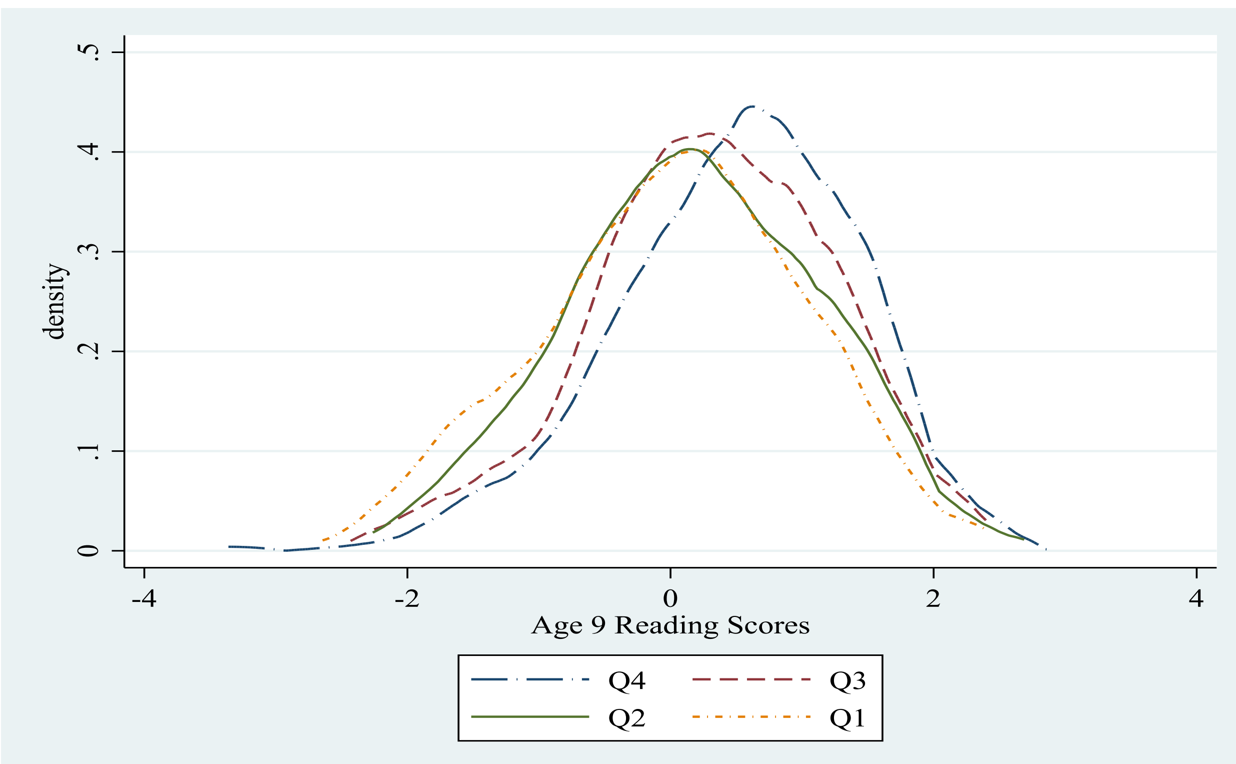

Figure 4: Distribution of Household Income by School Raw Junior Certificate Ranking

