Class Rank and Long-run Outcomes

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Abstract

A student's school environment can have both immediate and long lasting impacts. We propose to answer a fundamental question about one aspect of the school environment—what is the effect of a student's ordinal rank on future outcomes? Using administrative data from all public school students in Texas, we extend the rank literature by showing that 3rd grade academic rank among their elementary school peers has on lasting impacts on the long-term education and labor market outcomes. Conditional on ability and classroom effects, students with higher elementary school ranks have higher subsequent test scores, are more likely to take AP classes, graduate high school, enroll and graduate from college and ultimately higher earnings. Moreover rank effects are subject specific, with only students being high ranking in math being more likely to study AP math, or major in a STEM field. Given these findings, the paper concludes by exploring the tradeoff between higher ability peers and higher rank.

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1. Introduction

People are routinely organized into groups, and the composition of these groups can affect an individual's outcomes. It is well established that social interactions have impacts on productivity. There are many long-standing theories and manifestations where group characteristics influence individual outcomes. The classic peer effects papers consider the mean characteristics of others in the group (Sacerdote 2001, Whitmore 2005, Kermer and Levy 2008, Carrell et al. 2009, Black et al. 2013, Booji et al. 2017), but other relationships have also been considered such as bad apples or role models (Hoxby & Weingarth, 2006, Lavy et al. 2012). The common theme in the vast majority of these is that individuals suffer from the presence of low-performing peers.

In this paper we present a type of peer effect where having low- performing peers would have positive impacts on individual's later outcomes. Specifically, the importance of relative ranking within a group in determining future outcomes. We will explore a student's relative ordinal rank in their classroom and the persistence of this effect on their outcomes on into adulthood.[1]

We consider a student's rank in 3rd grade (8 or 9 years old), independent of their absolute achievement, on long term outcomes including graduation from high school, enrollment in college, and earnings. We use the universe of public school students in Texas from 1994-2007 and combine this with an identification strategy that leverages idiosyncratic variation in rank. We find that a student's rank in 3rd grade has long-term effects on high school graduation, college enrollment, and earnings. We document that some of the effect arises from the way the school system treats students–lower ranked students are more likely to be held back, conditional on achievement.

Our finding is part of a growing literature that documents that a childhood conditions affect adult outcomes. These conditions range from where a child lives (Chetty et al 2016), the quality of a student's teacher (Chetty et al 2014), size of a student's classroom (Chetty et al. 2011), the age of a student when they start school (Black et al 2011), and the presence of disruptive peers (Carrell et al 2016, Bietenbeck 2016) among others. We add to this list that a

[1] This can occur through various channels. These channels can be categorised as internal (learning about ability, development of non-cognitive skills) and external (parental and school investments). We will extend the current literature on rank by exploring these channels.

child's rank in their third grade classroom, independent of their absolute achievement, has meaningful effects on education and earnings in adulthood. We discuss the implications this has for classroom formation.

Academic achievement and rank are highly correlated and so we use the method developed in Murphy & Weinhardt (2014) to isolate the effect of a student's rank. To identify this effect, we use idiosyncratic variation in the distribution of test scores across schools, subjects and cohorts. In particular, we define a student's achievement by their test score expressed as a percentile of the state population. We then compute a student's rank within their school, subject, and cohort and express it as a percentile. The thought experiment is to compare students who have the same absolute math achievement (as defined by the state distribution) but differ in their rank in their school. Consider the following hypothetical: two students in successive cohorts of the same size, at the same school, who have the same math achievement (as measured by their place in the state-wide distribution). Because school cohorts are small relative to the state cohort, one student may be the fifth best student in the class and the other may be the eighth. This is the idiosyncratic variation we leverage to identify the effect of rank.

We isolate the effect of rank under the assumption that there exists an otherwise smooth relationship between future outcomes considered and a student's absolute achievement. Further, we must assume that we correctly model the true relationship between achievement and future outcomes. The large number of classes in our administrative data allows us to estimate very flexibly the relationship between achievement and later outcomes, as there is a large variation in rank for a given achievement score. Figure 1 provides example classrooms in Texas that demonstrate the idiosyncratic variation in the test score distribution across primary schools can create such a situation. Critically, the administrative data provides a large variation in rank for a given test score, which allows us to condition on a non-parametric function of baseline achievement when estimating the rank effects.

A concern is that despite being having the same absolute achievement measures, students may be in very different school contexts. To account for any mean shifting factors, we include fixed effects at the elementary school-subject-cohort (SSC) level. These fixed effects remove the between SSC-group differences in long run attainment growth due to any group-level factor that enters additively and affects all students similarly, such as measurement issues (bad weather on the test day), or dynamic complementarity factors (mean ability of the students in the classroom, impact of the teacher, school infrastructure). This extends the previous hypothetical to consider two students in successive cohorts of the same size, at the same school, who have the same achievement, whose classrooms have the same mean test scores.

We perform a battery of robustness checks to establish the underlying assumptions are valid including; higher order polynomials specifications of achievement, non-parametric controls of achievement, focusing on schools where there is likely to be one classroom per grade, among others.

