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# The Importance of Rank Position

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**Abstract**

We find an individual's rank within their reference group has effects on later objective outcomes. To evaluate the impact of local rank, we use a large administrative dataset tracking over two million students in England from primary through to secondary school. Academic rank within primary school has sizable, robust and significant effects on later achievement in secondary school, conditional on national test scores. Moreover we find boys gain four times more in later test scores from being top compared to girls. We provide evidence for a mechanism using matched survey data, which shows that rank affects an individual's self-concept. The paper discusses other potential channels but concludes that malleable non-cognitive skills such as confidence and belief in own ability are most likely to generate these results. We put forward a basic model where rank effects costs and effort allocation when faced with multiple tasks. We believe this is the first large-scale study to show large and robust effects of rank position on objective outcomes of that have consequences in the labour market.

Keywords: Rank, non-cognitive skills, peer effects
JEL Classifications: I21, J24, D01

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# 1 Introduction

A natural instinct for humans is to make comparisons, Philip is taller than Peter, David is stronger than Thomas, who is in turn stronger than Jack. These comparisons focus not on the magnitude of the differences but the ranking of individuals. These comparisons are important because rank position effects an individual's beliefs about themselves and their abilities. When surrounded by people who perform a task worse than oneself, one develops a positive self-concept in that area. Self-concept as a term for an individual's beliefs about their own skills and abilities is well established in the psychological literature (O'Mara et al. 2006). Individuals can have positive or negative self-concept about different aspects of themselves.

Following this intuition, the way we think of ourselves is partly determined by our immediate environment, and this self-concept can affect later outcomes, through influencing our actions and investment decisions. This principal can be applied to many different situations; a child being the best in their street at basketball may invest more time in playing basketball and so further develop their skills; in the marriage market early relative success in attracting a partner raises an individual's self-concept of their attractiveness and influence later actions; in the labour market individuals will rate their productivity in a task relative to their colleagues and so could sway in which field they specialized in; or siblings may form their identities with respect to the others' strength and weaknesses, and then act accordingly. In the education sector, students with higher rank could develop positive self-concept and develop positive non-cognitive skills [1] such as confidence, resilience, and perseverance (Valentine et al. 2004). This can be both subject specific self-concept and general academic self-concept. Importantly rather than just affecting measures of well-being [2], self-concept could affect individual actions and later objective outcomes that predict success in various aspects of the labour market.

To formalize this mechanism, this study proposes a very simple two-period behavioural model where individuals learn their local rank for tasks in the initial period and form a task specific self-concept. This self-concept then affects costs for that individual to perform that task in the second period. Using a basic production function setting, we model individuals trying to maximize output for given total effort and ability levels. An agent who experiences a decrease in the cost of a task relative to another will increase their investment of effort into

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[1] Heckman and Rubinstein (2001) call for more research on the formation of these non-cognitive skills.
[2] There is also recent evidence that humans value ordinal position within a group (Brown et al. 2008, Kuziemko et al. 2011, Card et al. 2012).

that task as the marginal return has increased. This generates a positive link between self-concept acquired in the initial period and later objective outcomes.

We test for this mechanism empirically using administrative data to follow 2.3 million school children from five cohorts in England when they move from a primary to secondary education. The English education setting is particularly useful for our exercise because all pupils take the national and externally marked Key Stage 2 exams (KS2) in English, Mathematics and Science (EMS) at the end of primary education at age-11, and are tested in the same subjects in Key Stage 3 exams (KS3) at age-14 during secondary education. This is an opportune age window to study the effects of academic self-concept in the education setting as the psychological literature has a consensus that the most formative years are before age 11 (Tiedemann 2000, Lefot et al 2010, Rubie-Davis 2011). We thus use KS2 national test scores as a measure of ability, and derive each pupils' local rank for each subject within their primary school cohort. We are interested in the effects of this primary rank on outcomes that post-date the compulsory transition into the secondary school environment.

To estimate the effect of rank we condition on flexible measures of individual test-scores (KS2) to account for individual ability, as well as allowing for school-subject-cohort effects on growth rates. This means the KS2 national test scores will additionally be accounting for the relative distance from school-cohort mean by subject, and therefore the rank parameter will only pick up the effects of ordinal rank position. We show that this is identified from differences in test score distributions across schools and subjects. Students with the same KS2 test scores and ability relative school mean will have different ranks as the shape of ability distributions varies.

We estimate effects of primary-school rank on outcomes after the secondary school transition. This accounts for many 'traditional' peer effects as there is a large re-mixing of students after the primary period with the average student facing 87% new peers in her secondary school. We include additional local controls for subject- and cohort-specific secondary peer quality to account for peer quality during secondary school, which we show has no meaningful effect on the estimates.[3]

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[3] Another possibility is that primary peer effects are transitory and only start to matter for later test scores. If this was the case, conditioning on this test score without accounting for these common classroom level shocks would lead to small biases. We show this by simulating a data generating process with individual general and subject specific ability, school effects, peer effects and measurement error. We find that controlling for primary-subject-cohort effects is sufficient to kill any spurious correlations between rank and end-of-primary test scores even with highly inflated transitory linear and non-linear peer effects (see Appendix 2).

Because we observe each student in three subjects, we can further include pupil fixed effects and show that students have later gains in subjects where they ranked relatively better during the primary phase, controlling for national end-of-primary school subject-test scores. These specifications account for individual specific effects that do not vary across subjects, such as school transitions, family disruption or competitiveness. Note that these specifications will also absorb any general academic self-concept that improves the confidence in all subjects and the remaining effect will be subject specific self-concept.

A final concern is that because test scores are a noisy measure of ability, it is arguable that rank could be picking up residual ability-related information. To check this, we randomly re-allocate pupils into primary schools and re-calculated their new ranks that they would have had in these schools using their (and their new peers') actual end of year test scores. Although these new ranks are similarly highly correlated with KS2 test scores, these placebo-ranks are not related to later outcomes using the same specifications. This dataset thus allows us to directly measure the effects of academic rank amongst peers at a young age during primary school on later academic outcomes during secondary education.

The main result is that rank position within primary school has sizeable, robust and significant effects on later academic achievement, conditional on national test scores. Keeping end-of-primary national test scores constant, moving a student's ordinal rank from the $25^{th}$ percentile to the $75^{th}$ in primary school improves secondary-KS3 test scores by 0.2 within pupil standard deviations. This is a relatively large effect in the context of the education literature and is for instance comparable to being taught by a teacher one-and-a-half standard deviations above average (Aaronson, et al. 2007; Rivkin et al. 2005). Furthermore we find that males are more affected by rank throughout the rank distribution relative to females and that disadvantage groups are less negatively affected by being ranked below the median but are more positively affected from being near the top of the distribution.

To support our interpretation of self-concept being the driver of these effects, we merge-in to our administrative dataset survey data from the Longitudinal Study of Young People in England (LSYPE) which includes questions on subject-specific self-concept. For the resulting subsample of about 12,000 students we find that those ranked higher in primary school have higher measures of self-concept conditional on national test scores, national test score progression, and primary-by-subject fixed effects. Additionally we find that their self-concept is still malleable in secondary school, where their new rank continues to effect self-concept when including secondary-by-subject and pupil fixed effects. Again there are large

differences by gender with males confidence being five times more effected by rank than female students, which mirrors our previous findings on test scores.

We subsequently discuss a number of competing mechanisms that could produce certain aspects of our findings (competitiveness, learning about ability, external (parental) investment by task, and environment favouring certain ranks), but conclude the mechanism that best accommodates all the empirical evidence is that ordinal rank position affects non-cognitive skills through changing self-concept, which in turn has large, robust, and significant effects on objective later outcomes. Given these findings, it is likely that ordinal rank position also affects other outcomes though induced changes in behaviour, which should be examined by future research.

We believe this paper makes four important contributions. First, to the best of the authors' knowledge this is the first large-scale study to document large and robust effects of local rank position on later outcomes. This has implications relating to informational transparency and productivity. Managers/teachers could improve productivity by highlighting an individual's local rank position if that individual has a high rank. If an individual is in a high performing peer group and therefore may have a low local rank but a high global rank, a manager should make the global rank more salient. Finally, for individuals who have low global and local ranks, then managers should focus on absolute attainment and make rank less salient, or emphasise other tasks where the individual is of a higher rank.

Secondly, this paper illustrates the importance of non-cognitive skills more generally. We show that conditional on ability those with higher ranks develop a higher self-concept and achieve better years later. The policy implication is that non-cognitive skills such as confidence, perseverance and resilience have large effects on achievement. Local rank can be thought of as a just one treatment that impacts on these behaviours, there are potentially many other interventions that could have positive effects on all individuals in a group and not just those above the median. Besides these general implications, our results also imply for individual parents that they should not always send their child to the 'best' school, if this would mean a low ranking for their child in that school.

Thirdly, the empirical finding of the importance of rank in schools adds to the literature on determinants of academic achievements in its own right. There is very large literature on the determinants of academic achievements including natural ability (Watkins et al. 2007), family background (Goldhader et al. 1999, Hoxby 2001), school inputs (Hanushek, 2006, Page et al.

2010), peer effects (Carrell et al. 2009, Lavy et al. 2012), and non-cognitive skills (Heckman et al. 2005), but rank position has not yet been researched.

Fourthly and finally, we believe the finding that ordinal rank matters for later outcomes has the potential to add to the explanation of findings in the following topics in the education literature: school integration; selective schools; ethnicity gaps; affirmative action; age in cohort; and gender specialisation, which is discussed in the next section.

The remainder of the paper is laid out as follows. After reviewing the literature relating to rank and self-concept, Section 3 proposes a basic model of self-concept development and effort allocation. We then set out the empirical strategy of how we separate out the confounding factors in Section 4. This is followed by a brief description of the UK educational system, our definitions of rank and the administrative data in Section 5. Section 6 documents the results and robustness checks. Section 7 presents further results on heterogeneity by gender and income. Section 8 discusses potential mechanisms and results from the LSYPE survey. Finally we conclude and set out policy implications as well as directions for future research.

## 2   Literature Review

This paper is related to four stands of literature on rank effects, self-concept, non-cognitive skills and educational outcomes.

The importance of ordinal rank has typically been overlooked compared with the attention paid to absolute levels or relative differences. However, it has recently been shown that ordinal rank ordering is important to individual wellbeing (Brown et al. 2008, Kuziemko et al. 2011, Card et al. 2012). The basis of the theory comes from the possibility of multiple reference points (Bygren, 2004; Ordonez et al. 2000), whereby increasing the number of reference points from just the mean to a set would generate a rank based utility measure (Kornienko, 2011). Similarly, the range frequency theory (Parducci, 1965; 1995) states that well-being is determined by the ordinal position of an individual's wage within a comparison set, rather than absolute or relative level.

Brown et al. (2008) use an experimental setting to illustrate this by showing that individuals constantly prefer a point X that is in higher rank but is the same in absolute terms and also distance from the mean, mid-point and end points as another point Y. Under traditional theory individuals should be indifferent between points X and Y. This finding was replicated in survey data that shows satisfaction is not only determined by relative income

within a workplace but additionally by an individual's earnings rank. If rank can affect utility then it is also likely to affect other attributes such as self-concept.

Being informed of rank has been found to be an important determinant of educational outcomes. Azmat & Iriberri (2012) find in lab based experiments that rank based feedback improves performance when related to an outcome, in this case pay. Rasul et al. (2012) similarly find students in a new educational environment who are provided with feedback has a positive effect on subsequent test scores. However both of these papers are establishing the effect of new information on performance, whereas this paper assumes that in a stable educational setting students are well informed of their rank due to continuous interactions with their peers and potential comparative marking by teachers and that effects arise through changes in self-concept[4]. Hoxby and Weingarth (2006) discus the Invidious Comparison model which is similar in that there are negative effects from being ranked below someone, but different, as it does not take account of the gains from being ranked above others. They find little evidence of the existence of these type of effects, however they are using variation originating from new peers who may not have had sufficient exposure to affect the self-concept of themselves or others.

Self-concept as a term for an individual's beliefs about their own skills and abilities is a well-known concept in the psychological and education literature. In the education literature, the focus is typically on academic self-concept, which is formed through individual experiences and interactions with the environment (O'Mara et al. 2006). Although there is no consensus on the exact age academic self-concept starts to develop, it is accepted that its formative years are before age 11 (age 3-5, Tiedemann 2000; age 7-8, Lefot et al 2010; age 10-11 Rubie-Davis 2011). Children evaluate their own academic abilities based on the feedback they receive from parents and teachers, but also from comparing themselves to their peers. It has also been found that pupils distinguish between the various domain-specific elements of academic self-concept e.g. math, reading, science (Marsh et al. 1988, Yeung et al., 2000, Ackerman, 2003).

To the best of our knowledge to date there has been no research directly on the effect of rank in an educational setting. However there are a number of literatures that have findings that corroborate this hypothesis.

1. The selective schools literature has mixed results with some papers finding insignificant results from attending selective schools with high ability peers (Cullen, Jacob and

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[4] We return to this question of information versus self-concept in Section 8.4.

Levitt, 2006 and Clark 2010). The potential benefits of a selective school may be attenuated by the development of negative self-concepts. This is consistent with Cullen, Jacob and Levitt (2006) who find that those whose peers improve the most gain the least: 'lottery winners have substantially lower class ranks throughout high school as a result of attending schools with higher achieving peers and are more likely to drop out'.