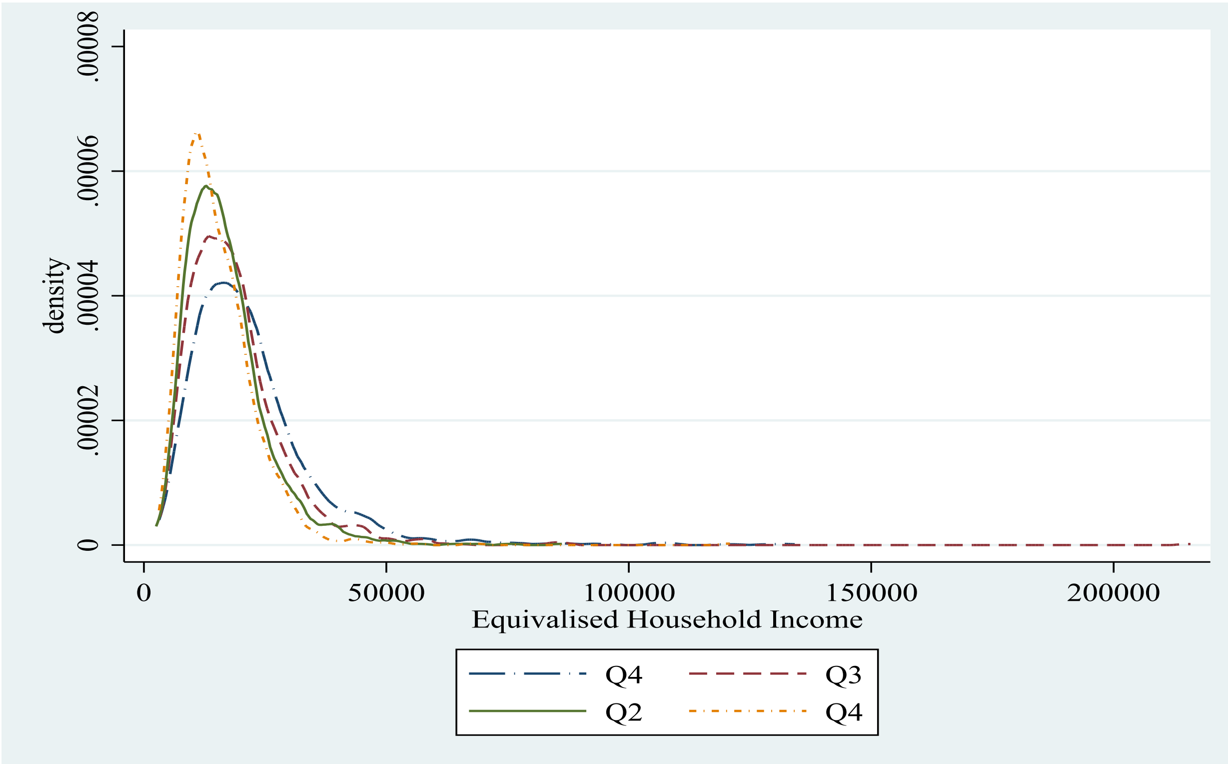

Figure 5: Distribution of Non-Cognitive Skills by School Raw Junior Certificate Ranking