Recent studies have documented that a student's relative rank matters above their absolute ability. Murphy and Weinhardt (2014) document that a student's rank at age 11 has and independent effect on age test scores and subject choice throughout high school, and provide evidence that confidence is a likely mechanism. Building on this work, Elsner & Ipshording (2017a) document that a student's rank in high school has an effect on the probability of attending college. We extend this literature by looking at the long-term effects of rank on adult outcomes.

In the educational literature, this type of effect is known as the Big-Fish-Little-Pond-Effect, which has been found in many countries and institutional settings (Marsh et al. 2008). In the economics literature, it has been referred to it as an invidious comparison peer effect (Hoxby & Weingarth, 2006). In addition to the peer effects operating in the opposite direction to standard peer effects papers, the other core difference is that we focus on the lasting impacts in a different peer environment rather than estimating contemporaneous effects of peers.

We document the effects of low ranking within your school in 3rd Grade throughout a child's life. We find that conditional on achievement students in the bottom 5 percent of students in a class are three times more likely to be retained than the median student. By the end of 8th grade students who previously ranked at the top of class compared to middle achieve 7.7 percentiles higher on the state exam.

Moving on to high school, students who were highly ranked in third grade in math are more likely to choose Advanced Placement (AP) calculus at the end of high school, but being ranked higher than the average in reading only marginally increases the likelihood of choosing AP Calculus. The mean AP Calculus enrollment rate is .07 percent, but conditional on achievement, students in the top 5 percent of their 3rd Grade class are 3.4 percentage points more likely to choose the subject than the median ranked student. There is a similar pattern for AP science, being highly ranked in math increases a student's likelihood of taking it, but there is no benefit from being ranked above the median. In addition to increasing AP enrollment, we find that a student's 3rd Grade rank has a significant impact on graduating from high school.

Finally, we look at the college enrollment and wages. Again, there are positive effects of being highly ranked for college enrollment. The effect of rank is larger for two-year colleges than for four-year colleges. We also find indicative evidence of student mis-match, with highly ranked students more likely to attend four-year colleges, but less likely to graduate. As we have the test scores of 3rd Grade students going back to 1994, we can calculate the impact on wages for individuals aged up to 27. We find that conditional on attainment that students in the top 5 percent of their class earn .11 more log points than those in the middle.

The rest of the paper proceeds as follows. Section 2 briefly sets out the literature. Sections 3 describes the data and Section 4 describes the identification strategy. Section 5 presents the results and robustness tests. Lastly, Section 6 concludes.

2. Literature

The impacts of relative position among peers is related to many different literatures. First, this broadly sits within the long-standing literature regarding the theories and empirical manifestations of social interactions and peer effects (Sacerdote, 2001; Hoxby and Weingarth, 2005; Whitmore, 2005; Kremer and Levy, 2008; Carrell et al., 2009; Lavy et al., 2012). These papers set out to determine how group characteristics or outcomes causally influence individual outcomes. However, to date, the long run effects of a student's relative position within a group has yet to be systematically examined.

Second, there is related literature that examines the introduction of relative achievement feedback measures in education settings. Azmat and Iriberri (2010) find that providing information on relative performance feedback during high school increases productivity of all students when they are rewarded for absolute test scores. In contrast, Azmat et al. (2015) find relative feedback in college causes significant short run decreases in student performance, but no long run effects. Our proposal differs from this literature in that are not examining the reaction to a providing information, but rather how students are reacting the existing structures.

Third, the clearest examples of individuals being concerned about their ranking is in competitive situations, such as in sports tournaments or firms with relative performance measures. These situations have been shown respectively to impact on individuals risk taking behavior (Genakos and Pagliero, 2012), and in effort applied (Vidal and Nossol, 2011). In education, students may also react to rank directly due to status concerns (Tincani, 2015) or when they are being graded on a curve (Bursztyn and Jensen, 2015).

Finally, the impact an individual's relative position has been shown to matter for subjective outcomes, such as well-being (Brown et al., 2008; Luttmer, 2005) and job satisfaction (Card et al., 2012). It leads from this that if relative position affects well-being, it might also affect investment decisions and subsequent productivity. This relates to the "Big Fish Little Pond" literature (for a review see Marsh et al., 2008), where individuals gain in confidence, and other positive non-cognitive skills, when they are they are highly ranked in their local peer group. Murphy and Weinhardt (2014) show that these type of effects are occurring in primary schools in England. A subsequent set of papers by Elsner and Isphording applies the same idea to the US using data from the National Longitudinal Study of Adolescent to Adult Health (AdHealth) to study effects of contemporaneous rank on high school completion, college going (2017a) and health outcomes (2017b).[2] We extend this line of research by considering rank at an early age (8-9 years old) and document this effect on subsequent long-term outcomes including employment. We also use administrative data from a large state which allows us to consider a large number of outcomes and understand the channels through which rank works. Because we have administrative data from a large state, we can flexibly control for student achievement, which is key for identification as we discuss in Section 3.