2. The school integration literature (i.e. Angrist and Lang, 2004), as well as 'neighbourhood effects' (i.e. Kling *et al.* 2007) literature generally fails to find positive effects on cognitive outcomes from enabling minority students to attend better schools. This could partly be because these students will have a low rank in their new schools and thus develop negative academic self-concepts.

3. Similarly, negative self-concept could partly explain why achievement gaps of minorities increase over the education cycle as documented by Fryer and Levitt (2006) using the Early Childhood Longitudinal Study database, or by Hanushek and Rivkin (2006, 2009).

4. The literature on affirmative action policies, which are policies that allow minorities to attend selective colleges, finds surprisingly little evidence for positive effects. Arcodiacono (*et al.* 2012) document that these students are more likely to switch majors potentially to avoid lowest rank positions. Robles and Krishna (2012) find that these students perform worse and earn less than if they had attended a less selective major. This is usually explained through mismatch but the development of a low self-concept might additionally explain these stylized facts.

5. Another related literature on age-effects in high schools shows that older children do better compared to their younger peers (for example in Grenet 2010). The development of positive self-concept is a potential mechanism for these findings as older peers have on average higher cognitive ability in the early years and the self-concept formed in these years may perpetuates these effects. A similar effect could take place between siblings, our comparison hypothesis would imply that siblings would specialise and exacerbate any differences between them.

6. Finally, the rank effect might contribute to the gender subject gap literature, where males are overly represented in mathematics and science despite girls outperforming boys at early ages in these subjects (Burgess et al. 2004, Machin & McNally 2005). Even if girls perform better in all subjects, if boys do comparatively less badly in

mathematics and are more affected by rank for investment decisions, then this could help explain the common finding of subject specialization by gender.

In this paper we attempt to highlight a determinant of non-cognitive skills such as confidence and perseverance that is applicable to all classroom taught pupils by showing that rank position predicts later test score outcomes and a student's academic self-concept.

# 3 Model

This section develops a very basic behavioural model of how rank could affect latter actions through self-concept. We assume there are two stages, a learning stage followed by the action stage. In the learning stage agents of heterogeneous ability in different tasks are randomly allocated into groups. Agents perform tasks and learn about their abilities relative to others in their group and form their self-concept for each task. In the second stage, when agents are removed from their initial reference group, agents' self-concept affects their costs of effort for each task[5]. Agents now chose how much effort they allocate to each task to maximise output for a given level of effort and ability. In this simplified model we assume that individuals do not include later rank directly in their objective function[6].

Without losing generality, we apply this to the education setting where students vary in ability across subjects and are randomly allocated to primary schools where they form self-concept in each subject during the first stage. This is generated through pupils interacting with their peers, such as observing who answers questions and teacher grading that is likely to be in some part rank based. For the purposes of the model we assume that pupils exert no effort during primary school with outcomes being a product of ability and school factors.

In the second stage we model students as grade maximising agents for a given total cost of effort and ability level. As our main specifications uses subject specific self-concept and focuses on subject specialisation, we assume the grade achieved $Y$ by a student $i$ in subject $s$ is a function of ability $A$ and effort $E,$ according to a separable production function where $0<\alpha<1$.

$$Y_{is} = f(A_{is}, E_{is}) = School. A_{is}. E_{is}^{\alpha}$$

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[5] Self-concept could plausibly instead affect an agent's ability for a task rather than cost of effort. This would lead to the same predicted changes in the effort ratios. Given the data available, we are unable to determine if it is costs or abilities that are affected. We have chosen costs as this is the more parsimonious and intuitive of the two.

[6] We are assuming that individuals are either myopic not relating investment decisions to later rank position, or that rank affects beliefs but not utility, or that they care about average rank over tasks which is equivalent to maximizing total output

Total test scores of individual $i$ is the sum of this function over subjects. For simplicity of notation we currently assume two subjects English $e$, and Maths $m$.

$$Y_i = School. A_{ie}. E_{ie}{}^\alpha + School. A_{im}. E_{im}{}^\alpha$$

Given the diminishing marginal returns to effort in each subject, isoquants can be drawn for a given total amount of grades and all the combinations of subject-specific effort ($Q_o$), see Figure 2.

$$E_{ie} = \left(\frac{Y_i - A_{im}. E_{im}^\alpha}{A_{ie}}\right)^{\frac{1}{\alpha}}$$

We assume that the self-concept in each subject generated in the first stage determines the student's cost of effort. Those with a positive self-concept will find the cost of effort lower e.g. when faced with a difficult Mathematics question a student who considers themself good at Mathematics would attempt to solve it for longer, compared to another student who may give up. Therefore cost of subject effort $c_s$ is a decreasing function of rank $R_s$, $C_s = g(R_s)$ where $g' < 0$. We assume costs of subject effort are linear in effort applied to that subject, and that total cost of effort $TC_i$ is fixed for a student and can be dependent on outside factors.

$$TC_i = C_{ie} E_{ie} + C_{im} E_{im}$$

This allows us to draw isocost lines using the cost of effort in each subject as the factor prices for a given total effort (see Figure 2) There is additionally a non-binding time constraint $1 > E_{ie} + E_{im}$. As standard, the solution is which is where the technical rate of substitution equals the relative factor prices[7] i.e. where the isoquant and isocost lines are tangential.

$$\frac{C_{ie}}{C_{im}} = \frac{A_{ie}. E_e^{\alpha-1}}{A_{im}. E_{im}^{\alpha-1}}$$

It is also clear that given this specification effort exerted in a specific subject is dependent only on the student's ability and cost of effort in that subject.

$$E_{is}^* = \left(\frac{\alpha. A_{is}}{C_{is}}\right)^{\frac{1}{1-\alpha}}$$

From the above solution we can see that if $C_{ie}$ was to decrease then $E_{ie}$ would increase as 0<α<0. A student that raises their English self-concept would now have a lower cost of learning English and therefore increase their English to Maths effort ratio. The reduced costs also cause an income effect shifting the isocost line outwards meaning that a higher isoquant can be reached. Note that this relies on our assumption that the time constraint is non-binding.

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[7] The basic workings can be found in the Appendix 1

As a result, the total grade levels that can be achieved for a given cost of effort and ability level is higher. The improvement in self-concept has improved the marginal return to effort in English and the student will choose to do English due to scale and substitution effects. Given this specification there would be a reduction in Maths effort, the extent of this depends on the shape and position on the isoquants. Any increase in general academic self-concept would reduce the cost for both subjects, and so there would only be an income effect, increasing effort spent in both subject but at the same ratio.

This two subject example is for exposition only but easily extends to a setting where an individual is maximising total grades over three subjects as is the case in our situation. We assume that students make decisions about where to invest effort to maximise grades for a given level of effort and ability between English, Maths and Science determined by their self-concept. Equally, it is conceivable that this model could be applied to different situations, for example workers defining themselves as "hard working" depending on their local reference group, who will then behave accordingly when confronted with new peers in the second stage.

## 4    Empirical strategy

### 4.1    Identification of Rank

To identify the effect rank on latter outcomes there are a host of issues that need to be addressed. $R_{ijc}$ is our measurement of rank for student $i$, in primary school j of cohort $c$. $R_{ijc}$ is their ordinal position within their primary school cohort according to their test scores on a national examination $KS2_{ijc}$ (Key Stage 2, see Section 5 for details). As the distribution of test scores varies across primary schools students with the same test score can have different ranks. Furthermore, as the test score distributions varies across subjects within a school, a single student with the same score in all three subjects could have different subject ranks.

The main outcome of interest $Y$ is the test scores of students in a subsequent national examination $KS3_{ijc}$. Rank will be highly correlated with student ability as on average those of high rank in primary school are going to be of higher ability, and therefore we control for KS2 scores. This is done using a 3$^{rd}$ degree polynomial as well as a fully flexible measure of KS2 test scores allowing for a separate effect of each test scores ranging from one to a hundred points. We also condition on a set of pupil level characteristics ($X$) that could affect academic achievement growth.

Finally we allow for school-subject-cohort effects to have an independent effect on later outcomes. Note that allowing for primary-classroom quality to have an effect on KS3 means that we are allowing for some primary schools to be more effective at teaching for a latter KS3 test subject than others, in a way that does not show up in the end-of-primary KS2 test scores. Including subject-cohort-primary effects is also necessary to account for potential measurement error in the KS2 scores arising through unobserved classroom-level shocks. In particular, if there are unobserved primary-school factors, these will create noise in the national KS2 score but not in the rank, as the ranking itself is mean-independent. As a result, the ranking variable could start to pick up ability-related information that cannot now be fully controlled for using the national KS2 rank. Including primary-school effects clears this kind of measurement error off the KS2 rank variable[8].

The inclusion of these school-subject-cohort effects also changes the variation used for estimation. Pupil KS2 test scores are now a measure of the distance from the mean score of that school-subject-cohort, i.e. a pupils relative score in that classroom. If all schools had the same distribution of test scores there would be a 1-to-1 correlation between rank and test score and we could not estimate the rank effect. Consequently our identification of the rank parameter $\beta_{Rank}$ relies on the heterogeneous distribution of test scores across primary schools and subjects. This is our first specification (1)[9], where X' is a vector of pupil characteristics, $\mu_{jsc}$ are school-subject-cohort effects and $v_{ijsc}$ is the error term.

$$KS3_{ijsc} = \alpha + \beta_{Rank}R_{ijsc} + f(KS2_{ijsc}) ....$$
$$+X'\beta + \mu_{jsc} + v_{ijsc} \qquad (1)$$

It's worth discussing this in more detail. Similar to Brown et al. (2008), when using school-subject-cohort effects, the KS2 parameters are picking up the effects of *relative ability*, and consequently $\beta_{Rank}$ is picking up the effect of *ordinal rank* only. Consider the case illustrated in Figure 1 (next page), which shows unimodal and bimodal distribution of English test scores in two hypothetical schools with ten students who have the same mean, minimum and maximum values. A pupil in each school achived the same national score Y and also have the same relative score compared to the mean of their peers, as they are both the same distance from the mean. However, due to the different distributions the student who

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[8] We return to various types of measurement error in Section 4.2
[9] All estimations have the errors clustered at the widest level, that of secondary school attended to allow for correlation in the KS3 scores

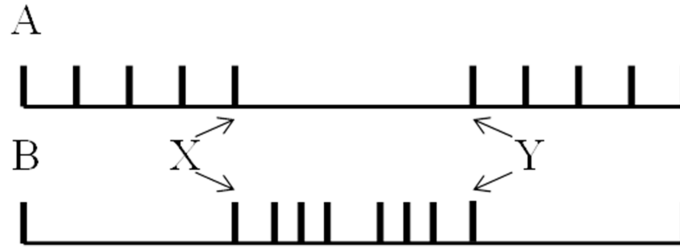scored Y in the unimodal school is ranked second, whist the one in the bimodal school is ranked fifth.



**Figure 1  Rank dependent on distribution given absolute and relative score**

*Source: Brown et al. (2008)*

Under our hypothesis the student who was ranked second would gain a higher academic self-concept, and so develop better non-cognitive abilties. This student will therefore have lower costs of effort in that subject and so apply more effort and score higher on latter tests compared to the student ranked fifth, despite them achiving the same absolute and relative test scores. The opposite would occur for a student who scored X at the unimodal score and is ranked ninth compared to the student who scored X at the bimodal school who is ranked 6th.

A further worry might be that students who had a particular rank position during primary school select secondary schools based on their rank rather than their ability. If, for example, students who were top of class aspire and achieve to gain access to better secondary schools, our estimates would be confounded by secondary school quality. Fortunately, our data allows us to address this concern. This is because we can track all students to each school they have attended. We can estimate a specification that allows for the achievement *Y* of student *i* from primary school *j* that attended secondary school *k* in subject *s* of cohort *c* to vary by secondary-subject-cohort as well as primary-subject-cohort[10]. Intuitively, we are now comparing students who are subject to the same secondary school influences, thus identifying effects net of any sorting into secondary education. Given that secondary school attended could be argued to be an outcome variable, specifications which include these effects are not our preferred specification and should only be used as an indication of the extent of secondary school selection potential has on the estimates.

$$KS3_{ijksc} = \alpha + \beta_{Rank}R_{ijsc} + f(KS2_{ijsc}) \dots$$
$$+ X'\beta + \mu_{jsc} + \pi_{ksc} + \epsilon_{ijksc} \ (2)$$

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[10] We use the Stata command `reg2hdfe` for these estimations (Guimaraes and Portugal, 2010).

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Even with this set of controls we are still not convinced that we can identify the pure effect of rank on latter educational attainment. The rank of a pupil in primary school may be correlated with other unobserved factors that affect students' outcomes. This may occur if there is there are relations between students' ability and other attributes of the school attended that aren't fully observed but correlate to a student's rank. An example for this could be unobserved individual or parental aspirations that could correlate with primary rank and later value added. Furthermore, using across-school variation might be problematic if schools transformed a student's ability into test scores non-monotonically[11].