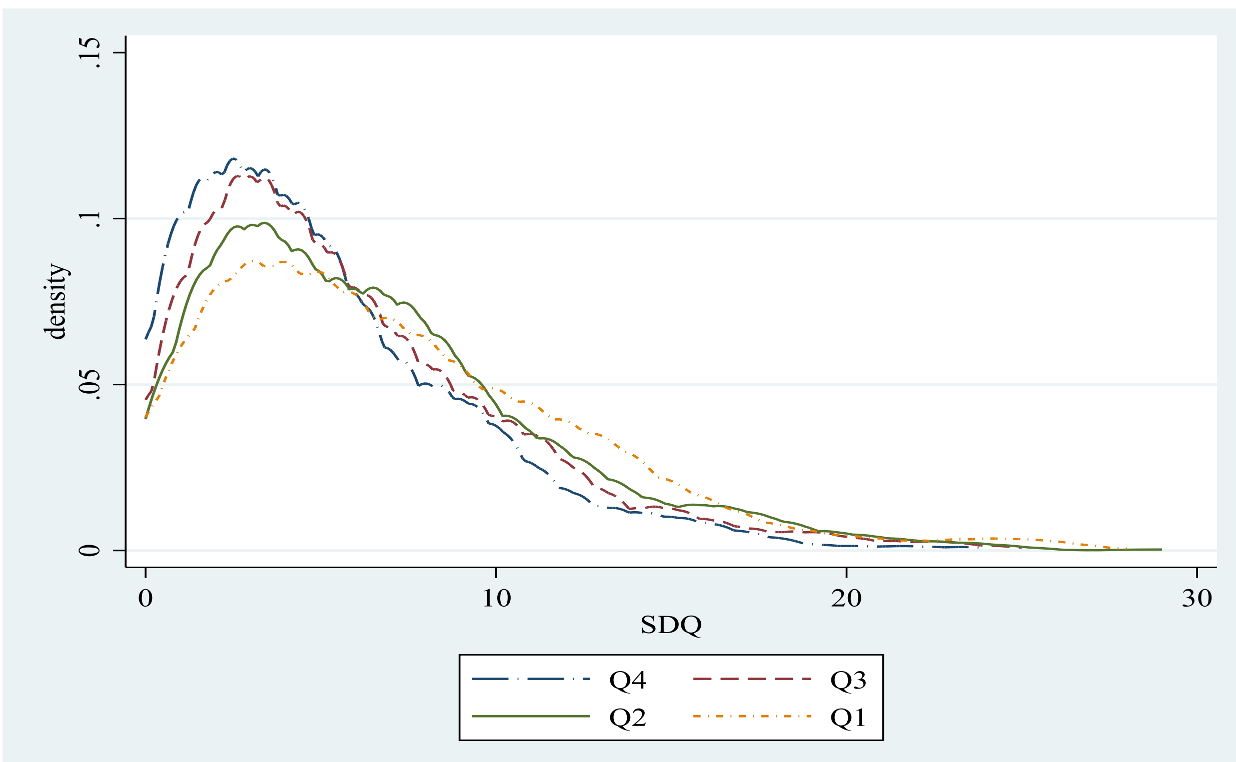

Figure 6: Value-Added Scores Ranked by Value-Added

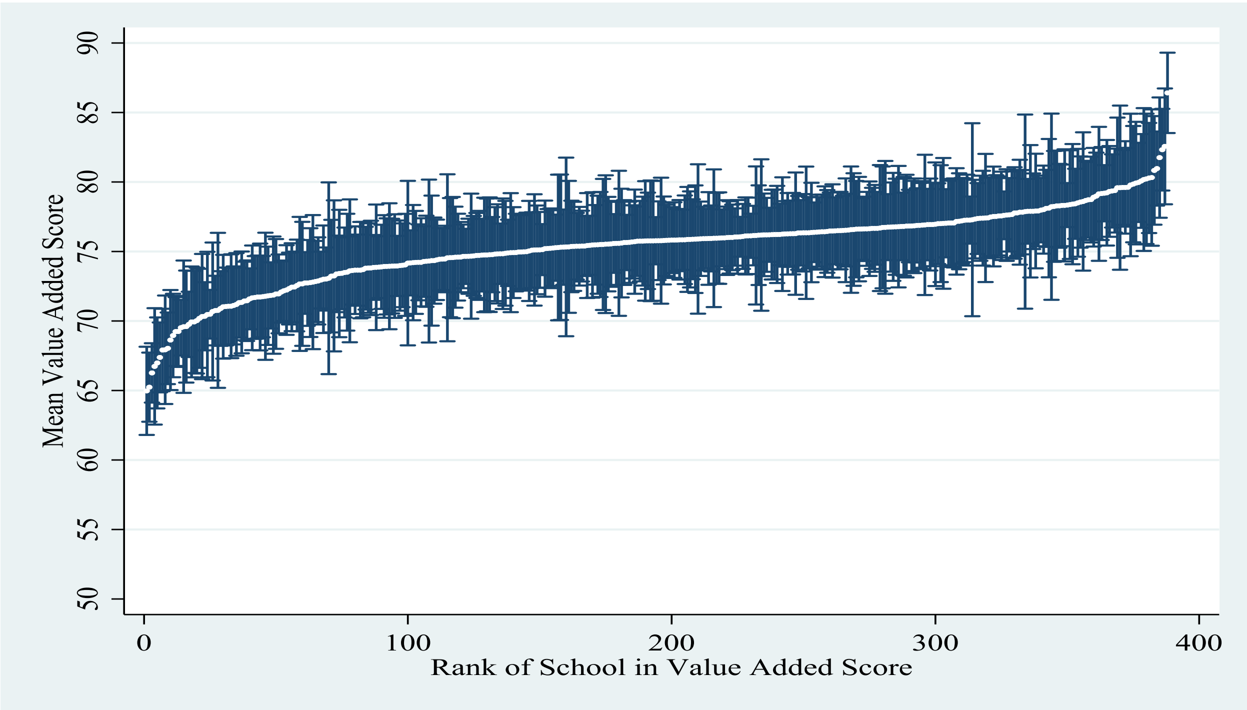

Figure 7: Raw and Value-Added Scores Ranked by Raw Scores

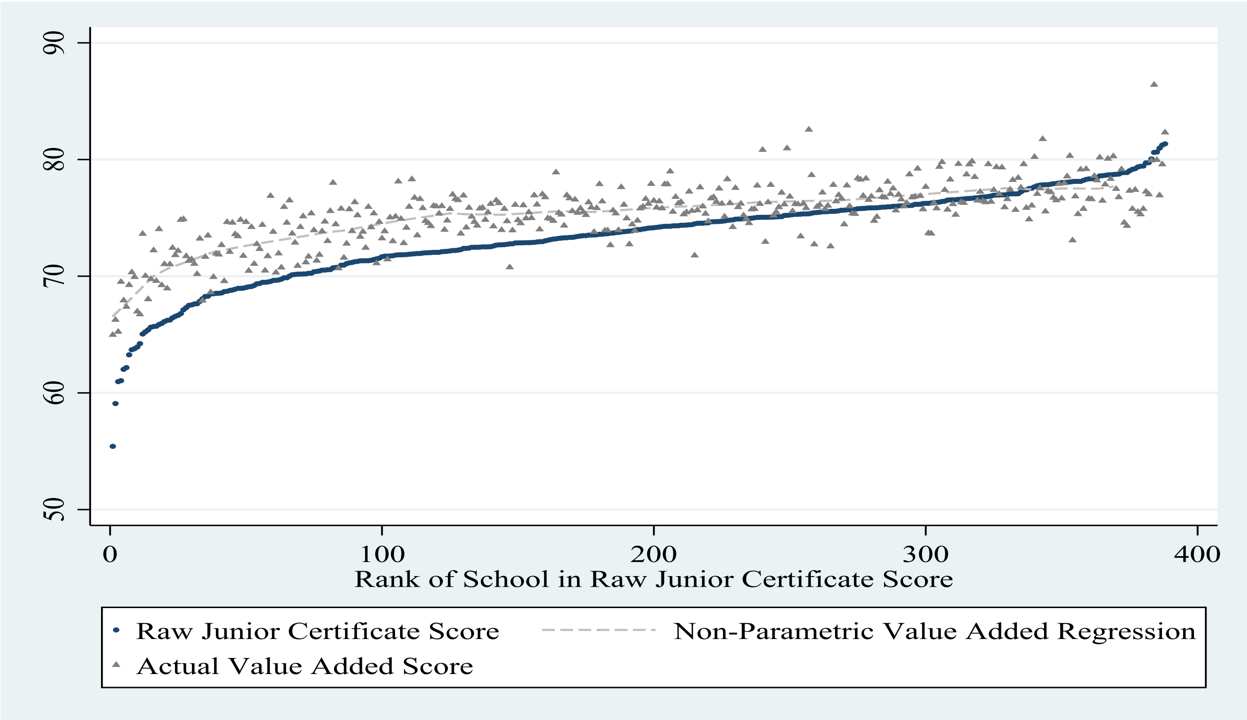

Figure 8: Correlation between Raw Rank and Rank in Value Added

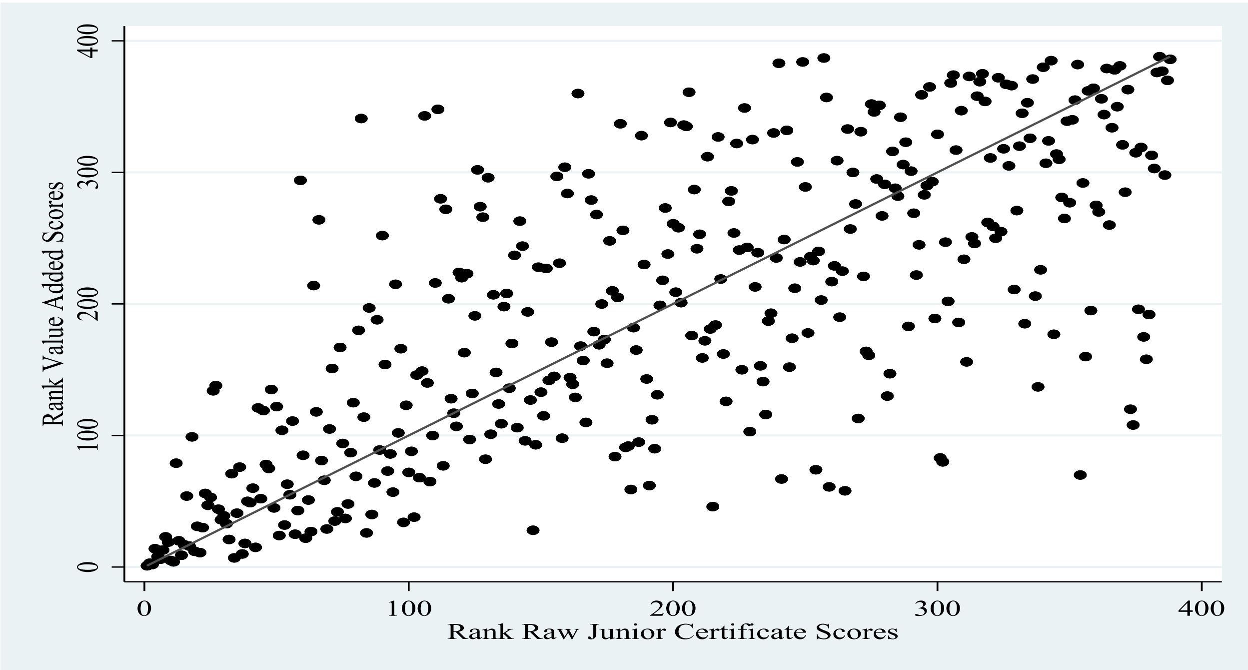

Figure 9: Distribution of Age 9 Maths Scores by Second-Level School Type

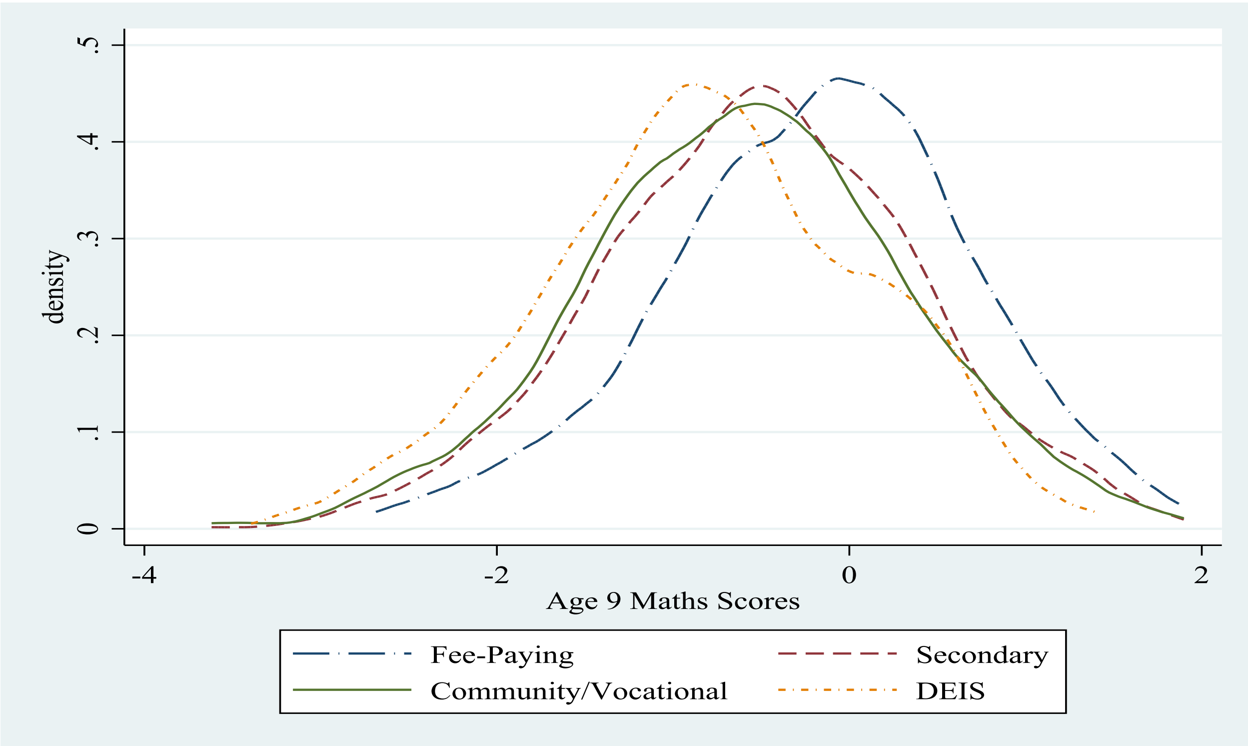

Figure 10: Distribution of Age 9 Reading Scores by Second-Level School Type

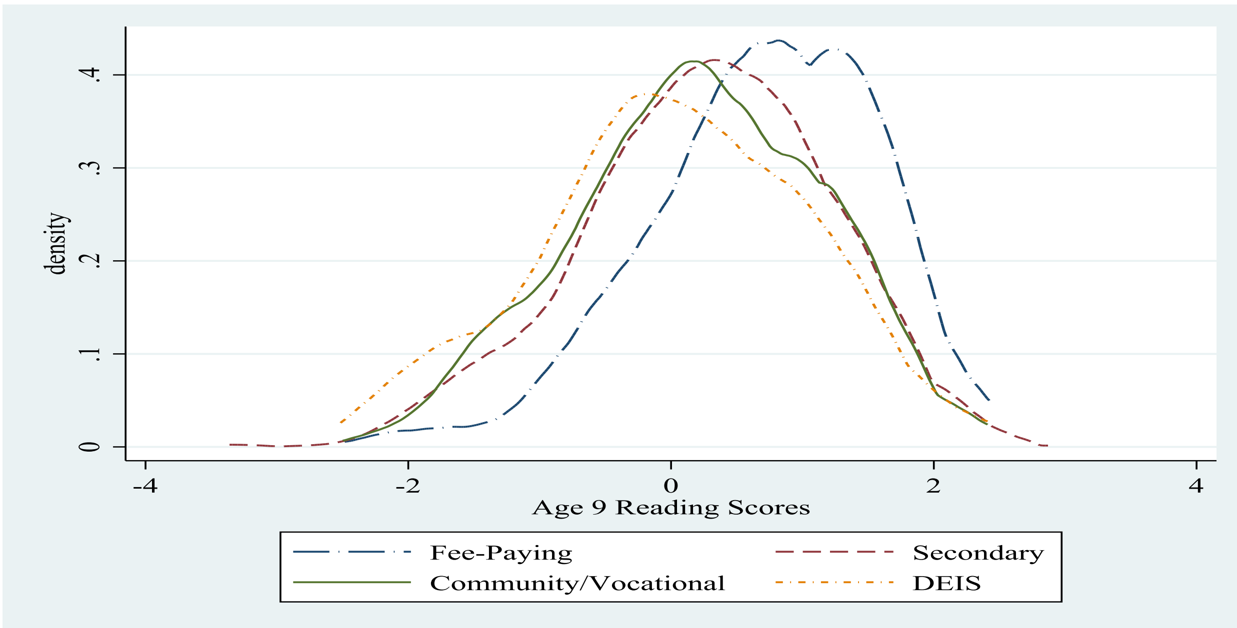

Figure 11: Distribution of Household Income by Second-Level School Type

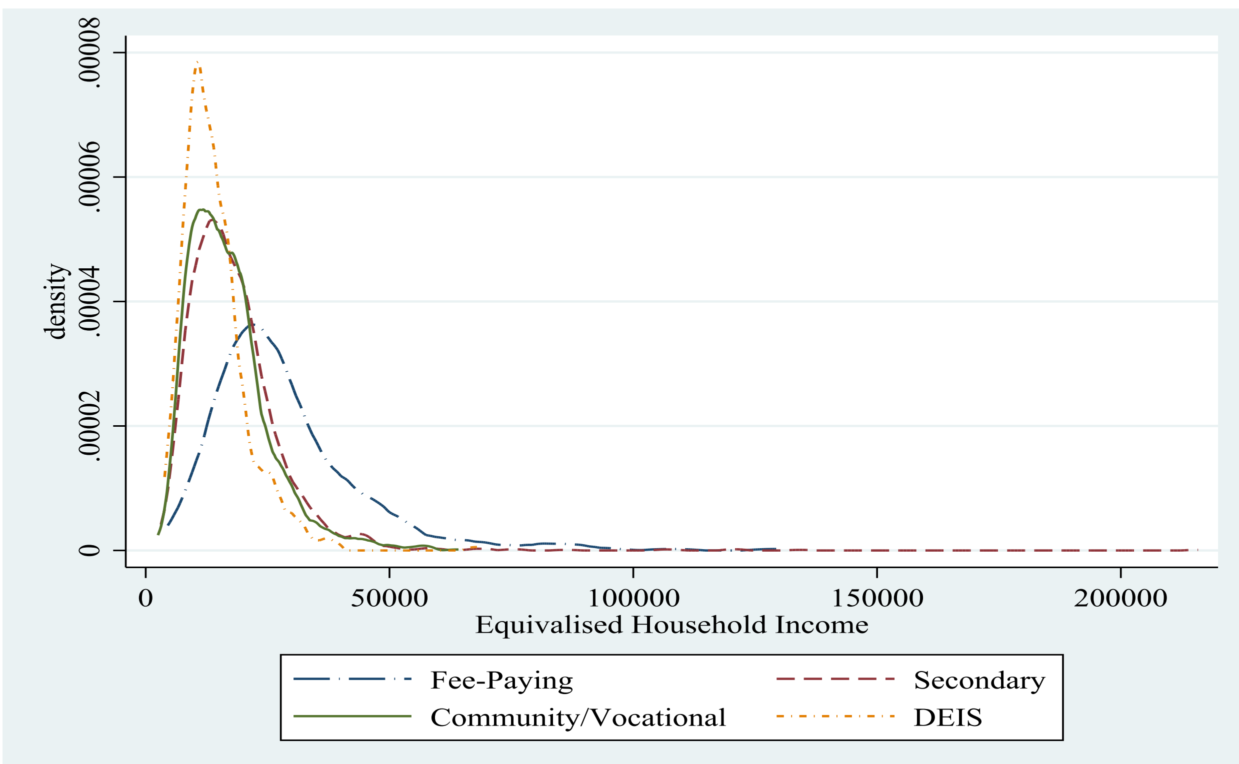

Figure 12: Distribution of Non-Cognitive Skills by Second-Level School Type

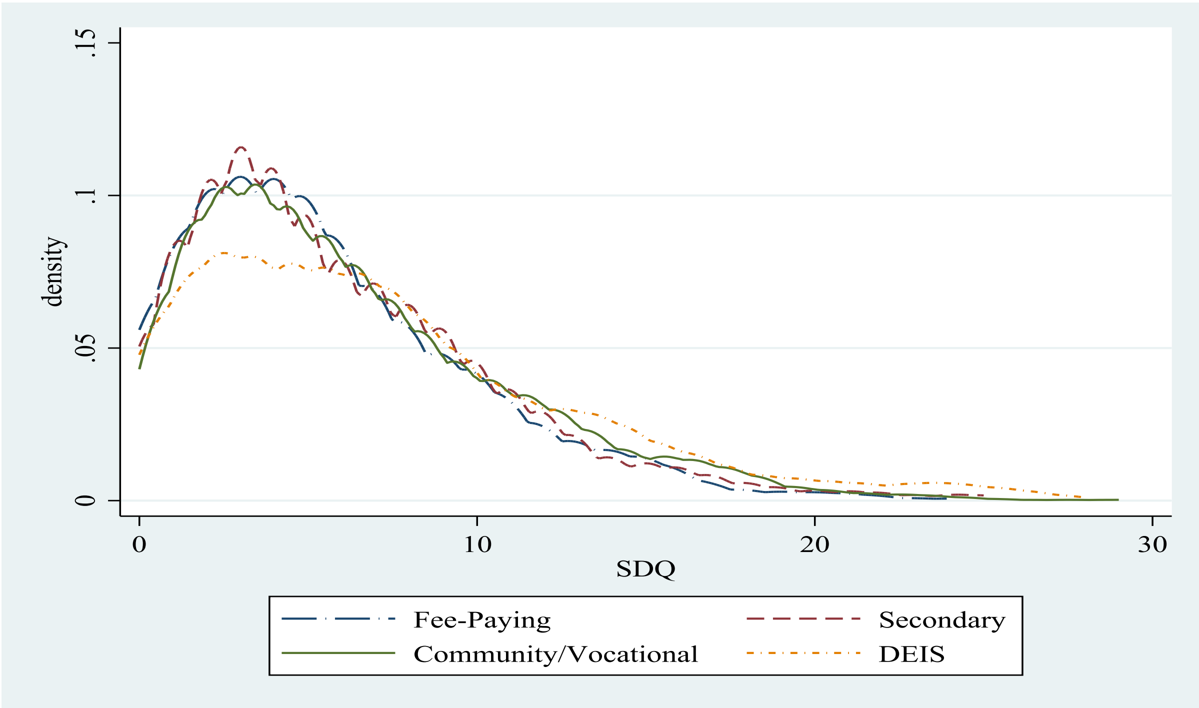

Figure 13: Correlation between Raw Rank and Rank in Value Added by School Type

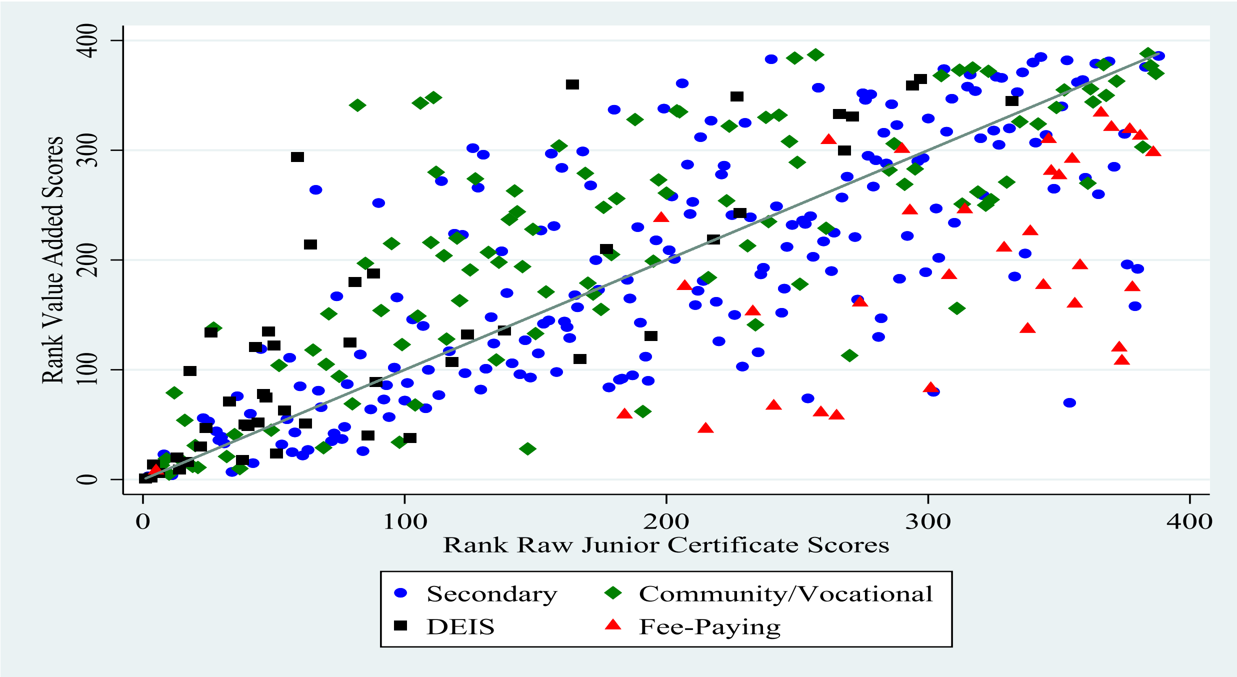

Table 1: Summary Statistics

	Across Individuals Mean (Standard Deviation)		Across Schools Mean (Standard Deviation)