3. Empirical Design

[2]The AdHealth home-survey only contains a sample of 34 students of each school cohort which introduces significant measurement error into the measure of rank. Elsner and Isphording (2017a, 2017b) do not compute ranks based on a measure from a previous period but using a contemporaneous measure of cognitive ability. This requires the assumption that cognitive ability is predetermined and not affected by the school environment or health behavior itself. The view of ability being predetermined and not by a joint process of genetic endowments and environmental factors has long been rejected (i.e. Carlson et al. 2005, Kendler et al. 2015). Moreover, the AdHealth data does not allow studying specific choices during the educational careers, which are an important outcome in their own right but also important mechanisms for explaining rank effects on subsequent labor market outcomes.

We closely follow the method of Murphy and Weinhardt (2014), this method is ideal for large administrative data with many small groupings of students. This is to ensure that we have sufficient variation; specifically, for a given test score we have a range of different rankings.

For an illustration of the variation we use consider Figure 1, representing two schools that have the same mean, minimum, and maximum test scores. However, the distribution of test scores is different, with school A being bi-polar and school B being uni-polar. Students that have the same test score, but attend different schools will have a different rank due to these differences in the distribution. We will account for any underlying differences between schools that would cause the average outcomes to be different with the use of school fixed effects. This means that we would then be effectively comparing students with the same score, relative to the mean of their peers, but have a different rank due to variation in the test score distribution. We will exploit the changes in the test score distribution within school over time. This follows a similar strategy of Hoxby (2000), among others, and compares the outcomes of students in adjacent cohorts within the same school. We discuss the formal assumptions needed for identification in section 3.2.

3.1. Specification

Specifically to estimate the impact of rank on a range of later outcomes we use the following specification

$$Y_{ijsc} = \rho R_{ijsc} + f\left(T_{ijsc}\right) + \boldsymbol{X_i}'\beta + \mu_{jsc} + \epsilon_{ijsc} \tag{1}$$

where Y_{ijsc} is the outcome of student i who attended elementary school j in subject s from cohort c. This will be a function of academic rank, R_{ijsc}, in 3rd grade, a flexible measure of 3rd grade test scores $f\left(T_{ijsc}\right)$ in each subject, observable student demographic information $\boldsymbol{X_i}$, and set of elementary school-cohort-subject (SSC) fixed effects, μ_{jsc}.

Since we have student achievement and rank information in two subjects (math and reading), we stack the data over subjects in our main analysis for the primary analysis.[3] One may consider the level of variation for the treatment to be at the SSC, as it is caused by the variation in the distribution of peers test scores. However to be conservative we cluster the

[3] We also consider subject-specific specifications for outcomes such as taking AP Calculus

error term at the level of the elementary school in all our estimations to allow for unobserved correlations across cohorts and subjects.

Our preferred specification investigates potential non-linearities in the effect of ordinal rank on later outcomes, by replacing the linear ranking parameter with indicator variables according to quantiles in rank. We allow for non-linear effects according to ventiles in rank, which can be applied to all the specifications presented. We use data for a large state for many cohorts, which allows us to be very flexible in estimating the effects of rank.

$$Y_{ijsc} = \sum_{n=1,n\neq 10}^{20} I_n R_{ijsc}\, \rho_n + f\left(T_{ijsc}\right) + X_i{}'\beta + \mu_{jsc} + \epsilon_{ijksc} \qquad (2)$$

For many outcomes, especially longer-run outcomes, the effects seem to be largely nonlinear. Hence, we will primarily focus on equation 2. We model $f\left(T_{ijsc}\right)$ many ways, but our preferred specification controls for test scores non-linearly using twenty indicators for a student's achievement according to their ventile position in the state-wide achievement distribution. Note all standard errors presented are at the elementary school level j. This is broader than the unit of randomization which is the school-subject-cohort level jsc, and so is more conservative as allows for the outcomes to will be serially correlated across cohorts and subjects within a school.

In summary, if students react to ordinal information as well as cardinal information, then we would expect the rank in addition to relative achievement to have a significant effect on later achievement when estimating these equations. This is what is picked up by the ρ parameter. The following sections discuss identification, the setting, and how rank is measured before we turn to the estimates.

3.2. Identification

We must make two assumption for our estimates of ρ or ρ_n to be causal. The first assumption is about identification. Let $Y_{ijsc}(r)$ be the distribution of potential outcomes for an outcome Y as a function of potential rank r. Formally,

Assumption A1: $[E\left(Y_{ijsc}(r) \middle| A_{ijsc}, X_{ijsc}, \mu_{jsc}, R_{ijsc}\right] = [E\left(Y_{ijsc}(r) \middle| A_{ijsc}, X_{ijsc}, \mu_{jsc}\right]$

This assumption is that the distribution of potential outcomes are conditionally orthogonal to observed rank. This assumption is motivated by the thought experiment that a student rank is as good as random after controlling for ability, SSC fixed effects, and student demographics. If students sort into class on the basis of mean characteristics of the SSC such as peer achievement, this would be captured by μ_{jsc}. Further, $f(T_{ijsc})$ captures effects on later outcomes driven solely by student achievement.