To address these remaining concerns, we can use the within student subject-to-subject variation for estimation (Specification 3). This is related to Lavy (*et al.* 2012), who use a pupil-fixed effects strategy to estimate ability peer effects. Applied to our setting, allowing for pupil effects we effectively compare relative rankings within an individual, controlling for national subject-specific ability. The variation arises from differential growth for a specific subject within each pupil, depending on prior subject-specific ranking. This means that any individual characteristic that is not realised in KS2 test scores but contributes towards KS3 test scores is accounted for. Therefore any unobserved pupil, primary school, or sorting into secondary schools, are completely controlled for, as long as these are not subject specific. This is because students attend the same schools for all subjects.

$$KS3_{ijsc} = \alpha + \beta_{Rank}R_{ijsc} + f(KS2_{ijsc}) \ldots$$
$$+\tau_i + \mu_{jsc} + \varepsilon_{ijsc} \qquad (3)$$

Note that the rank effect that is identified conditional on the pupil fixed effect differs from the previous specifications for two reasons. Firstly, as discussed above, the pupil fixed effect controls for any unobserved effects common across subjects that were not already captured by the controls or school-fixed effects. Secondly, the rank effect identified in Specification (3) is net of any spill-over effect from one to another subject. If a high primary rank in Mathematics for example increased self-concept for Mathematics and Science, the pupil fixed effect specification will only pick up effect on how much more Mathematics value added gained compared to Science value added. This is why we would expect the coefficient of the rank effect in Specification (3) to be smaller.

To fully investigate potential non-linarites in the effect of ordinal primary school rank position on later outcomes, we can replace the ranking parameter with indicator variables

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[11] If some schools are better at teaching low (high) ability students then the ranking technology for ability may be different across schools.

according to the vingtiles in rank excluding those at the top and bottom which have been allowed to have separate effects. This allows for non-linear effects of rank and can be applied to all the specifications present.

$$KS3_{ijksc} = \beta_{R=0}Bottom_{ijsk} + \sum_{n=1}^{20} I_n R_{ijsc} \beta_{n,Rank} + \beta_{R=1}Top_{ijsc}$$
$$+ f(KS2_{ijsc}) + \tau_i + \mu_{jsc} + \varepsilon_{ijksc} \qquad (4)$$

## 4.2 Further threats to identification

Some non-trivial empirical challenges in estimating the effect of rank conditional on ability in our dataset arise because we do not independently observe both, a students' rank and a student's ability. Instead, we have to rely on anonymously marked and nationally standardised tests (KS2 test) at the end of primary school to derive a student's local rank during primary education, as well as using this measure to control for a student's subject-specific ability.

### 4.2.1 Peer effects

Firstly given that we are discussing an atypical peer effect it is important to address the issues associated with a typical peer effects[12]. Any primary school peer effects on end-of-primary school test scores will not affect our coefficients because we can condition on KS2 scores. Furthermore, we can account for secondary peer quality, which has almost zero effects on our coefficients partly because of the large re-mixing of students during the primary-to-secondary transition.

However, if peer effects have a transitory effect on test scores, any estimation of the effect of rank on KS3 test scores whilst controlling for KS2 will be biased to the extent that both KS2 and rank will both be correlated with primary peer effects. This is because in the presence of transitory peer effects a student with lower quality peers would attain a lower KS2 result than otherwise and also have a higher rank than otherwise. Thus, when controlling for KS2 in the KS3 estimations, when students have a new peer group, those who previously had low quality peers in KS2 would appear to gain more. Since rank is negatively correlated with peer quality in KS2, it would appear that those with high rank make the most gains.

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[12] The standard reflection problem is not a first order issue in this situation as pupils are surrounded by 87% new peers when they transfer to secondary school, and the rank effect is generated by primary school peers.

Therefore having a measure of ability confounded by peer effects would lead to an upward biased rank coefficient.

However, conditioning on school-subject-cohort effects will absorb average transitory or long run[13] peer effects. We test this by running simulations of a data generating process where KS test scores are not affected by rank and are only a function of ability and individual peer effects which are 20 times larger than those found in Lavy et al. (2012). We show that not controlling for the peer group generates biased results but that this bias is negligible when allowing for school-subject-cohort effects. These simulations can be found in Appendix 2 and Appendix Table 1.

*4.2.2  Measurement error*

In addition to classroom-specific measurement error, individual test scores are likely to be measured with error. Given that both a rank and test scores will both be affected by the same measurement error, but to different extents due the heterogeneous test score distributions, calculating the size of the bias is intractable. To gauge the extent of measurement error we again simulate the data assuming 30% of the variation in test scores is random noise, 60% pupil ability and 10% school effects (Appendix 3). This shows that normally distributed individual-specific measurement error would work against finding any effects.

The intuition is the following: if a particular student had a large positive measurement error this would result in an inflated end-of-primary national KS2 result and local rank measure. Both of these would work against finding positive effect of rank on later outcomes. This is because we always control for prior KS2 attainment. This student's later KS3 test scores would hence be benchmarked against other student's KS2 with the same KS2 result but higher actual ability. Equally, since our student really only got this high local rank because of the measurement error, this would downward bias any positive rank effect estimate.

# 5  Institutional setting, data and descriptive statistics

## 5.1  The English School System

The compulsory UK educational system is made up of a series of four Key Stages (KS); at the end of each stage pupils are evaluated in national exams. Key Stage Two (KS2) is conducted at the end of primary school after the first six years of schooling (age eleven). The median

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[13] Long run peer effects will be absorbed both by the KS2 test score and the school-subject-cohort effects.

size of a primary school cohort is 27 pupils, furthermore the average class size of a primary school over this period is also 27 (DFE, 2011). Therefore when referring to primary school rank, one could consider this as class rank[14]. At the end of the final year of primary school pupils take the KS2 tests in English, Maths and Science (EMS) which are graded nationally and are awarded test scores spanning the range 0-100. Pupils do not receive these raw test scores, and are instead given one of five broad attainment levels.

Pupils then transfer to secondary schools, where they start working towards the third Key Stage (KS3). During this transition the average primary school sends pupils to six different secondary schools. Secondary schools are much larger than primary schools, with 111 pupils per school year. On average secondary schools receive students from 16 different primary schools. The KS3 takes place over three years, school years 7/8/9 and at the end of the academic year 9 all pupils take KS3 examinations in EMS at age fourteen. KS3 as such is not a high-stakes test in the educational development but does correlate highly with later outcomes.

Two years later students take the national Key Stage 4 test at age sixteen (KS4), which marks the end of compulsory education in England. The KS4 is graded from one to eight and pupils have some discretion in choosing the subjects they are tested in and at what level. Since KS3 is graded on a very fine scale, and tests everyone in the same compulsory subjects only, we prefer this as the outcome measure for the purpose of our study. However, our results also hold using KS4 test scores (results can be obtained from the authors).

## 5.2   Data Construction

In England the Department for Education (DfE) collects data on all pupils and all schools in state education. The Pupil Level Annual School Census (PLASC) collects pupil information such gender, ethnicity, language skills, Special Educational Needs (SEN), or entitlement to Free School Meals (FSM). The number of pupils and pupil characteristics are used to determine school funding. The National Pupil Database (NPD) contains pupil attainment data throughout their Key Stage progression in each of the three compulsory subjects. Each pupil is given a unique identifier so that they can be linked to schools and followed over time to produce value added measures. These data are used to publish school league tables. As the functions of both of these datasets are at the school level, no class level data is collected.

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[14] The maximum class size at KEY Stage 1 is 30 pupils. A parallel set of results have been estimated using only cohort sizes of 30 and below assuming these are single class cohorts. The results are qualitatively the same and are available from the authors upon request.

We have combined these data to create a database following the entire population five cohorts of English school children. This begins at the age of 10/11 (Year 6) in the final year of Primary School when they take their Key Stage 2 examinations through to age 13/14 (Year 9) when they take Key Stage 3 tests. KS2 examinations were taken in the academic years 2000/2001 to 2005/2006 and so it follows that the KS3 examinations took place in 2003/2004 to 2007/8. From 2009 students no longer sat externally assessed evaluations at the end of Key Stage 3[15] and so we stopped our analysis with this cohort. It is for this reason that all of our analysis of KS3 outcomes is based on pre-2009 test scores.

We imposed a set of restrictions on the data to obtain a balanced panel of pupils. We use only pupils who we can track with valid KS2 and KS3 exam information and background characteristics. This is 83% of the population. Secondly we remove pupils who appear to be double counted (1,060) or school identifiers do not match (12,900) which amount to 0.6% of the remaining sample. Finally we remove all pupils who attended a primary school who's cohort size was smaller than 10 as these small schools are likely to be atypical in a number of dimensions, this represents 2.8% of pupils[16]. This leaves us with approximately 454,000 pupils per cohort, with a final sample of just under 2.3 million pupil observations or 6.8 million pupil-subject observations.

The Key Stage test scores for both levels are percentalized by subject and cohort, so that each individual has six test scores between 0 and 100 (three KS2 and three KS3). This means that the scores all have uniform distribution across subjects and cohorts and that students of the same nationally relative ability have the same indicator for test scores, or national percentile rank. This allows for comparisons to be made across subjects and across time and does not impinge on our estimation strategy which relies only on heterogeneous test score distributions across schools to generate variation in local rank[17].

We rank pupils according to their three KS2 national test scores within their primary school by cohort. In order to have a comparable local rank measurement across schools of different cohort size we transform the rank position of individual i with the following normalisation:

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[15] From 2009 teacher assessment is used to evaluate pupils in Mathematics, English and Science

[16] Estimations using the whole sample are very similar only varying at the second decimal point. Contact authors for further results.

[17] Estimations using standardised rather than percentalized tests scores provide similar estimates to the first decimal place in linear specification. For non-linear specifications the effect of rank appears more cubic in nature. However these estimations suffer from non-comparability or requiring a large set of interaction terms to ensure comparability which made estimations extremely computationally intensive given our already demanding specification. Results are available from the authors upon request.

$$R_{ijsc} = \frac{n_{ijsc} - 1}{N_{jsc} - 1}, \quad R_{ijsc} = [0,1]$$

Where $N_{jsc}$ is the cohort size of school j in cohort c of subject s, $n_{ijsc}$ is individual's *i* ordinal rank position within this set which is increasing in test score and $R_{ijsc}$ is the standardised rank of the pupil. For example a pupil who had the second best score from a set of twenty-one students ($n_{ijsc}$=20, $N_{jsc}$=21) will have $R_{ijsc}$=0.95. This rank measure will be bounded between 0 and 1, with the lowest rank pupil in each school cohort having R=0. In the case of draws of national percentile rank each of the students are given the lower local rank.

Pupil rank is dependent on own test scores, but is also highly dependent on the scores of the others in their set. A pupil with a test score of 70 could have R=1 in one school but in another school would have R=0.6. It is the different distribution of peers test scores that allow for the separate identification of the rank parameter.

Note that as the pupils do not receive their detailed test scores they will not be able to derive this same rank score themselves, nor will they be given an official ranking. Instead our measure of local rank is a proxy for the pupils' experiences over the past six years of interacting with their peers in the classroom. It is highly plausible that pupils would not require knowledge of these results to form beliefs about their rank position within their class.

Notice that we have information for three subjects for every pupil. This means a pupil can have a different rank for each subject within her primary school. This feature of the data allows us to include pupil fixed effects in some of our regressions.

## 5.3 Measure of Self-Concept

The hypothesis of this paper is that rank in primary school affects latter academic outcomes through changes in self-concept. In addition to testing the main effect we also directly estimate the effect of rank on students' self-concept, using a representative survey of 16,122 students from our first cohort. The Longitudinal Survey of Young People in England (LSYPE) is managed by the Department for Education and follows a single cohort of young people, collecting information on their academic achievements, out of school activities and attitudes.

We merge student survey responses with our generated dataset using a unique pupil identifier. Resulting in a dataset where we can track pupils from a primary school, determine their academic ranks and observe their latter measurements of self-concept and attainment. We are the first researchers to merge LSYPE responses to the NPD for primary school information.

At age 14 the students are asked for each of the compulsory subjects how good they consider themselves to be, with 5 possible responses which we code in the following way; 2 'Very Good'; 1 'Fairly Good'; 0 'Don't Know'; -1 'Not Very Good'; -2 'Not Good At All'. We use this simple scale as a measure of academic self-concept. Whilst it is much more basic than specific surveys that focus on self-concept, it does capture the essence of this concept.

The matching between the NPD and LSYPE was perfect. However, the LSYPE also surveys those attending private schools that are not included in the national datasets moreover as we had removed pupils that we couldn't accurately track over time we could not match 3,731 survey responses. Moreover 1,017 state school pupils did not fully complete these questions and so could not be used for the self-concept analysis. Our final dataset contains 11,898 pupil observations with self-concept measures. Even though the survey will not contain the attitude measures of every pupil in a school cohort, by matching it to the NPD we will know where that pupil was ranked. This means we will be able to determine the effect of rank on self-concept conditional on test scores and school-cohort-subject fixed effects.

## 5.4   Descriptive statistics

### 5.4.1   Main sample

Our data has the complete coverage of the pupil population from age 10 to 14.[18] We follow each pupil from their primary school through to secondary school linking their rank in class to their later outcomes. Table 1 shows summary statistics for all students used the analysis. The Key Stage percentiles have a mean of 50 with a standard deviation of 28 for all three subjects.

The within-pupil standard deviation across the three subjects English, Maths and Science is 12.68 national percentile points, with a standard deviation of 7.70 points for KS2. These numbers are similar for the KS3 tests. This is important as it shows that there is sufficient variation within pupil in order to run pupil fixed effects regressions.

Information relating to the background characteristics of the students is shown in the lowest panel of Table 1, half the student population is male, over four-fifth are white British and about 15 per-cent are Free School Meal Eligible (FSME).