Junior Certificate Overall Performance Score	73.24 (7.43)	Fee-Paying	0.09 (0.28)
Reading Score -age 9	0.10 (0.99)	Non-DEIS Secondary	0.51 (0.50)
Maths score – age 9	-0.67 (0.92)	Non-DEIS Vocational	0.27 (0.45)
SDQ Score	6.5 (4.94)	DEIS	0.13 (0.34)
Attention Span – medium	0.33 (0.47)	Boys' School	0.21 (0.40)
Attention Span- high	0.56 (0.50)	Girls' School	0.24 (0.43)
Male	0.50 (0.50)	Medium Size	0.52 (0.50)
Irish	0.93 (0.25)	Large Size	0.28 (0.45)
		Religious Ethos	0.70 (0.46)
Family Equivalised Income	16,662 (10,352)	Streaming	0.18 (0.39)
		Class Tutors	0.98 (0.14)
Parent Degree or Higher	0.33 (0.47)	Student Mentors	0.86 (0.35)
		Study Skills	0.78 (0.42)
Father Not Present in Household	0.23 (0.42)	Female Principal	0.39 (0.48)
		Literacy Problems	0.50 (0.50)
		Numeracy Problems	0.52 (0.50)
		Emotional Problems	0.21 (0.41)
		Average Daily Attendance	89.2% (16.16)
		Local Unemployment Rate	4.89 (1.65)
N (individuals)	4577		N (Schools) 338

Table 2: First Stage Value Added Regressions: Dependent Variable is Junior Cert Score[10]