Violations of A1 would occur if student sorted into SSCs based on what their rank would be. Observing student rank in a SSC before enrolling in the SSC would be difficult for three reasons. First, this would require parents to know the ability of their child and of the potential peers in each of the potential schools. Second, we will show that there is considerable cohort to cohort variation *within* a school such that knowing previous cohorts would not be sufficient to predict rank accurately. Third grade retention, grade acceleration, or changing school all change the initial composition of a school cohort and so will change the ranking of students when they or other students leave the school cohort. Hence, it is difficult for a parent to observe the rank of their child in various SSCs.

Further, Hastings et al. (2009) show that parents prefer schools that have high mean performance. They also show that higher ability students' parents are more likely to prefer schools with higher mean achievement than the parents of low-ability students. This implicitly goes against sorting to schools for higher ranks.[4]

We illustrate the variation in rank we use for a given test score relative to the mean demonstrated in Figure 1 Panel A. Figure 1 Panel B replicates this stylized example using seven elementary school classes in Math from our data. Each class has a student scoring 22 and 38 and have a mean test score of 30. Four of the classes have a student scoring 35, however the different test score distributions means each student has a different rank. In Panel C, we can see the percentile ranks of the student scoring 35 are 0.88, 0.69, 0.71, and 0.88, despite all students having the same absolute and relative to the class mean test scores. This also shows that there is variation in rank for a given test score throughout the achievement distribution.

[4] Texas implemented the Top Ten Percent Rule in 1998. This gave high school students in the top decile of their class automatic admission to any public university in Texas. Student rank for this rule was determined in 11th or 12th grade. Cullen et al (2013) document that some students changed their enrollment behaviour in response to this rule. However, the number of students was small—Cullen et al (2013) estimate that 211 students per cohort changed the high school they attended and that this was driven by students opting out of magnet schools and into their assigned public school. This sorting is very unlikely to be driving 3rd grade sorting into SSCs for a number of reasons. First, some of the cohorts we examine were before the implementation of the top 10 percent rule. Second, performance in elementary and middle schools does not directly factor into top ten percent performance. Third, 3rd grade students are at least six years away from entering high school and so the decision is likely not salient.

We illustrate the difficulty of sorting into a SSC based on rank as well as the amount of natural occurring variation in rank in Figure 2. In Figure 2 we focus on students at the median of the state test distribution. The horizontal axis indexes schools. Within each school, we plot the rank a student who scored at the state-wide median would have in at that school cohort. We sort schools based on the average rank of the statewide median student over all cohorts. Hence, schools on the left are relatively high performing because students at the median have relatively low rank.

The vertical thickness of the distribution indicates the support throughout the rank distribution of approximately 20 percentiles. This means that within school, there is considerable variation in where the median student would rank depending on their cohort. In fact, the within school standard deviation of a student with the median statewide test score in the statewide distribution is 0.08. Further, the average within-school-subject difference in rank between highest rank and lowest rank for the median student is 0.17.

This figure demonstrates that within school-subjects, there is a lot of variation in observed rank across cohorts. Hence, knowing a students' exact rank (conditional on achievement and school subject averages) would be very difficult meaning sorting based on rank would be difficult. Moreover, it shows that we have sufficient naturally occurring variation in our data to include even non-parametric controls for the primary school baseline achievement measure.

Our second assumption, A2, is that we correctly specify the relationship between outcomes Y and $R_{ijsc}, X_i, T_{ijsc}, \mu_{jsc}$. Formally:

$$\text{A2: } [E\left(Y_{ijsc}(r) \middle| A_{ijsc}, X_{ijsc}, \mu_{ijsc}, R_{ijsc}\right] = f(R_{ijsc}) + f\left(T_{ijsc}\right) + X_i{}'\beta + \mu_{jsc} + \eta_{ijsc}$$

$$\text{and } \eta_{ijsc} \perp R_{ijsc} .$$

In the above equation η_{ijsc} is specification error. We must assume that this error is uncorrelated with rank. A special case is that $\eta_{ijsc} = 0$ which says that we correctly model the true relationship between outcomes Y_{ijsc} and $R_{ijsc}, X_i, T_{ijsc}, \mu_{jsc}$. If there is specification error, that is if $\eta_{ijsc} \neq 0$, we still recover the causal effect of rank as long as the specification error is uncorrelated with observed rank R_{ijsc}. A similar assumption is required for many empirical settings such as differences in differences.

We model the relationship between achievement and outcomes in many ways and find consistent result. This suggests that assumption A2 is likely to hold. This assumption highlights the benefit of using large data sets that allow for very flexibly estimates of the relationship between achievement and outcomes.