Similar to the national percentile ranks the local rank characteristics are also uniformly distributed by construction. Therefore in Appendix Table 4 we present how the characteristics of pupils change by their position in the national rank distribution and local school rank distributions.. This shows that whilst FSME pupils represent 14.6% of the national population

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[18] Our data does not cover the private sector, which enrolls about 7% of the student population.

they only represent 4.8% of the top 5% of KS2 students. However, they make up 8.1% of students ranked in the top 5% of their school. This difference between the proportion ranked in the top 5% nationally and top 5% locally illustrates that there is some sorting to primary schools by parental income. A similar pattern is followed by Special Educational Needs (SEN) pupils and minority students.

As we are using variation in the distribution of test scores across schools it is informative to show the extent of this heterogeneity.

Figure 3 shows the position of top and bottom ranked pupils within each school cohort in the national rank distribution. We can clearly see the large variation across schools in the test scores or the top ranked pupils even within narrowly defined groups of the top and bottom 5%. This means that in one school a student with a score of 80 percentile points in English might be the Top student, while he might be average in another primary school.

For a comparison to the theoretical Figure 1 we show the rank of an individual dependent on the distribution of test scores even when maximum, minimum and mean test scores were the same across schools in Figure 4. The upper panel illustrates the case of English test scores across six primary schools. Each row represents a primary school which has a pupil in the national top and bottom percentiles, and has the same mean score (54). Each dot represents a student test score and all of these schools have a pupil at the 93rd percentile, but each has a different rank. This is a very specific case. For the estimations we use the support across all subjects and all distributions whilst accounting for mean school-subject-cohort test scores. The lower panel of Figure 4 plots the rank of each pupil in EMS by test score. The vertical thickness of the distribution of points indicates the support at each point in the rank distribution. For median students we have nearly full rank support.

*5.4.2   Longitudinal Study of Young People in England*

Appendix Table 3 shows descriptive statistics for the LSYPE sample which we use to estimate rank effects on a direct measure of self-concept in Section 8.5, as well as conduct some balancing exercises in Section 6.4. The LSYPE is a survey of about 12,000 pupils that we can merge into the first cohort of our main sample. As we can see from Appendix Table 3 these pupils are representative for the main sample, though KS2 test scores are a little lower and 18.6% are in receipt of Free School Meals, compared to the national average of 14.6 (see Table 1).

In the LSYPE students are asked to rate themselves in each of the subjects from 'Not good at all' to 'Very Good' which is summarized in Appendix Table 5. Our measure of self-

concept is coarse with only five categories to choose from and around 60% choosing "fairly good". We can see that pupils do think about their own ability with less than 0.2% not having an opinion. As would be expected those who considered themselves to be poor performers did tend to have lower average national KS2 percentile rank and lower rank within their school. However there is also large variance in these ranks within these self-evaluated categories. For every subject each self-assessment category with an opinion has at least one individual in the top 9% nationally including those who considered themselves 'Not Good'. Similarly each category has an individual in the lowest performing percentile nationally, even those who consider themselves very good.[19]

# 6   Main Results and Robustness Checks

### 6.1   Effect of Rank: comparing across schools

We begin our discussion of the results by presenting estimates of the impact of primary school rank on KS3 test outcomes. The estimates are reported in Panel A of Table 2, with the specifications becoming increasingly flexible moving across columns to the right. Due to computational constraints we are unable to run all specifications with a fully flexible set of controls for Key Stage test scores, which are shown in the first row. The second row instead uses a third order polynomial of Key Stage 2 test scores. It appears that this is sufficient to account for the vast majority of the effect of test scores.

The first column is a basic specification which only controls for KS2 test scores, pupil characteristics along with cohort and subject fixed effects. This shows a comparatively large estimate compared to the rest of the education literature, comparing a pupil at the bottom of their cohort to a top pupil increases their KS3 test scores by 11.6 national percentile ranks, or 0.42 standard deviations, *ceteris paribus*. However, this regression does not condition on school-subject-cohort effects and therefore the parameter cannot be interpreted as a pure rank effect. Furthermore it exploits variation in average quality of students across schools, which might correlated to family background characteristics, later school quality, or other unobserved variables and any peer effects would upward bias the estimates. Indeed, this is what we find in column (2), which additionally allows for any primary school-by-subject-by-

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[19] In Appendix Table 5 we also show the performance of the top and the bottom 10% of students within each self-assessment category which are less affected by outliers. We continue to see very large variance within categories. Consider Science in Panel C, of those who consider themselves 'Very Good' the bottom 10% performers in this category are ranked at the 17 percentile point nationally, whereas the top 10% of performers in the category that rated themselves 'Not very good at all' ranked at 64th percentile nationally.

cohort effects and can be interpreted as a rank effect. Using this specification, the effect of going from the bottom rank to the top rank *ceteris paribus* is associated with a gain in 7.96 national percentile ranks (0.29 standard deviations) with cubic KS2 controls. We see that when additionally including cohort-secondary school effects, allowing for differences in growth rates by secondary school have only a marginal effect on the estimates (Specification 2 from Section 4.1).

Given the distribution of test scores across schools very few students would be bottom ranked at one school and top at another school. For comparability we can also state that a one standard deviation increase in rank is associated with increases in later test scores by 0.085 standard deviations.

## 6.2  Effect of Rank: within pupil analysis

We now turn to estimates that use the within pupil variation in test to estimate the rank effect, as in Specification (3). This within pupil variation allows for pupil effects to be included that allow for individual growth rates which accounts for observable and unobservable pupil characteristics and of the schools they attended. This reflects the relative growth rates within pupil according to differing rank in primary school. It is not required that pupils have a different score in each subject, but only that the other pupils in the cohort to have different scores by subject. Since pupils always attend to same school across subjects, any general school quality or school sorting is also accounted for and absorbed by the individual fixed effect.

Besides removing potential bias, the main difference in the interpretation of this parameter compared to the previous ones is that the pupil effect will also absorb any general academic self-confidence gained through high rank and is only identifying the relative gains in that subject. This estimate also does not pick up any spill-over reduction in costs due to improvement in general academic self-concept from higher ranks in other subjects. We do find the within pupil estimate to be considerably smaller. The effect from moving to the bottom to top of class *cetrius paribus* increases national percentile rank by 4.56 percentiles, as we see in Panel A, column (3) of Table 2. To make a comparison in terms of standard deviations we should scale this effect by the within pupil standard deviation of national percentile rank (11.32). Therefore when controlling for pupil and school-subject-cohort effects the maximum effect of rank is 0.40 standard deviations. This seems like a large effect, but a change from last to best rank *within pupil* represents a very large treatment. It is more conceivable for a pupil to move 0.5 rank points, e.g. being at the 25th percentile in one school

and 75th at another. Our estimates imply that this pupil would gain 0.20 standard deviations in national KS3 percentiles. In terms of effect size, given that a standard deviation of the rank within pupil is 0.138 for any one-standard deviation increase in rank, test scores increase by about 5.6% of a standard deviation[20].

Again, if there was any general gain in academic self-concept through achieving a high rank in one subject, this would reduce the costs in all subjects and accordingly increase the grades in all subjects. However the within pupil estimates of the rank parameter absorb any general gains or losses in self-concept and pick up the total differences between subjects and so could be interpreted as a lower bound of the effect of being highly ranked, or just the between subject substitutions. The difference between the within school estimates (7.96) and the within pupil estimates (4.56) can be interpreted as an upper bound of the gains due to general self-confidence only.

## 6.3 Placebo tests: Is rank just picking up ability?

These estimates of primary school subject-specific rank are relatively large, given that we are conditioning KS2 test scores and individual growth. As rank is highly correlated with ability and test scores there is a concern that measurement error in the test scores for ability may be recovered in the rank measurement, if rank is measured with less error than test scores. Furthermore the linear nature of the effects in the basic specification gives rise to the concern that rank is mechanically using ability information left in the residual.

We already discussed measurement error issues and simulation results in Section 4.2. However to address the specific measurement error problem of rank having less measurement error than test scores and so contain residual ability information, we also randomly re-allocate pupils into primary schools and re-calculating their new ranks that they would have had in these schools with their original KS2 test scores but with new peers. These new placebo ranks are similarly highly correlated with KS2 test scores. If this new placebo-rank was found to be significant, this would indicate that rank is also picking up ability not captured in KS2 outcomes. We re-estimate all the specifications using these placebo-ranks and present the results in Panel B of Table 2. We find no effects of these placebo ranks on KS3 results. This is re-assuring and in line with the simulation results and we conclude that our findings are unlikely to be driven by measurement error in test scores and rank.

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[20] For students with similar ranks across subjects the choice of specialization could be less clear. Indeed, in a sample of the bottom quartile of pupils in terms of rank differences the estimated rank effect is 25per cent smaller than those from the top quartile. Detailed results available on request.

### 6.4    Are pupil effects enough? Balancing of primary rank

The causal interpretation that we give to our estimates relies on the assumptions made when conditioning on student effects. Given these and KS2 test scores, a student's rank needs to be orthogonal to other subject-varying determinants of a student's achievement. The variation need not be orthogonal to general determinants of the student's achievement.

An example of this could be the occupational background of the parents. Children of scientists may have a higher learning curve in science throughout their academic career. Similarly children of journalists for English and accountants in maths. This is fine as long as conditional on the covariates parental occupation is orthogonal to primary school rank. Or more broadly, there would be a problem if conditional on other factors rank was correlated to subject-varying factors that will affect future achievement and this might well be the case if parents who are engineers, for example, want their child to rank top in that field.

We test this by using the LSYPE sample that has information on parental occupation. We classify all occupations into English, Maths/Science or Other and indicate for each student-subject if they have a parent who works in that field[21]. This is shown to be predictive of KS2 achievement conditional on school effects and pupil effects (Table 3, Panel A). Then using rank as the dependent variable we test for an violations of the orthogonality condition in Panel B of Table 3.   Here we see that whilst parental occupation does predict pupil achievement by subject, it does not predict rank. We can therefore reject that the orthogonality condition does not hold with respect to parental background.


## 7    Further results

### 7.1    Testing for non-linearity

The current specification assumes the effect of rank is linear, however it is conceivable that the effects of rank are greater at the ends of the rank distribution. To address this we now allow for non-linear effects of rank by replacing the rank parameter with a series of 20 indicator variables according to the vingtiles in rank plus top of and bottom of class dummies.

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[21] Parental Standard Occupational Classification 2000 grouped in Science, Maths, English and Other. **Science**; 2.1 Science and technology, 2.2 Health Professionals, 2.3.2 Scientific researchers, 3.1 Science and Engineering Technicians. **Maths**; 2.4.2 Business And Statistical Professionals, 3.5.3 Business And Finance Associate Professionals. **English**: 2.4.5.1 Librarians, 3.4.1 Artistic and Literary Occupations, 3.4.3 Media Associate Professionals. **Other**: Remaining responses.

We plot the estimates form columns (1) and (3) from Table 2 in Figure 5. The effect of rank appears to be quite linear throughout the rank distribution with small flicks at the top and bottom. Reassuringly, the placebo ranks from Table 2 Panel B turn out to be insignificant even allowing for non-linear effects. On the other hand, all real rank coefficients are significantly different from the reference group of the median ranked pupils (10th ventile). This indicates that the effect of rank exists throughout; even those pupils ranked just above the median perform better three years later than those at the median. Our interpretation of this is that students are good at ranking themselves within the classroom. This is conceivable because of the constant exposure to peers over the length of primary school, which continually reinforces the effect on self-concept such that by the end of primary school they have strong beliefs in where they rank. Finally, the fact that the rank effect exists throughout the distribution is in line with the idea that self-concept forms according to relative position. If students only cared about being the best, for example, is less clear why a rank effect would be (almost) linear.

## 7.2 Heterogeneity by gender and parental income

We now turn to how the effects of rank vary by pupil characteristics, using the pupil fixed effects Specification 3 with non-linear rank effects and interacting the rank variable with a dichotomous characteristic of interest. These characteristics are Male:Female and, FSME:Non-FSME. The baseline group coefficients and the interaction plus baseline coefficients are plotted to show the effect of rank on test scores for both groups illustrating how the different groups react to primary school rank[22].

The first plot in Figure 6 shows the how rank relates to the gains in later test scores by gender. We see that males are more affected by rank throughout 95% of the rank distribution. Males gain four times more from being at the top of the class but also lose out marginally more from being in the bottom half.

The second plot in Figure 6 also shows that Free School Meal Eligible (FSME) students are less negatively affected by rank and more positively affected than Non-FSME students. FSME students with a high rank gain more than Non-FSME students especially those ranked top in class. FSME students who are below the median have limited negative effects on latter test scores. This could be interpreted as these students already having a low self-concept for

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[22] The pupil characteristics themselves are not included in the estimations as they are absorbed by the pupil effects. These  characteristics interacted by rank however are not because there is variation within the pupil due to having different ranks in each subject.

other reasons and therefore the negative effects of low rank have less of an effect. In other words, the interpretation that Non FSME students are less affected could be due to these students having their academic self-concept also being affected by out of school factors.

# 8 Mechanisms

In the following we discuss a number of mechanisms that could potentially give rise to this new stylised fact, that local rank position affects later outcomes conditional initial ability.