	Junior Cert Score
Reading Score -age 9	2.09***
	(0.11)
Maths score – age 9	1.44***
	(0.12)
SDQ Score	-0.25***
	(0.02)
Attention Span – medium	0.77***
	(0.29
Attention Span- high	2.61***
	(0.29)
Male	-0.44**
	(0.23)
Irish	-0.57*
	(0.33)
Family Equivalised Income/1000	0.054***
	(0.0009)
Parent Degree or Higher	1.59***
	(0.19)
Father Not Present in Household	-1.33***
	(0.20)
N (individuals)	4577

se in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

[10] School Fixed Effects included.

Table 3: Determinants of School Raw Rank and Value-Added Rank

	(1) Junior Cert Raw Rank	(2) Junior Cert Raw Rank	(3) Junior Cert Value-Added Rank	(4) Junior Cert Value-Added Rank
Constant	330.83***	353.02***	208.23***	194.56***
	(28.36)	(60.75)	(31.07)	(68.15)
Non-DEIS Secondary	-119.78***	-86.80***	-13.75	14.81
	(19.95)	(25.68)	(21.86)	(22.55)
Non-DEIS Community/ Comprehensive	-133.14***	-91.04***	24.47	61.32**
	(25.83)	(25.68)	(28.29)	(28.80)
DEIS	-212.10***	-143.54***	-57.26*	-6.75
	(27.41)	(28.76)	(30.03)	(32.26)