4. Data

The data we use in this study is the de-identified data from the Texas Education Research Center (ERC), which contains information from a number of state level institutions.[5] Data concerning students' experience during their school years cover the period 1994–2012, although the primary estimating sample will focus on 1995–2008. These data contain demographic and academic performance information for all students in public K–12 schools in Texas provided by the Texas Education Agency (TEA). These records are linked to individual-level enrollment and graduation from all public institutions of higher education in the state of Texas using data provided by the Texas Higher Education Coordinating Board (THECB). Ultimately, these records are linked to students' labor force outcomes using data from the Texas Workforce Commission (TWC). This contains information on quarterly earnings, employment and industry of employment for all workers covered by Unemployment Insurance (UI).[6]

4.1. Constructing the Sample

The sample used for this analysis consists of students who took their third grade state examinations for the first time between 1995 and 2008.[7] We focus on students taking the exam for the first time to alleviate concerns regarding the endogenous relationship between class rank and previous retention. We focus on students taking their exams in English, rather than Spanish. During this period, the third grade students took tests annual reading and math assessments, although the testing regime changed.[8] Consequently, we percentilize student achievement by subject and cohort. This ensures that the test score distribution for each subject

[5] For more information on the ERC see https://research.utexas.edu/erc/

[6] Unemployment insurance records include employers who pay at least $1500 in gross wages to employees or have at least one employee during twenty different weeks in a calendar year regardless of the wages paid. Federal employees are not covered.

[7] Students are defined as taking their third grade exam for the first time if the student was observed not being in the third grade in the previous year.

[8] Until 2002, the Texas Assessment of Academic Skills (TAAS) was used. Starting in 2003, the Texas Assessment of Knowledge and Skills (TAKS) was used. The primary differences had to do with which grades offered which subject tests. This does not affect this study substantively as all students took exams in math and reading for 3rd and 8th grade

is constant for each cohort. For each student we generate a rank within their elementary school cohort for math and reading based on their test scores including those who had been retained.

We link students to subsequent outcomes including performance in reading and math in 8th grade. We also consider classes taken in high school including Advanced Placement courses, and graduation from high school. We then consider whether students enroll in a public college or university in Texas (separately by two year and four schools) and whether student the student graduates from college. Lastly, we look at the probability of earnings and the probability of having positive wages UI wages.

For binary outcomes such as AP course taking, high school graduation, and college enrollment, we define the variable as 1 for the event occurring in a school covered by our data and 0 otherwise. For eighth grade test scores, we only consider students who took 8th grade tests. For earnings, we consider both average earnings including zeroes as well as excluding zeroes.

To maximize the sample, we consider as many cohorts as possible for each outcome. This means that we have more cohorts for outcomes closer to third grade and fewer cohorts for later outcomes. For K-12 and initial college attended outcomes, we have 13 cohorts of students who took their third Grade tests between 1994 and 2006, 6,025,902 student-subject observations. For graduating college in four years, we have 10 cohorts (1994-2003) 4,507,290. For graduating in six years and post college outcomes for individuals aged 23-27 we have eight cohorts (1994-2001) or 3,551,734 student-subject observations. This explains the discrepancy in sample size across different outcomes. However, results are similar for a consistent subsample.[9]

Table 1 presents summary statistics. The sample is 47 percent white, 35 percent Hispanic, and 15 percent African American. 71 percent of students in the sample eventually graduate from a Texas public high school. 47 percent of students attend a public university or college in the year after "on time" high school graduation.[10] Within three years of on time high school graduation, 23 percent attending a public four-year institution in Texas and 31 percent attending a Texas community college. When students are 23-24 years old, 65 percent have non-zero wages and at age 27-28, 63 percent have non-zero wages. Average wages including zeroes at age 27-28 is $32,000 in 2016 dollars.

[9] Results available upon request.
[10] On time graduation is defined as graduation if a student did not repeat or skip any grades after grade 3.

4.2. Rank Measurement

We rank each student among their peers within their grade at their school according to their scores in standardized tests in each tested subject. Simply, a student with the highest test score in their grade will have the highest rank. However, a simple absolute rank measure would be problematic, because it is not comparable across schools of different sizes. Therefore like state test scores we will percentilize the rank score individual i with the following transformation:

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

where N_{jsc} is the cohort size of school j in cohort c of subject s. An individual *i* has ordinal rank position within this group is n_{ijsc},, which is increasing in test score. Here R_{ijsc} is the standardized rank of the student which we will used for our analysis. For example, a student who had the second best score in math from a cohort of twenty-one students (n_{ijsc}=20, N_{jsc}=21) will have R_{ijsc}=0.95. This rank measure will be approximately uniformly distributed, and bounded between 0 and 1, with the lowest rank student in each school cohort having R=0. In the case of ties in test scores, each of the students with the same score is given the mean rank of all the students with that test score in that school-subject-cohort. However, our results are similar if we break ties by assigning students the bottom rank, randomly break the ties, or only consider "on time" students in the third grade class.[11] We will calculate this rank measure for each student for each standardized test they participate in.

5. Results

We will primarily present results of equation 2 by plotting the estimate coefficients, ρ_n, along with the 95 percent confidence intervals. All estimates will be relative to the ventile that includes students ranked from 45-50 in their class. Because there are many estimates for each outcome, we present the results visually.[12]

5.1. K-12 Outcomes

[11] Our main analysis limits the sample to students who took the their third grade test on time. However, their actual classroom consists of students who are on time and students who are not. We show that our results are very similar when we calculate rank only using students taking third grade on time. Results using different methods to break ties are available upon request.
[12] Estimates and standard errors are available in table form upon request.