## 8.1 Hypothesis 1: The environment favours certain ranks

An possible explanation for this finding is that the environment could favour the growth of certain ranks of agents. In this case we could think of primary school teachers teaching to the median ability pupil if faced with a heterogeneous class group[23]. If this was the case, teachers would design their classes with the needs of the median to ability pupils in mind. This means that pupils with median ability could get KS2 scores and pupils at the extremes loose out. What would this mean for the rank effect estimator? Consider two pupils of the same ability who went to the same secondary school but different primary schools where one was top in year. The top pupil would get less attention for KS2 and so get a lower grade. At secondary school they have the same attention due to their same ability and get the same KS3 scores. In our estimation controlling for KS2 test scores will make it appear that the top pupil had higher growth and so generate the positive effect of rank. Therefore, teachers teaching to the median pupil could also generate a rank effect. However, if this the case the rank effect would need to follow a u-shaped curve, with *both* pupils at the bottom and the top of the distribution gaining relatively more in secondary school, relative to primary school. Since we find a linear effect of rank on KS3 test scores (Figure 5) with pupils at the bottom of the rank distribution losing out in KS3 we doubt that his is the dominant reason for the effect.

## 8.2 Hypothesis 2: Competiveness

If the goal of agents was just to be better than their peers, this could produce some elements of ourresults. Pupils of much higher ability than their primary peers would need to try less

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[23] We have run estimations controlling for the within school-cohort-subject variance to take into account that high variance classes may be more difficult to teach. However, these cannot include school-cohort-subject or pupil effects and therefore the estimates should not be cleanly interpreted as ordinal rank affects. Therefore these specifications only allowed for general school effects or no school effects. The inclusion of a school-cohort-subject variance into these specifications does not significantly alter the rank parameter. Our findings and can be presented upon request.

hard at their Key Stage 2 tests. By a similar argument to that outlined above this negative correlation of ability and effort would generate the positive effect for the highest ranked students in KS3 test scores when controlling for KS2. However, if this was the case, we would mainly expect to see these effects only near the top of the distribution. For example, this competition to be the best-ranked pupil in class could not explain the observed negative effects of being the worst pupil in terms of local subject-rank. Furthermore, even if pupils just wanted to compete in being different to the average so that lowest ability kids wanted to be the worst and highest ability kids wanted to be the best, there would be no effect in the middle of the distribution. However, as we discussed in Section 7.1, the effects we document are near linear.

### 8.3    Hypothesis 3: External (parental) investment by task

It may not be the pupils that are applying different effort by subject but the parents of the pupils. Parents can assist the child at home with homework or other extra-curricular activities. If the parents know that their child is ranked highly in one subject they might encourage the child to do more activities and be more specialised in this subject. Note as we are controlling for pupil effects, this must be subject specific encouragement rather than general encouragement for school work, and the additional investment must take place between ages 11 and 14.

   However, there are two counter arguments for this mechanism we believe. Firstly, whilst some parents may choose to specialise the child others may want to improve their child's weakest subject. If parental investment focussed on the weaker subject this would reverse the rank effect for these pupils. In order to explain the positive rank effect that we find, one would need to assume that the majority of parents wanted their child to specialise, which seems unrealistic for the ages eleven to fourteen, where students have only limited subject choices. Secondly it would be reasonable to assume that parents are not highly informed of their child's rank in class. Teacher feedback to parents will convey some information for the parents to act on such as the pupil being the best/worst in class but is likely not to be able to discern difference from the near the middle of the cohort rankings. Our results show significantly different effects from the median for all vingtiles with school-cohort-subject effects[24].

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[24] Information on the within pupil comparative advantage by subject would be easier for a teacher to communicate, and so parents could use this to specialize the pupil. However, these effects would then appear less significant in the school-cohort-subject effects specifications.

### 8.4 Hypothesis 4: Students learn about their ability

Another possibility is that students use the information obtained by their local rank to update their beliefs about their subject-specific abilities and as a result allocate effort accordingly. Note that this mechanism is different to changes in self-concept as self-concept would induce *real* changes in costs. On the other hand, if students used their local ranks to learn about national ability this would only impact their *perceived* abilities.

Note that if students used local rank to update beliefs about ability, particular students with large differences between local and national rank would allocate effort non-optimally. These students would then misallocate effort across subjects, depending on how much local rank is different to national rank. The larger the difference between local rank to national rank (in absolute terms) the more distorted the local rank information is about true ability. The resulting misallocation of effort should lead to lower overall grades compared to students where local ranks closely align with national ranks. This is because this misallocation would lead to inefficient effort allocation across subjects and thus reduce average grades obtained.

Unfortunately, we do not have direct data on effort allocation to test for misallocation. However, we test for this mechanism by regressing average Key Stage 3 tests on average rank, Key Stage 2 results, our usual controls, and an additional explanatory variable that captures the amount of misinformation a student obtains through observing her local rank. More precisely, we compute the absolute difference between local and national rank for each student and subject, which ranges from zero to one. This measure takes the value zero for students where the local rank happens to correspond exactly to the national rank. A large value, on the other hand, indicates large differences between local and national rank. We now average this indicator within student to test directly if a student with a large amount of disinformation does significantly worse, ceteris paribus.

We obtain the following estimates using our full sample of 2,271,999 pupils: the coefficient for the effect of misinformation is estimated to be -0.065 and insignificant at any conventional level with a p-value of 0.8, and an estimated standard error of 0.263. Based on these results we therefore conclude that an information story seems unlikely to generate our results.

### 8.5 Main hypothesis: Rank position develops self-concept

As spelled out in Section 3, our underlying hypothesis is that relative performance in a task amongst your peers affects your self-concept. This has an impact on non-cognitive skills like

resilience and persistence, which affects the costs of effort for that task. When considering education this is interpreted as the cost for studying a subject and so determines investment decisions about where to apply effort to maximise grades. We see these relative changes in efforts through later test scores.

To provide evidence for this mechanism we link this data to the Longitudinal Survey of Yong People in England (LSYPE). This survey of about fifteen thousand pupils contains questions referring to self-concepts for each subject. This allows us to test directly if rank position within primary school has an effect on these measures of self-concept whilst controlling for KS2 scores. The specifications are equivalent to the main estimations and the results can found in Table 4. Since this survey was only run for one cohort, we control for subject-effects and interactions but do not further interact these with cohort.

These results show that conditional on test scores students with a higher rank position are significantly more likely to say that they are good in a certain subject. When controlling for school-subject effects the impact of moving from the bottom of class to the top is 0.19 points on a 5-point Likert scale. This suggests that pupils develop a clear sense of their strength and weaknesses depending on their local rank position, controlling for actual test outcomes in the national context.

While we would prefer to have a measure of self-concept directly at age-11 at the end of primary school, these measures are only available to us at age-14, which is just prior to the KS3 tests. Therefore in Panel B we additionally control for contemporaneous attainment at Key Stage 3, which is of course an outcome. To cautiously interpret these estimates, students with 'the same' KS2 and KS3 results, i.e. the same trend, have higher self-concept if they had a higher local rank in that subject in primary school. The specifications allowing for primary-subject effects cannot reject the null that rank has no effect on self-concept. The reason for this is that there are very few pupils per primary school in this survey (4.5 pupils conditional on at least one pupil being in the survey), this is because the survey was conducted at secondary schools. The small number of students per school severely limits degrees of freedom given the school-subject. This is exacerbated with the pupil fixed effects considering 46% of the pupils are from primary schools with 3 or less pupils being surveyed along with the coarseness of the self-concept variable.

To obtain a clearer view of the effect of rank on self-concept we also estimate how KS3 rank within a secondary school subject effects subject confidence conditional on secondary-subject effects and individual effects. The advantage of this is that for schools which have

pupils in the survey, there are on average 20 pupils[25]. These results can be found in Panel C of Table 4, where we see that conditional on school-subject effects, moving from bottom to top of class improves confidence by 0.43 on a 5 point scale. Allowing for individual effects, such as certain pupils being generally confident across all subjects, this reduces to 0.38 but remains significant at 1%. Furthermore, we estimate the effect of KS3 rank on confidence separately by gender conditional on pupil and school-subject effects. We find that the effect on male confidence is five times larger than the effect on females ($\hat{\beta}_{rank\,male} = 0.60$, $\hat{\beta}_{rank\,female} = 0.12$), which mirrors the results we find for the effect of rank on later test scores[26]. Unfortunately due to sample size, we are unable to produce the effects by FSME status or non-linearly.

The magnitudes of these KS3 ranks effects are large, but we may expect the true contemporaneous effect of KS2 rank on confidence at age 11 to be larger as self-concept thought to be more malleable at this age. However we do find indicative evidence that later confidence is effected by previous primary school rank.

## 9   Conclusions

This paper examined how local rank affects later outcomes. In an education setting we establish a new effect, that rank position within primary school has significant effects on later achievement, conditional on end-of-primary national test scores. Moreover we also show that higher rank conditional on ability increases a pupil's self-concept in that subject. We also find that these effects are considerably larger for males compared to females. Male confidence in a subject is five times more effected by their local rank compared to females. Accordingly, we find that male students gains four times more in later test scores from being top of class compared to a comparable female students. Students with low parental income background, on the other hand, do not seem to additionally be hurt by low rank positions during primary education.

With specific regards to education the importance of rank  leads to a natural question for a parent deciding on where to send their child. Should my child attend "a 'better school' or a 'worse school' where she/he will be higher in the rank ordering?" The authors are currently

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[25] The reason why we do not look at the effect of KS3 rank on later outcomes is due to the tracking by subject in secondary school, which will be related to rank. This is not an issue with primary school rank as even if there was tracking in primary schools, when moving to secondary school students with the same test scores (but different primary ranks) would be assigned to the same track.

[26] Tables of these results can be obtained from the authors on request.

not aware of any study that identifies the effectiveness of schools in terms of standard deviations[27], therefore we use estimates of the impact of teachers as an indicative measure for effects of school quality for this benchmarking exercise. A teacher who is one standard deviation better than average improves pupil test scores by 0.1 to 0.2 standard deviations (Aaronson, et al. 2007; Rivkin et al. 2005). We find that a student with one standard deviation higher rank in primary school will score 0.08 standard deviations better at age 14.[28] Forthcoming work will look at the longer run impacts of primary school rank and changes in school ranks from moving schools.

We believe these findings have general implications to productivity in the classroom or work place relating to informational transparency and productivity. To improve productivity it would be optimal for managers/teachers to highlight an individual's local rank position if that individual had a high local rank. If an individual is in a high performing peer group and therefore may have a low local rank but a high global rank a manager should make the global rank more salient. Finally, for individuals who have a low global and local ranks then managers should focus absolute attainment and make rank less salient, or other tasks where the individual has higher ranks. We believe these are exiting directions for future research.

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[27] Evaluations of school effectiveness using admission lotteries (Hoxby et al. 2009, Angrist et al. 2010, Dobbie and Fryer 2011, Abdulkadiroglu et al. 2011) are comparing effectiveness between types rather than the whole distribution of effectiveness.

[28] Note that these are still not directly comparable as the effect of the teacher is annual, but quickly fades out. Whereas the rank treatment lasts the duration of primary school (5 years), but the effect is found three years later.

# Tables and Figures

**Table 1: Descriptive statistics of the main sample**

|  | Mean | S.D. | Min | Max |
|---|---|---|---|---|
| *Panel A: Pupil Characteristics* | | | | |
| KS2 English | 50.29 | 28.03 | 1 | 100 |
| KS2 Maths | 50.52 | 28.19 | 1 | 100 |
| KS2 Science | 50.01 | 28.03 | 1 | 100 |
| Within Pupil KS2 S.D. | 12.68 | 7.70 | 0 | 57.16 |
| KS3 English | 51.23 | 28.18 | 1 | 100 |
| KS3 Maths | 52.89 | 27.55 | 1 | 100 |
| KS3 Science | 52.91 | 27.53 | 1 | 100 |
| Within Pupil KS3 S.D. | 11.32 | 7.19 | 0 | 56.59 |
| | | | | |
| *Panel B: Rank Characteristics* | | | | |
| Rank English | 0.488 | 0.296 | 0 | 1 |
| Rank Maths | 0.491 | 0.296 | 0 | 1 |
| Rank Science | 0.485 | 0.295 | 0 | 1 |
| Within Pupil Rank S.D. | 0.138 | 0.087 | 0 | 0.58 |
| | | | | |
| *Panel C: Background Characteristics* | | | | |
| SEN | 0.175 | 0.380 | 0 | 1 |
| FSME | 0.146 | 0.353 | 0 | 1 |
| Male | 0.499 | 0.500 | 0 | 1 |
| Ethnicity | | | | |
| White British | 0.837 | 0.370 | 0 | 1 |
| Other White | 0.019 | 0.135 | 0 | 1 |
| Asian | 0.058 | 0.234 | 0 | 1 |
| Black | 0.030 | 0.171 | 0 | 1 |
| Chinese | 0.003 | 0.053 | 0 | 1 |
| Mixed | 0.017 | 0.128 | 0 | 1 |
| Other | 0.011 | 0.104 | 0 | 1 |
| Unknown | 0.026 | 0.158 | 0 | 1 |

Notes: 6,815,997 obs over 5 cohorts. Cohort 1 takes KS2 in 2001 and KS3 in 2004, cohort 5 takes KS2 in 2005 and KS3 in 2008. Test scores are percentalized tests scores by cohort-subject

.