Boys' School	-14.24	-3.17	-21.24	-7.41
	(17.19)	(17.02)	(18.83)	(19.10)
Girls' School	22.45	10.15	8.06	-6.14
	(16.67)	(16.97)	(18.25)	(19.04)
Medium Size	-27.26	-24.06*	-28.19*	-23.05
	(14.60)	(14.83)	(15.99)	(16.01)
Large Size	-5.41	1.95	-30.77*	-23.55
	(16.14)	(15.96)	(17.68)	(17.91)
Religious Ethos	3.34	12.77	30.04	36.48*
	(18.27)	(17.55)	(20.02)	(19.67)
Streaming		-17.57		-14.96
		(14.03)		(15.73)
Class Tutors		8.95		-30.31
		(37.75)		(42.35)
Student Mentors		-8.39		17.99
		(15.31)		(17.17)
Study Skills		-6.81		4.99
		(12.92)		(14.48)
Female Principal		27.93**		36.59***
		(12.58)		(14.11)
Literacy Problems		3.87		7.20
		(21.33)		(23.93)
Numeracy Problems		-19.37		-8.59
		(21.70)		(24.33)
Emotional Problems		-14.56		-6.95
		(14.11)		(15.83)
Average Daily Attendance		0.28		0.50
		(0.33)		(0.37)
Local Unemployment Rate		-17.57		-14.26***
		(3.46)		(3.88)
N Schools	338	338	338	338

se in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Parental Choice and School Rankings (Probit Marginal Effects)