We first consider the probability of repeating third grade in Figure 3. Figure 3 panel A shows that lower ranked students are more likely to repeat third grade even after conditioning on achievement. The effects are unsurprisingly coming from the lower ranked students. Moving a student from being ranked last to being ranked in the 25th percentile reduces the probability for retention by roughly 1 percentage point. Given the mean retention rate of 1.6 percent, this represents a sizable shift. There is a discontinuous jump for those in the lowest ventile of the rank distribution, which is double that of the next highest ventile (1.6 percent versus 0.8 percent). This result shows that rank affects how students are treated by their schools, independent of their ability.

We next examine the effect of 3rd grade rank on achievement in 8th grade where achievement in 8th grade is measured in state percentiles. Figure 3 Panel B shows an approximately linear effect of rank in third grade on academic performance. Moving from the 25th percentile to the 50th percentile in rank improves performance by approximately 3 percent. This is similar to the estimates in Murphy and Weinhardt (2014) that consider outcomes at comparable ages in England, finding the same change in rank at the end of primary school (age 10/11) improves performance national test scores at age 13/14 by 1.9 percent.[13]

The results on 8th grade test scores are not novel, but they do corroborate that similar rank effects occur in different educational systems, establishing the external validity of each estimate. Moreover, they do provide a mechanism for the later outcomes we observe. In particular, student achievement in 8th grade is correlated with many outcomes including high school achievement, class taking, college enrollment and success, and labor market outcomes.

We also consider whether a student takes advanced placement courses in Figure 4. The first two panels of Figure 4 (A & B), we use our standard specification where the two observations for math and reading for each student are stacked and so we are estimating the mean rank coefficients. We see that elementary school achievement rank linearly affects the probability of taking AP Calculus or AP English. In both cases, the point estimates are similar for AP Calculus and AP English. However, the baseline rate for taking AP Calculus and AP English for our sample is 7 percent and 19 percent respectively.

[13] We only consider students who took the test in 8th grade "on time." However, rank causes some students to be retained. Hence, the estimates of the effect on 8th grade test scores are difficult to interpret. Using test scores for the year that students are in 8th grade would result in some low-ranked students taking the test one year later (and one year older) which makes interpretation difficult. No simple correction can be used to address this problem, so we present results for on-time 8th graders but note the difficulty in interpreting these results.

The second two panels of Figure 4 (C & D) we consider the effect of rank separately by school subject. Here we run specifications where we control for achievement in third grade math and reading separately and simultaneously allowing there to be a different effect for math and reading. In Panel C, a higher rank in math causes students to take AP Calculus. Most of this effect occurs for students above the median in rank, whereas below the median there are small difference in the probability of taking AP Calculus. In contrast, a student's rank in reading has very little effect on taking AP Calculus for students with rank above the median. For students below the median, low ranks have small effects on taking AP Calculus. In Panel D, rank in Math again has a stronger effect than rank in reading. However, rank in reading does positively affect taking AP English Courses. This is evidence that any rank effects are subject specific and have spillover effects into other subjects.

The final set of K-12 outcomes we consider is whether a student graduated from high school. This can be seen in Figure 5. There is a significant effect of rank on graduating from high school. However, this primarily comes from students who are above the median in class rank. We consider within 3 years of "on time" high school graduation as defined by nine years after their third grade to avoid issues of grade retention.

In summary, a student's rank in 3rd grade independently affects grade retention, testing performance 5 years later, class selection, and ultimately graduation. As we examine longer term outcomes, these changes throughout schooling will be some of the channels that affect things such as college education and earnings. Many of these findings are novel in and of themselves—in particular, a student's rank in their elementary school classroom at age 8 or 9 affects their probability of graduation from high school.[14]

5.2. College Outcomes

Given that rank in 3rd grade impacted outcomes during high school, examining college entry is a natural next step. Figure 5 Panel B presents "On-time" enrollment in any public college in Texas. The relationship between rank and college enrollment is a bit puzzling. There is a u-shaped relationship with low ranked students more likely to attend college, no effect around the median rank, and then positive effects on enrollment for students in the top of their class.

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[14] Elsner and Isophording (2017a, 2017b) document that a student's rank in high school affects graduation from high school and risky behavior.

To understand this pattern better, we consider enrollment in two-year and four-year schools separately. Figure 6 Panel A considers enrollment in two-year institutions where the effects on enrollment are again U-shaped. Low ranking increases the probability of going to community college; similarly, high rank increases the probability of attending community college. The effects sizes are large relatively to the baseline community college enrollment rate. A student in the 90th percentile for rank is nearly 4 percentage points more likely to attend community college than a student with the median rank. The baseline rate is 31 percent. Figure 6 Panel B shows enrollment in a four-year institution and finds that very high and very low rankings affect college going. Low ranked students are less likely to attend college ($0\text{-}10^{th}$) percentile, and high ranked students are more likely to attend college ($90\text{-}100^{th}$) percentile.