## Table 2: Rank on KS3 Test Scores in Secondary School

|  | (Raw) | (1) | (2) | (3) |
|---|---|---|---|---|
| *Panel A: The effect of primary rank* |  |  |  |  |
| Primary Rank – Flexible KS2 | 11.551** | 7.662** |  |  |
|  | *0.293* | *0.145* |  |  |
| Primary Rank – Cubic KS2 | 11.001** | 7.960** | 7.901** | 4.562** |
|  | *0.298* | *0.145* | *0.146* | *0.132* |
| *Panel B: The effect of placebo rank* |  |  |  |  |
| Placebo Rank – Flexible KS2 | 0.0055 | 0.015 |  |  |
|  | *0.100* | *0.011* |  |  |
| Placebo Rank – Cubic KS2 | 0.0045 | 0.013 | 0.016 | -0.008 |
|  | *0.100* | *0.116* | *0.119* | *0.137* |
| Pupil characteristics | ✓ | ✓ | ✓ | Abs |
| Key Stage 2 controls | ✓ | ✓ | ✓ | ✓ |
| Primary-cohort-subject Effects |  | ✓ | ✓ | ✓ |
| Secondary Effects |  |  | Abs | Abs |
| Secondary-cohort-subject Effects |  |  | ✓ |  |
| Pupil Effects |  |  |  | ✓ |

Notes: Results obtained from twelve separate regressions based on 2,271,999 pupil observations and 6,815,997 pupil-subject observations. The dependent variable is by cohort by subject percentalized KS3 test scores. All specifications control for Key Stage 2 results, pupil characteristics, cohort effects and subject effects. Pupil characteristics are ethnicity, gender, free school meal (FSME) and special educational needs (SEN). Coefficients in columns (2) and (3) are estimated using Stata command reg2hdfe. Standard errors in italics and clustered at 3,800 secondary schools. Abs indicates that the effect is absorbed by another estimated effect. ** 1% sig.

## Table 3: Balancing by parental occupation

|  | (1) | (2) |
|---|---|---|
| *Panel A: Effects on Key Stage 2* |  |  |
| Parental Occupation | 7.722** | 1.706* |
|  | *0.840* | *0.783* |
| *Panel B: Effects on Ordinal Rank* |  |  |
| Parental Occupation | -0.004 | 0.000 |
|  | *0.005* | *0.034* |
| Primary-subject Effects | ✓ | ✓ |
| Pupil Effects |  | ✓ |

Notes: Results obtained from regressions based on 31,050 subject-pupil observations for which parental occupations could be identified from the LSYPE. Detailed occupational coding available from the authors on request. Panel A has KS2 as dependent variable, in Panel B KS2 with polynomials up to cubic are included as controls. All regressions control for pupil characteristics and subject effects. Regressions in column (2) estimated using Stata command reg2hdfe. ** 1%,* 5% sig.

**Table 4: Rank on Self-Concept**

|  | (1) | (2) | (3) |
|---|---|---|---|
| *Panel A: KS2 test scores on Self-Concept* | | | |
| Primary Rank – Cubic KS2 | 0.563** | 0.196* | 0.056 |
|  | *0.038* | *0.117* | *0.18* |
| *Panel B: KS2 & KS3 test scores on Self-Concept* | | | |
| Primary Rank – Cubic KS2 & KS3 | 0.436** | 0.109 | 0.014 |
|  | *0.039* | *0.115* | *0.079* |
| *Panel C: KS3 test scores on Self-Concept* | | | |
| Primary Rank – Cubic KS3 | 0.897** | 0.427** | 0.382** |
|  | *0.048* | *0.099* | *0.155* |
| School-by-subject Effects |  | ✓ | ✓ |
| Pupil Effects |  |  | ✓ |

Notes: Results obtained from nine separate regressions based on 11,558 pupil observations and 34,674 pupil-subject observations from the LSYPE sample. For descriptives see Appendix Table 3. There are 4,372 Primary groups, 13,116 Primary-subject groups, 796 Secondary groups and 2388 Secondary-Subject groups. The dependent variable is a course measure of self-concept by subject. All specifications control for Key Stage 2 results, pupil characteristics and subject effects. Pupil characteristics are ethnicity, gender, free school meal (FSME) and special educational needs (SEN). Standard errors in parenthesis and clustered at 796 secondary schools. In Panels A amd B School Effects refer to Primary schools, in Panel C to Secondary schools. Abs indicates that the effect is absorbed by another estimated effect. ** 1% sig. * 10% sig.

**Figure 1:** *see in text*


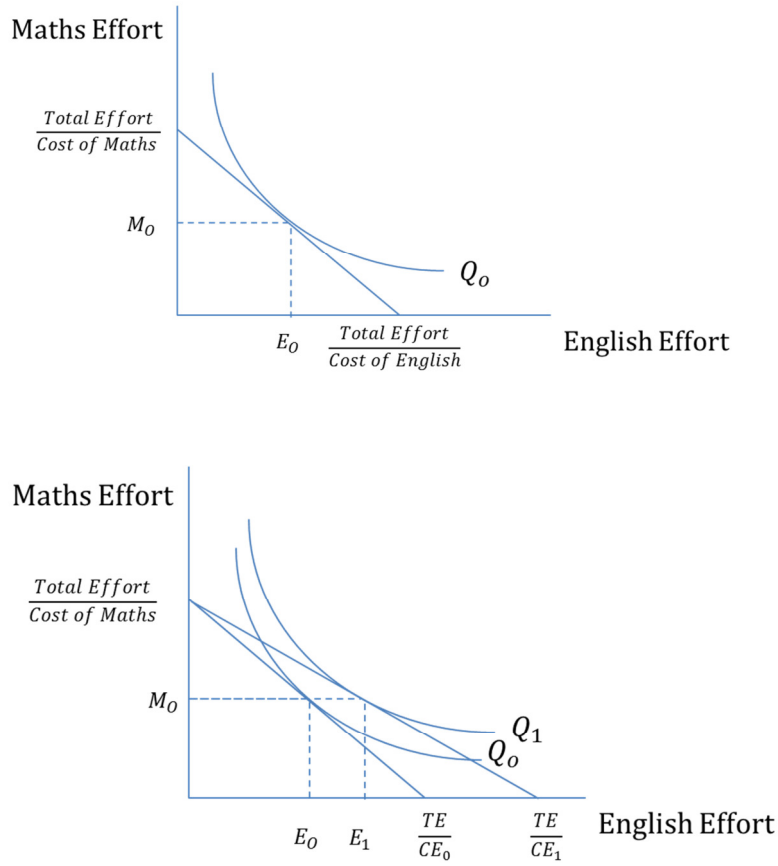**Figure 2: Optimal allocation of effort**



Maths Effort

$\frac{Total\ Effort}{Cost\ of\ Maths}$

$M_O$

$Q_O$

$E_O$ $\quad \frac{Total\ Effort}{Cost\ of\ English}$ $\quad$ English Effort




Maths Effort

$\frac{Total\ Effort}{Cost\ of\ Maths}$

$M_O$

$Q_1$
$Q_O$

$E_O$ $\quad E_1$ $\quad \frac{TE}{CE_0}$ $\quad \frac{TE}{CE_1}$ $\quad$ English Effort
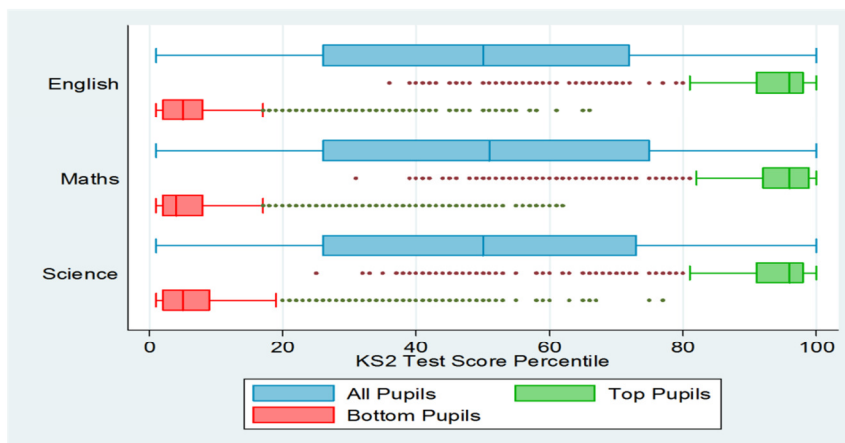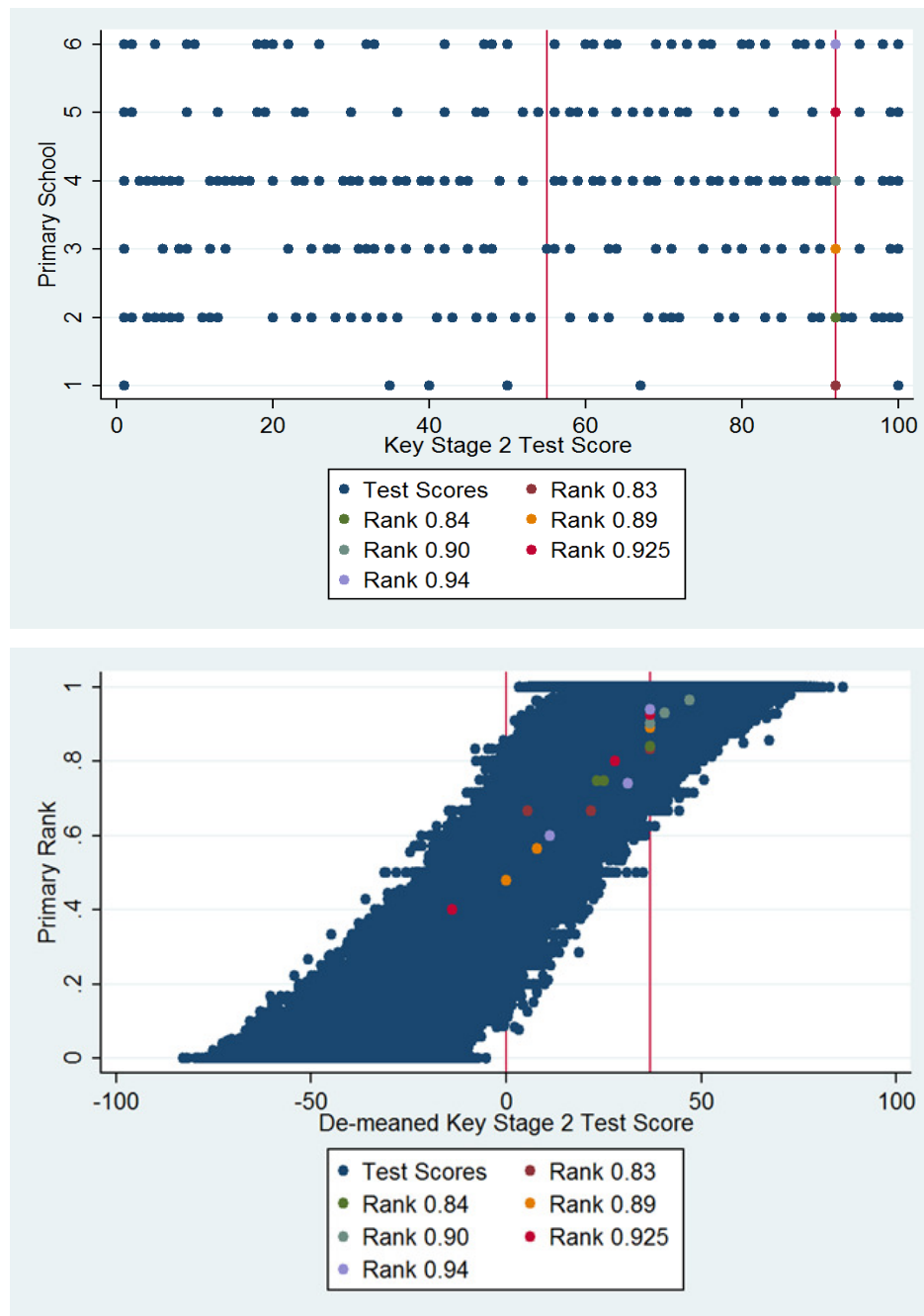

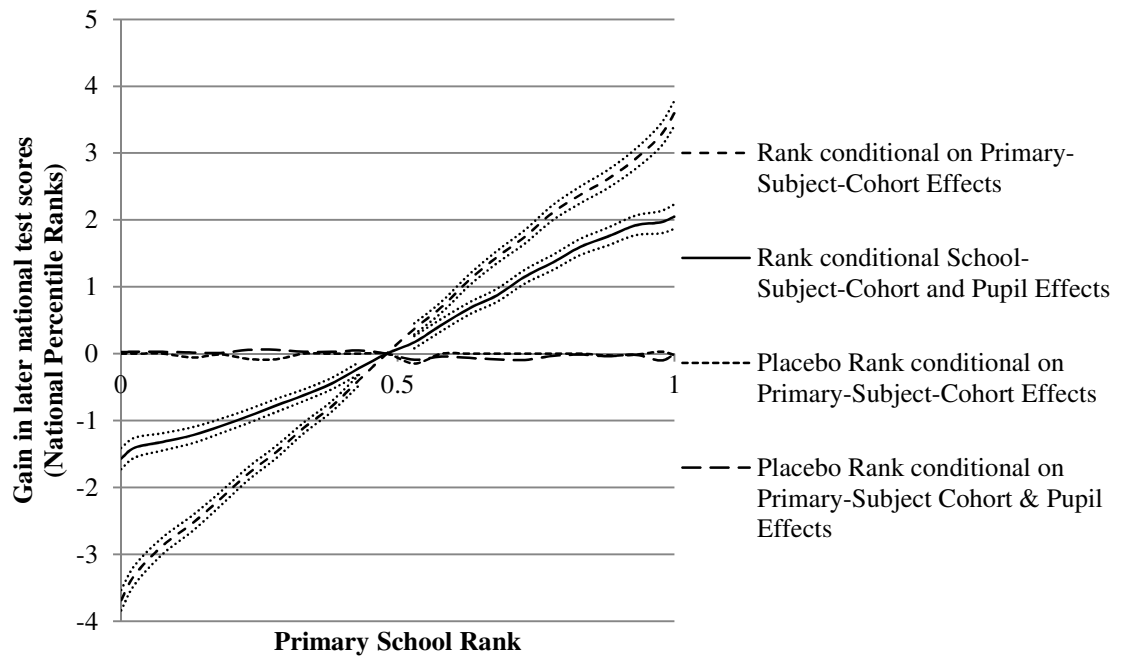**Figure 3: Distribution of Top and Bottom pupils**



Notes: Box plots of Key Stage 2 test scores. Top Pupils are defined as pupils ranked in the top 5% of their school-subject-cohort ($Top\ Pupil = R_{ijs}[0.95, 1]$). Bottom Pupils are defined as pupils ranked in the bottom 5% of their school-subject-cohort ($Bottom\ Pupil = R_{ijs}[0, 0.05]$). Note that individual test scores have been randomly altered enough to ensure anonymity of individuals and schools. This does in no way affect the interpretation of this figure.