Dependent Variable is an Indicator Variable for School Oversubscribed

	(1)	(2)	(3)
Rank in Raw Junior Certificate Score	0.0004*		0.001***
	(0.0002)		(0.0003)
Rank in Value-Added Score		-0.0002	-0.001***
		(0.0002)	(0.0003)
N	378	378	378

se in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

.

Appendix 1 : Conversion of Junior Certificate Grades to Performance Scores

Higher	Ordinary	Foundation	Performance Score
A			12
B			11
C			10
D	A		9
E	B		8
F	C		7
	D	A	6
	E	B	5
	F	C	4
		D	3
		E	2
		F	1

References

ABDULKADIROGLU, A., J. ANGRIST, and P. PATHAK (2014): "The Elite Illusion: Achievement Effects at Boston and New York Exam Schools," *Econometrica*, 82, 137-196.

ABDULKADIROGLU, A., P. A. PATHAK, J. SCHELLENBERG, and C. R. WALTERS (2017): "Do Parents Value School Effectiveness?," *National Bureau of Economic Research Working Paper Series*, No. 23912.

ANGRIST, J., P. HULL, P. PATHAK, and C. WALTERS (2017): "Leveraging Lotteries for School Value-Added: Testing and Estimation," *Quarterly Journal of Economics*, 132, 871-919.