The patterns in Figure 6 are consistent with some low ranked students moving from four-year institutions to two-year institutions. However, low rank induces some students to attend two-year institutions that would not have attended any college. This may be the result of tracking students into different trajectories based on rank. These different educational paths could encourages students to attend two-year schools where more vocational training is available.

Figure 7 considers graduation with a bachelor's degree within various time frames—4 years (Panel A), 6 years (Panel B), and 8 years (Panel C) after "on-time" graduation from high school. In all cases, there is an unusual pattern where rank has an inverted-U relationship to graduation with a bachelor's degree. It is not surprising that rank below the median causes students to graduate at lower rates. However, it is unexpected that higher ranked students are *less* likely to graduate with a bachelor's degree.

One potential explanation is that rank induces students to attend colleges that are more demanding or major in more demanding majors. In Figure 7 Panels B, D, and F, we control for the quality of a college crudely by controlling for the average 3^{rd} Grade state percentile of the students in that college. When we control for this crude measure of quality, we find that low ranked students remain less likely to earn a bachelor's degree. However, high ranked students are no longer less likely to graduate with a bachelor's degree.

This provides evidence that rank may lead to "overmatch" where students attend colleges where they are not prepared. This is consistent with overconfidence arising from rank. This deleterious effect of rank contrasts with other outcomes including high school graduation, class taking, etc.

5.3. Employment

We consider the effects on employment outcomes. We can examine employment outcomes for students ages 23-27 (or 15-18 years after third grade). We stack observations for average annual earnings between the ages for 5 cohorts of students who took their 3 Grade examinations between 1994-1998 (employment years 2009-2016). Figure 8 considers the probability of having positive earnings from age 23-27. The pattern suggests there is not much effect of rank on the probability of having positive earnings until class rank is above the 80th percentile. Because we have earnings from Unemployment insurance, this effect could be a few things. First, it could be a labor supply response where it is an actual increase in positive earnings. Second, it could be an increase in the probability of staying in state or working in sectors covered by unemployment insurance.[15] People with higher educational attainment are more likely to migrate (Greenwood 1997). This suggests that students with third grade rank may be more likely to leave the state due to their higher academic performance. However, we find that higher rank leads to an *increase* in the probability of observing wages. This pattern suggests the effect on wages is likely a labor supply response.

Figure 8 Panel B shows that increasing rank increases earnings. Low ranked students have meaningful earnings penalties. High ranked students see increases in earnings as well, but the effect is concentrated among the highest ranked students. Figure 9 Panel A shows that the effects are similar if students with zero wages are excluded. Figure 9 Panel B shows that rank affects the log of average wages throughout the distribution of rank.

Taken together, rank in third grade affects labor market outcomes. Moving from the 25th percentile to the 75th percentile in rank causes log wages to increase by approximately 7 log points.

Robustness

We show that our results are robust to several alternative specifications and samples. First, we model the relationship between achievement and outcomes using various functional

[15] Unemployment Insurance records cover employers who pay at least $1,500 in gross wages to employees or have at least one employee during twenty different weeks in a calendar year. Government employees are not covered. Andrews et al. (2016) uses Census data to show that for students who attended the two flagship universities in Texas, there does not appear to be a systematic difference in earnings for those in state versus those who leave the state.

forms. Figure 10 presents results for four main outcomes, 8th grade test scores, graduation from high school, the probability of attending any college, and real wages. The point estimates are displayed for various controls for student achievement. We model student achievement using various polynomials from first order to a seventh order. Similarly, we control for achievement using ventiles in student achievement (our preferred specification). The results are substantively similar once achievement is controlled for with a quadratic. Hence, our results are not dependent on the functional form chosen to model achievement.

One data limitation is that we do not observe which a classroom identifier for third grade students. Hence, our main results use fixed effects for school-subject-cohort. As a robustness check, we estimate the effects separately on SSCs with fewer than 30 third graders in a school subject cohort. These schools are likely to have one classroom of third graders. Figure 11 presents the point estimates by SSC size. In particular, we present results for under 30, under 60, and under 90 students in a SSC as well as our main specification with all SSCs. We show that our results do not vary meaningfully when we focus on small SSCs. The notable exception is earnings which is much noisier for small SSCs.

In our main specification, we handle ties in rank by assigning students the mean of the rank. We consider other methods including breaking ties including assigning the lowest rank, randomly breaking ties, and a rank only among students who are "on-time" in third grade. Our results are qualitatively similar regardless of our method of dealing with ties. The results tend to be slightly smaller when we break ties randomly which we attribute to the introduction of noise into our measure of rank.[16]

We also perform our analysis on a consistent subsample. That is, we fix the sample as the cohorts who we observe for the most distant outcome (earnings age 23-27) and estimate all of the outcomes on that sample. Our results are qualitatively similar with larger standard errors as would be expected.[17]

Rank and achievement are measured using the same test score; as a result, measurement error in test scores would generated correlated measurement error in the rank variable, which could affect the interpretation of rank effects. Murphy and Weinhardt (2016) show that this issue would non-linearly downward bias the effect of class rank depending on the extent of the

[16] Results from different methods of breaking ties are available upon request.
[17] Results from this analysis are available upon request.

measurement error. Additional measurement error equal to 30 percent of the original standard deviation (and recalculating the ranks) reduces the rank coefficient by 34 percent.