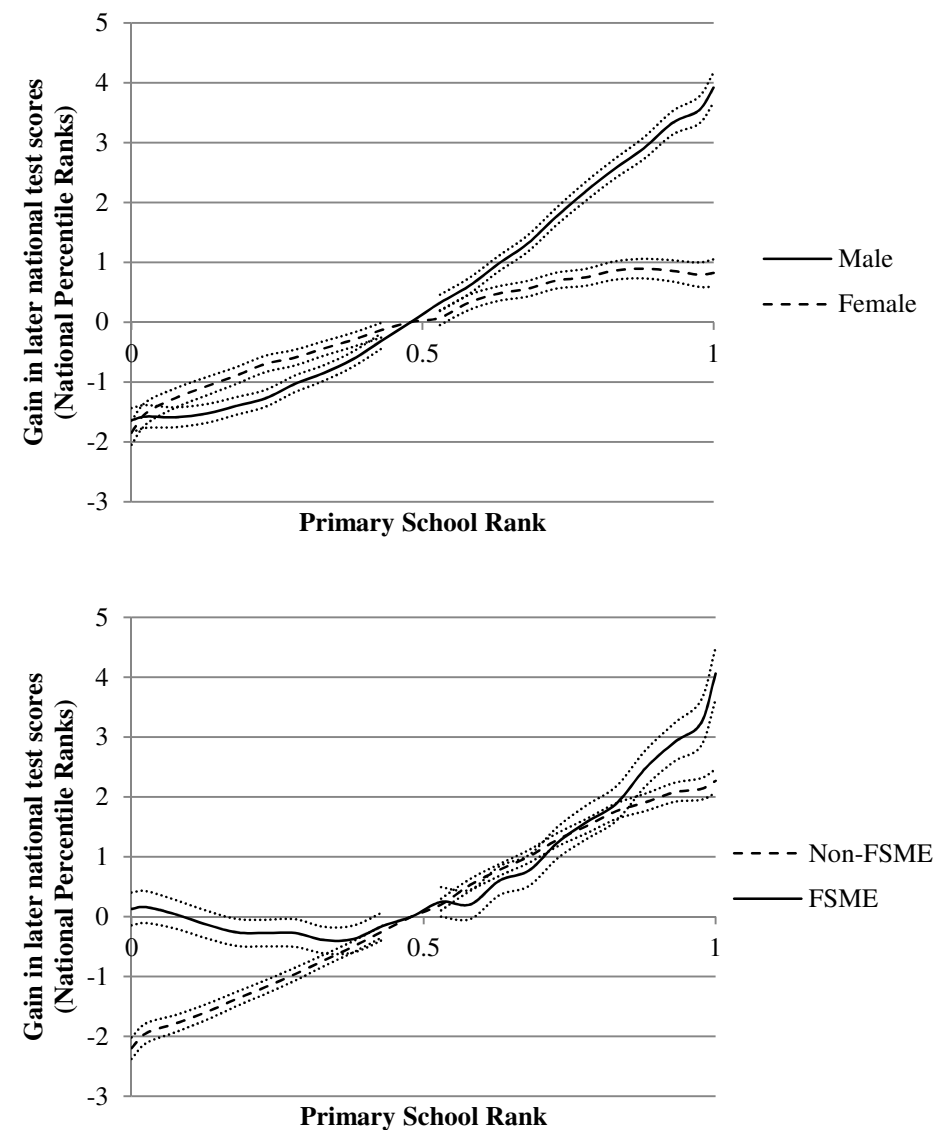**Figure 4: Rank distributions in schools and across subjects**



Notes: In the upper panel each point represents a student's Key Stage 2 test score. The six schools that are represented that have the same mean (54), minimum (0) and maximum (100) tests scores in English, and also have a pupil with a test score of 93. The lower panel shows all pupils in our data. Test scores have been de-meaned by primary school-subject-cohort. The colored points represent the three different test scores and ranks of pupils from Figure 5 with a test score of 93 in English. Note that the number of students per school as well as individual test scores have been randomly altered enough to ensure anonymity of individuals and schools. This does in no way affect the interpretation of these figures.

**Figure 5: Effect of Placebo Primary School rank on Secondary School outcomes**



Notes: Non-linear effect with dummies for the vingtiles of rank plus a dummy for being top or bottom of school-subject-cohort. All specifications have subject specific rank and test score across three subjects. Placebo rank generated from actual test scores but randomly allocated peers, using the actual distribution of primary school size. All standard errors clustered at the actual secondary school attended. Specification 1: Pupil characteristics and primary, subject and cohort effects. Specification 2: Primary-subject-cohort group effects and pupil effects. Dashed lines represent 95% confidence intervals.

**Figure 6: Effect of Primary School rank on Secondary School outcomes by pupil characteristics**



Notes: FSME stands for Free School Meal Eligible student. Effects obtained from estimating the effect of rank on Non-FSME (Female) students and the interaction term with FSME (Male) students. Non-linear effect with dummies for the vingtiles of rank plus a dummy for being top or bottom of school-subject-cohort. All estimates use subject specific rank and test score across three subjects and condition on Primary-subject-cohort group effects and pupil effects. Dashed lines represent 95% confidence intervals.

# Appendix 1: Model

We model students as grade maximising agents for a given total cost of effort and ability level. The grade achieved (Y) by a student $i$ in subject $s$ is a function of ability $A$ and effort $E$ according to a to a separable production function where $0<\alpha<1$.

$$Y_i = f(A_{ie}, E_{ie}) + f(A_{im}, E_{im}) = School.A_{ie}.E_{ie}{}^\alpha + School.A_{im}.E_{im}{}^\alpha$$

We assume costs of subject effort $c_s$ are linear in effort applied to that subject, and that total cost of effort $TC_i$ is fixed for a student which can be dependent on outside factors.

$$TC_i \geq C_{im}E_{im} + C_{ie}E_{ie}$$

There is additionally a non-binding time constraint where

$$1 > E_{ie} + E_{im}$$

Therefore student $i$ solves:

$$\max_{E_e E_m} Y(E_e, E_m) = f(E_e) + f(E_m)$$

$$= School.A_{ie}.E_{ie}{}^\alpha + School.A_{im}.E_{im}{}^\alpha \quad (1)$$

$$s.t. \ TC_i \geq C_{ie}E_{ie} + C_{im}E_{im} \quad\quad (2)$$

$$1 > E_{ie} + E_{im}$$

$$l = Y_i + (1 - E_{ie} - E_{im}) - \lambda(TC_i - C_{ie}E_{ie} - C_{im}E_{im})$$

$$\frac{dl}{dE_e} = 0 \ \rightarrow \ \frac{\partial Y}{\partial E_e} = \lambda\,C_e$$

$$\frac{dl}{dE_m} = 0 \ \rightarrow \ \frac{\partial Y}{\partial E_m} = \lambda\,C_m$$

$$\frac{dl}{d\lambda} = 0 \ \rightarrow \ C_{ie}E_{ie} + C_{im}E_{im} = TC$$

$$\frac{dY}{dE_s} = \alpha.School.A_s E_s^{\alpha-1}$$

Therefore

$$\alpha.School.A_s^{1-\alpha} E_s^{\alpha-1} = \lambda\,C_s$$

Where $\lambda$ reflects the marginal grade per effort and $\lambda>0$

$$\frac{\alpha.School.A_e E_e^{\alpha-1}}{C_e} = \lambda = \frac{\alpha.School.A_m E_m^{\alpha-1}}{C_m}$$

This gives

$$\frac{C_{ie}}{C_{im}} = \frac{A_{ie}.E_{ie}^{\alpha-1}}{A_{im}.E_{im}^{\alpha-1}}$$

And

$$E_{is}^* = \left(\frac{C_{is}}{\alpha A_{is}}\right)^{\frac{1}{\alpha-1}}$$

As $C_s = g(R_s)$ $where$ $g'(R_s) < 0$, any increase in rank in subject $s$ will increase the effort allocated to subject $s$.

## Appendix 2: Peer Effects

There are concerns that with the existence of peer effects, peer quality jointly determines both a pupil's rank position, as well as their KS2 results. This mechanical relationship could potentially bias our estimation. This is because in the presence of peer effects a student with lower quality peers would attain a lower KS2 result than otherwise and also have a higher rank than otherwise. Thus, when controlling for KS2 in the KS3 estimations, when students have a new peer group, those who previously had low quality peers in KS2 would appear to gain more. Since rank is negatively correlated with peer quality in KS2, it would appear that those with high rank make the most gains. Therefore having a measure of ability confounded by peer effects would lead to an upward biased rank coefficient.

This situation could be present in our data. We propose a resolution by the inclusion of subject-by-cohort-by-primary school controls. These effects will absorb any average peer effects across classroom. However, they will not absorb any peer effects that are individual specific. This is because all students will have a different set of peers (because they cannot be a peer to themselves). Therefore including class level controls will only remove the average class peer effect. The remaining bias will be dependent on of the difference between the average peer effect and the individual peer effect and its correlation with rank. Given that the difference between average and individual peer effect decreases as class size increases, that the bias with be further attenuated as the correlation between the difference and rank will be less than one and both effects are small we are confident that the effect of peers on the rank parameter will be negligible.

We test this by running simulations of a data generating process where KS test scores are not affected by rank and are only a function of ability and school/peer effects, and then estimate the rank parameter given this data. We allow for the data generating process to have linear mean-peer effects, as well as non-linear peer effects (Lavy *et al.* 2012). We are conservative and assume very large peer effects, allowing both types of peer effects to account for 10% of the variance of a student's subject-specific outcome. Given that the square root of the explained variance is the correlation coefficient, this assumption implies a one standard deviation increase in peer quality improves test scores by 0.31 standard deviations.

In reality Lavy *et al.* (2012) find a 1sd increase in peers only increases test scores by 0.015standard deviations, a 20th of the size.

The data generating process is as follows:

- We create 2900 pupils to 101 primary schools and 18 secondary schools of varying school sizes[29].

- Pupils have a general ability $\alpha_i$ and a subject specific ability $\delta_{is}$ taken from normal distributions with mean 0 and standard deviation 1.

- All schools are heterogeneous in their impact on pupil outcomes, which are taken from normal distributions with mean 0 and standard deviation 1.

- Linear mean peer effects are the mean subject and general ability of peers not including themselves.

- Non Linear peer effect is the negative of the total number of peers in the bottom 5% of pupils in the population in that subject.

- We generate individual's *i Key Stage* test scores as a function of general ability $\alpha_i$ subject specific ability $\delta_{is}$, primary peer subject effects $\rho_{ijs}$ or secondary peer subject effects $\sigma_{iks}$, primary school effects $\mu_j$ or secondary school effects $\pi_k$ , Key Stage 2 and 3 measurement error $\varepsilon_{ijs}$ or $\epsilon_{ijks}$ , and for one KS3 specification primary school Rank $\omega_{ijs}$

  o Key Stage 2 test scores
  $$KS2_{ijs}=0.7*(\alpha_i+ \delta_{is}) +0.10*\mu_j +0.1*\rho_{ijs} +0.1\varepsilon_{ijs}$$

  o Key Stage 3 test scores where rank has no effect (Panel A):
  $$KS3_{ijs}=0.7*(\alpha_i+ \delta_{is}) +0.10* \pi_k+0.1*\sigma_{iks} +0.1\epsilon_{ijks}$$

  o Key Stage 3 test scores where rank has an effect (Panel B):
  $$KS3_{ijks}=0.6*(\alpha_i+ \delta_{is}) +0.10* \pi_k+0.1*\sigma_{iks}+ 0.1\omega_{ijs} +0.1\epsilon_{ijks}$$

We simulate the data 1000 times and then estimate the rank parameter using the following specifications, with and without school-subject effects.

$$KS3_{ijks} = \beta_{rank}Rank_{ijs} + \beta_{KS2}KS2_{ijs} + \varepsilon_{ijks}$$

$$KS3_{ijks} = \beta_{rank}Rank_{ijs} + \beta_{KS2}KS2_{ijs} + \sigma_{ijs} + \epsilon_{ijks}$$

---

[29] Primary school sizes; 14 pupils, 16, 25 pupils (x4 schools), 26 pupils (x5), 27 pupils (x10), 28 pupils (x10), 29 pupils (x10), 30 pupils (x60). Secondary School sizes: 26 pupils, 89 pupils, 153 pupils, 160 pupils, 162 pupils, 170 pupils, 174 pupils, 178 pupils, 180 pupils (x9),

The results from these estimations can be found in appendix Table 1 & 2 below. When rank does not have an effect we would expect $\beta_{rank} = 0$, and when it does $\beta_{rank} = 0.1$. With these inflated peer effects sizes we find that controlling for school-subject-cohort removes enough of the positive bias to make the effect of peers negligible (Appendix Table 1 & 2, column 3). If there are very large non-linear peer effects then this specification introduces a negative bias and so our results could be seen as upper bounds (Appendix Table 2, column 3).