BEUERMANN, D., and C. K. JACKSON (2018): "Do Parents Know Best?: The Short and Long-Run Effects of Attending the Schools That Parents Prefer." IDB Working Paper Series no. idb-wp-914

BEUERMANN, D., C. K. JACKSON, L. NAVARRO-SOLA, and F. PARDO (2018): "What Is a Good School, and Can Parents Tell? Evidence on the Multidimensionality of School Output," *National Bureau of Economic Research Working Paper Series*, No. 25342.

CHETTY, R., J. N. FRIEDMAN, and J. E. ROCKOFF (2014): "Measuring the Impacts of Teachers I: Evaluating Bias in Teacher Value-Added Estimates," *American Economic Review*, 104, 2593-2632.

CULLINAN, J., K. DENNY, and D. FLANNERY (2018): "A Distributional Analysis of Upper Secondary School Performance." Working Papers 201808, Geary Institute, University College Dublin.

CUNHA, J., and T. MILLER (2014): "Measuring Value-Added in Higher Education: Possibilities and Limitations in the Use of Administrative Data," *Economics of Education Review*, 42, 64-77.

DARMODY, M., and E. SMYTH (2013): "Governance and Funding of Voluntary Secondary Schools in Ireland." ESRI Research Series No. 34.

DEARDEN, L., J. MICKLEWRIGHT, and A. VIGNOLES (2011): "The Effectiveness of English Secondary Schools for Pupils of Different Ability Levels," *Fiscal Studies*, 32, 225-244.

DEARDEN, L., A. MIRANDA, and S. RABE-HESKETH (2011): "Measuring School Value Added with Administrative Data: The Problem of Missing Variables," *Fiscal Studies*, 32, 263-278.

DEMING, D. (2014): "Using School Choice Lotteries to Test Measures of School Effectiveness," *American Economic Review*, 104, 406-411.

EHLERT, M., C. KOEDEL, E. PARSONS, and M. PODGURSKY (2016): "Selecting Growth Measures for Use in School Evaluation Systems: Should Proportionality Matter?," *Educational Policy*, 30, 465-500.

EHLERT, M., C. KOEDEL, E. PARSONS, and M. J. PODGURSKY (2014): "The Sensitivity of Value-Added Estimates to Specification Adjustments: Evidence from School- and Teacher-Level Models in Missouri," *Statistics and Public Policy*, 1, 19-27.

EYLES, A., C. HUPKAU, and S. MACHIN (2016): "Academies, Charter and Free Schools: Do New School Types Deliver Better Outcomes?," *Economic Policy*, 31, 453-501.

HALLINGER, P., L. DONGYU, and W.-C. WANG (2016): "Gender Differences in Instructional Leadership: A Meta-Analytic Review of Studies Using the Principal Instructional Management Rating Scale " *Educational Adminstration Quarterly*, 52, 567-601.

HANNAN, D., and M. BOYLE (1987): "School Decisions: The Origins and Consequences of Selection and Streaming in Irish Post-Primary Schools." ESRI Working Paper no. 136.

HECKMAN, J., J. STIXRUD, and S. URZUA (2006): "The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior," *Journal of Labor Economics*, 24, 411-482.

JENKINS, S., and P. VAN KERM (2006): "Trends in Income Inequality, Pro-Poor Income Growth, and Income Mobility," *Oxford Economic Papers-New Series*, 58, 531-548.

KOEDEL, C., and J. BETTS (2010): "Value Added to What? How a Ceiling in the Testing Instrument Influences Value-Added estimation," *Education Finance and Policy*, 5, 54-81.

LADD, H. F., and R. P. WALSH (2002): "Implementing Value-Added Measures of School Effectiveness: Getting the Incentives Right," *Economics of Education Review*, 21, 1-17.

MEYER, R. (1997): "Value-Added Indicators of School Performance: A Primer," *Economics of Education Review*, 16, 283-301.

NICOLETTI, C., and B. RABE (2018): "The Effect of School Spending on Student Achievement: Addressing Biases in Value-Added Models," *Journal of the Royal Statistical Society Series a-Statistics in Society*, 181, 487-515.

OECD (2004): *Learning for Tomorrow's World: First Results from Pisa 2003*.

PFEFFERMANN, D., and V. LANDSMAN (2011): "Are Private Schools Better Than Public Schools? Appraisal for Ireland by Methods for Observational Studies," *The Annals of Applied Statistics*, 5, 1726-1751.

RESCH, A., and E. ISENBERG (2018): "How Do Test Scores at the Ceiling Affect Value-Added Estimates?," *Statistics and Public Policy*, 5, 1-6.

SHAKED, H., J. GLANZ, and Z. GROSS (2018): "Gender Differences in Instructional Leadership: How Male and Female Principals Perform Their Instructional Leadership Role," *School Leadership & Management*, 38, 417-434.

SOFRONIOU, N., G. SHIEL, and J. COSGROVE (2000): "Explaining Performance on the Junior Certificate Examination: A Multilevel Approach," *The Irish Journal of Education / Iris Eireannach an Oideachais*, 31, 25-49.

STONE, L. L., R. OTTEN, R. C. M. E. ENGELS, A. A. VERMULST, and J. M. A. M. JANSSENS (2010): "Psychometric Properties of the Parent and Teacher Versions of the Strengths and Difficulties Questionnaire for 4- to 12-Year-Olds: A Review," *Clinical child and family psychology review*, 13, 254-274.

WEIR, S., and L. KAVANAGH (2018): "The Evaluation of Deis at Post-Primary Level: closing the Achievement and Attainment Gaps." Educational Research Center Monograph.