### Appendix 3: Measurement error in test scores

Key Stage test scores are scores are an imprecise measure of ability. Could this measurement error be driving the results? Given that both a rank and test scores will both be affected by the same measurement error, but to different extents due to heterogeneous test score distributions across classes, calculating the size of the bias is intractable. To gauge the potential effect of measurement error, we simulate the data generating process. This allows us to have a true measure of ability and a student test score of which 20% of the variation is measurement error. Comparing the estimates of the rank parameter with an without measurement error provides us an indication of the extent to which measurement error could be driving the results. The rank measurement is then derived from the noisy test score measure in both cases.

The data generating process is as follows:

- 2900 pupils to 101 primary schools and 18 secondary schools of varying school sizes[30].
- Pupils have a general ability $\alpha_i$ and a subject specific ability $\delta_{is}$ taken from normal distributions with mean 0 and standard deviation 1.
- All schools are heterogeneous in their impact on pupil outcomes, which are taken from normal distributions with mean 0 and standard deviation 1.
- We generate individual's $i$ *Key Stage* test scores as a function of general ability $\alpha_i$ subject specific ability $\delta_{is}$, primary school effects $\mu_j$ or secondary school effects $\pi_k$, Key Stage 2 and 3 measurement error $\varepsilon_{ijs}$ or $\epsilon_{ijks}$, and for one KS3 specification primary school Rank $\omega_{ijs}$
  - Key Stage 2 test scores

---

[30] Primary school sizes; 14 pupils, 16, 25 pupils (x4 schools), 26 pupils (x5), 27 pupils (x10), 28 pupils (x10), 29 pupils (x10), 30 pupils (x60). Secondary School sizes: 26 pupils, 89 pupils, 153 pupils, 160 pupils, 162 pupils, 170 pupils, 174 pupils, 178 pupils, 180 pupils (x9),

$$KS2_{ijs}=0.7*(\alpha_i+\delta_{is})+0.10*\mu_j+0.2\varepsilon_{ijs}$$

- o Key Stage 3 test scores where rank has no effect (Panel A):

$$KS3_{ijs}=0.7*(\alpha_i+\delta_{is})+0.10*\pi_k+0.2\epsilon_{ijks}$$

- o Key Stage 3 test scores where rank has an effect (Panel B):

$$KS3_{ijks}=0.6*(\alpha_i+\delta_{is})+0.10*\pi_k+0.1\omega_{ijs}+0.2\epsilon_{ijks}$$

We simulate the data 1000 times and then estimate the rank parameter using the following specifications, with and without school-subject effects, controlling either for ability ($\alpha_i+\delta_{is}$) or KS2 test scores.

$$KS3_{ijks}=\beta_{rank}Rank_{ijs}+\beta_{Ability}Ability_{ijs}+\varepsilon_{ijks}$$

$$KS3_{ijks}=\beta_{rank}Rank_{ijs}+\beta_{Ability}Abiliyt_{ijs}+\sigma_{ijs}+\epsilon_{ijks}$$

$$KS3_{ijks}=\beta_{rank}Rank_{ijs}+\beta_{KS2}KS2_{ijs}+\varepsilon_{ijks}$$

$$KS3_{ijks}=\beta_{rank}Rank_{ijs}+\beta_{KS2}KS2_{ijs}+\sigma_{ijs}+\epsilon_{ijks}$$

The results of these specifications can be found in appendix Table 3 below. The ability specification produces unbiased results. When there is measurement error in the test score there is a downward bias to the rank effect when rank has an effect (Appendix Table 3, Column 5, Panel B). We find that including school-subject-cohort and pupil fixed effects removes this downward bias.

**Appendix Table 1: Simulation of rank estimation with peer effects**

| | Mean peer effects | | Non-linear Peer Effects | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Panel A: Rank has no effect $\beta_{rank}=0.0$* | | | | |
| Mean $\hat{\beta}_{rank}$ | 0.046 | 0.000 | 0.302 | -0.041 |
| Mean SE of $\hat{\beta}_{rank}$ | 0.014 | 0.018 | 0.015 | 0.019 |
| SE of $\hat{\beta}_{rank}$ | 0.015 | 0.019 | 0.031 | 0.020 |
| 95% Lower Bound | 0.015 | -0.037 | 0.243 | -0.079 |
| 95% Upper Bound | 0.077 | 0.035 | 0.364 | -0.003 |
| *Panel B: Rank has an effect $\beta_{rank}=0.1$* | | | | |
| Mean $\hat{\beta}_{rank}$ | 0.099 | 0.100 | 0.304 | 0.068 |
| Mean SE of $\hat{\beta}_{rank}$ | 0.014 | 0.017 | *0.014* | *0.018* |
| SE of $\hat{\beta}_{rank}$ | 0.015 | 0.018 | 0.027 | 0.018 |
| 95% Lower Bound | 0.069 | 0.066 | 0.252 | 0.033 |
| 95% Upper Bound | 0.129 | 0.133 | 0.358 | 0.104 |
| KS2 and Rank | ✓ | ✓ | ✓ | ✓ |
| School-Subject-Effects | | ✓ | | ✓ |

Notes: 1000 iterations, 95% confidence bounds are obtained from 25th and 975th estimate of ordered rank parameters..

**Appendix Table 2: Simulation with measurement error**

| | Condition on true ability: No measurement error | | | Condition on test scores: Large measurement error | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Rank has no effect $\beta_{rank}=0.0$* | | | | | | |
| Mean $\hat{\beta}_{rank}$ | -0.001 | 0.000 | 0.000 | -0.010 | 0.015 | -0.000 |
| Mean SE of $\hat{\beta}_{rank}$ | 0.021 | 0.020 | 0.025 | 0.029 | 0.034 | 0.041 |
| SE of $\hat{\beta}_{rank}$ | 0.037 | 0.021 | 0.025 | 0.030 | 0.036 | 0.042 |
| 95% Lower Bound | -0.074 | -0.039 | -0.047 | -0.068 | -0.054 | -0.082 |
| 95% Upper Bound | 0.076 | 0.041 | 0.050 | 0.048 | 0.086 | 0.079 |
| *Panel B: Rank has an effect $\beta_{rank}=0.1$* | | | | | | |
| Mean $\hat{\beta}_{rank}$ | 0.099 | 0.100 | 0.100 | 0.053 | 0.113 | 0.100 |
| Mean SE of $\hat{\beta}_{rank}$ | 0.021 | 0.020 | 0.025 | 0.027 | 0.032 | 0.038 |
| SE of $\hat{\beta}_{rank}$ | 0.037 | 0.021 | 0.025 | 0.029 | 0.033 | 0.039 |
| 95% Lower Bound | 0.026 | 0.061 | 0.053 | -0.002 | 0.048 | 0.024 |
| 95% Upper Bound | 0.176 | 0.141 | 0.150 | 0.109 | 0.179 | 0.176 |
| Ability and Rank | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| School-Subject-Effects | | ✓ | ✓ | | ✓ | ✓ |
| Pupil Effects | | | ✓ | | | ✓ |

Notes: 1000 iterations, 95% confidence bounds are obtained from 25th and 975th estimate of ordered rank parameters..

**Appendix Table 3: Descriptive statistics of LSYPE sample**

|  | Mean | S.D. | Min | Max |
|---|---|---|---|---|
| *Panel A: Pupil Characteristics* | | | | |
| KS2 English | 49.48 | 27.77 | 1 | 100 |
| KS2 Maths | 50.11 | 28.37 | 1 | 100 |
| KS2 Science | 48.69 | 28.30 | 1 | 100 |
| Within Pupil KS2 S.D. | 12.71 | 7.69 | 0 | 47.44 |
| KS3 English | 50.67 | 28.00 | 1 | 100 |
| KS3 Maths | 52.99 | 27.61 | 1 | 100 |
| KS3 Science | 52.21 | 27.71 | 1 | 100 |
| Within Pupil KS3 S.D. | 12.71 | 7.69 | 0 | 47.44 |
| | | | | |
| *Panel B: Rank Characteristics* | | | | |
| Rank English | 0.491 | 0.295 | 0 | 1 |
| Rank Maths | 0.496 | 0.297 | 0 | 1 |
| Rank Science | 0.482 | 0.294 | 0 | 1 |
| Within Pupil Rank S.D. | 0.140 | 0.086 | 0 | 0.49 |
| | | | | |
| *Panel C: Background Characteristics* | | | | |
| SEN | 0.166 | 0.372 | 0 | 1 |
| FSME | 0.186 | 0.389 | 0 | 1 |
| Male | 0.498 | 0.500 | 0 | 1 |
| Ethnicity | | | | |
| White British | 0.651 | 0.477 | 0 | 1 |
| Other White | 0.026 | 0.159 | 0 | 1 |
| Asian | 0.175 | 0.380 | 0 | 1 |
| Black | 0.081 | 0.273 | 0 | 1 |
| Chinese | 0.002 | 0.048 | 0 | 1 |
| Mixed | 0.002 | 0.046 | 0 | 1 |
| Other | 0.035 | 0.184 | 0 | 1 |
| Unknown | 0.028 | 0.164 | 0 | 1 |

Notes: 34,674 observations from the cohort who took KS2 in 2001 and KS3 in 2004. Test scores are percentalized tests scores by cohort-subject.

**Appendix Table 4: Descriptive statistics Top and Bottom ranked pupils**

*Panel A: Top*

| | National Average | Ranked in Top 5% Nationally (KS2) | Ranked in Top 5% of School (KS2) | Self-concept Considered themselves: Very Good |
|---|---|---|---|---|
| Male | 49.9% | 49.3% | 49.5% | 53.5% |
| FSME | 14.6% | 4.8% | 8.1% | 18.5% |
| SEN | 17.5% | 2.2% | 2.8% | 11.2% |
| Minority | 16.3% | 13.8% | 15.5% | 41.1% |
| Obs. | 6,815,997 | 353,464 | 365,176 | 8,192 |

*Panel B:Bottom*

| | National Average | Ranked in Bottom 5% Nationally (KS2) | Ranked in Bottom 5% of School (KS2) | Self-concept Considered themselves: Not Good |
|---|---|---|---|---|
| Male | 49.9% | 50.9% | 51.5% | 44.6% |
| FSME | 14.6% | 30.8% | 23.7% | 20.1% |
| SEN | 17.5% | 68.8% | 61.4% | 25.2% |
| Minority | 16.3% | 22.1% | 17.9% | 28.8% |
| Obs. | 6,815,997 | 280,675 | 467,208 | 5,211 |

Notes: Data from 5 cohorts. Cohort 1 has KS2 in 2001 and KS3 in 2004, which is the only cohort we have self-concept measures for from the LSYPE dataset. Pupil characteristics are ethnicity, gender, free school meal (FSME) and special educational needs (SEN), minority is non-white.

**Appendix Table 5: Descriptive Statistics of Self-concept, National and Local Rank**

| | Proportion | National KS2 Percentile Rank | | | Local School KS2 Rank*100 | | | Obs. |
|---|---|---|---|---|---|---|---|---|
| | | Mean | 10th | 90th | Mean | 10th | 90th | |
| *How good do you think you are at…* | | | | | | | | |
| | | | | | | | | |
| *Panel A: …English?* | | | | | | | | |
| Not Good At All | 1.1% | 28 | 4 | 62 | 27 | 0 | 62 | 132 |
| Not Very Good | 13.5% | 35 | 7 | 70 | 33 | 3 | 73 | 1563 |
| Don't Know | 0.1% | 31 | 10 | 53 | 35 | 0 | 63 | 11 |
| Fairly Good | 62.5% | 49 | 12 | 85 | 48 | 9 | 88 | 7222 |
| Very Good | 22.8% | 62 | 21 | 95 | 63 | 20 | 96 | 2630 |
| | | | | | | | | |
| *Panel B:…Maths?* | | | | | | | | |
| Not Good At All | 1.6% | 25 | 3 | 56 | 22 | 0 | 56 | 188 |
| Not Very Good | 11.9% | 31 | 5 | 62 | 29 | 2 | 64 | 1377 |
| Don't Know | 0.1% | 53 | 12 | 90 | 56 | 10 | 93 | 15 |
| Fairly Good | 63.8% | 47 | 12 | 85 | 47 | 9 | 86 | 7371 |
| Very Good | 22.6% | 70 | 30 | 97 | 71 | 31 | 98 | 2607 |
| | | | | | | | | |
| *Panel C:…Science?* | | | | | | | | |
| Not Good At All | 2.1% | 32 | 5 | 64 | 31 | 3 | 70 | 237 |
| Not Very Good | 14.8% | 37 | 6 | 76 | 36 | 3 | 75 | 1714 |
| Don't Know | 0.2% | 38 | 17 | 76 | 40 | 11 | 68 | 21 |
| Fairly Good | 57.4% | 48 | 10 | 86 | 47 | 8 | 88 | 6631 |
| Very Good | 25.6% | 59 | 17 | 94 | 60 | 18 | 95 | 2955 |

Notes: Results obtained from 11,558 pupil observations and 34,674 pupil-subject observations from LSYPE sample. Standard deviation of the measure is 0.99.

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