Discussion

We estimate the effects of rank net of SSC fixed effects. Traditional peer effects suggest that better peers should hurt performance. However, we show that having more better peers also has a negative effect by lowering rank. In this section we quantify the effects of rank as compared to the benefits of having good peers.

Consider the following though experiment. A parent may move their child to a "better" school. This would come with a decrease in their child's rank and a likely increase in the quality of their child's peers. What is the positive gain from the quality of

To operationalize this, we regress 8th grade test scores on fixed effects for a student's third grade school. This fixed effect would capture many things including peer effects, resource differences, etc. This is the average outcome difference. The standard deviation of these fixed effects is .091. Similarly, we calculate a school value added measure where we control for student 3rd Grade ability. The standard deviation of these value added measures is .055. So moving to a one standard deviation better school would give a bump of .055 in 8th grade test scores (or .091 if you make the implausible assumption that average outcomes for schools are causally all due to the school).

Student rank could vary systematically by school value-added which we investigate in Table 2. In Table 2 we show three things for each ventile of achievement. First, we show the average rank of students in that ventile. Because rank is approximately uniformly distributed, this generally moves up by .05 for each ventile of achievement. Next we show the average rank of a student in a given achievement decile in a "good" school and a "bad" school where good and bad are define by being one standard deviation above or below the mean in value added. One last piece of information is that if we assume a linear relationship between rank and 8th grade test score, the estimate of ρ from equation 1 is .09.

To be concrete, a student in the 10th ventile (45-50th percentile) has an average rank of .49. A student in a school from that ventile with a value added one standard deviation above the mean is .39, compared to a rank of 0.54 if attending a school one standard deviation below the mean. Therefore, if a student went from a "bad" school to a "good" school, their rank would decrease by .15. Their 8th grade test score would be expected to increase by .11. So a student in that decile would get a positive bump of .11 in 8th grade test scores for that move but there would be a -.15*.09=-.0135. Hence the effect of a better school is roughly eight times the size of the rank effect.

While this rank effect is relatively small compared to school quality, we are the first to demonstrate that it has meaningful effects on long term outcomes. This effect is implicitly in every linear-in-means peer effect paper but is generally not directly accounted for.

Conclusions

We demonstrate that a students' rank among their peers at a young age has long lasting impacts. This affects a student's performance in school including tests, courses taken, progress through toward graduation. Ultimately, it also affects student graduation from high school. Relative position affects the decision to enroll in post-secondary education. Most strikingly, it affects a student's real earnings in their mid-twenties.

This finding has distributional implications for the design of classrooms. If students are tracked into classrooms by ability, there will be winners (relatively highly ranked students with low absolute ability in low ranked classrooms) and losers, relatively low ranked students with high absolute ability. However, our calculations show that the gains from rank are generally smaller than the gains from a higher quality school (and associated higher ability peers)

We also add to a growing list of papers that demonstrate conditions for young children have long lasting consequences. In contrast to other papers that focus on policy differences that students face, we document the effect of an unavoidable phenomenon in groups—relative rank. Documenting these differences raises the question if policies explicitly focusing on lower ranked students rather than low ability students may raise student outcomes for some students. These policies need not replace policies focusing on low ability students but may serve as a useful complement.

In fact, some of the effect of rank may be coming via teachers and administrator interactions with students. We document that students are more likely to be retained in third grade which is a decision made not by the student but by teachers, administrators, and families.

Future research on rank should focus on what the interaction between rank and policies that exaggerate or mediate the effects of rank. Future research should also consider the effect of rank in groups outside of school settings.

References

Rodney J. Andrews, Jing Li, and Michael F. Lovenheim (2016) Quantile Treatment Effects of College Quality on Earnings J. Human Resources, 51:200-238;

Azmat, G., Bagues, M., Cabrales, A., and Iriberri, N. (2015). What You Know Can't Hurt You, For Long: A Field Experiment on Relative Performance Feedback. Mimeo, Queen Mary University.

Azmat, G. and Iriberri, N. (2010). The importance of relative performance feedback information: Evidence from a natural experiment using high school students. Journal of Public Economics, 94(7-8):435–452.

Bietenbeck, J. (2016) "The Long-Term Impacts of Low-Achieving Childhood Peers: Evidence from Project STAR" mimeo.

Black, S., Devereux, P., and Salvanes K. (2013) "Under Pressure? The Effect of Peers on Outcomes of Young Adults" Journal of Labor Economics, Vol. 31, No. 1 (January 2013), pp. 119-153

Black, S., Devereux, P., and Salvanes K. (2011) "Too young to leave the nest? The effects of school starting age", The Review of Economics and Statistics, 92, 2, pp 455—467

Booji, A., Leuven, E. and Oosterbeek, H. (2017) "Ability peer effects in university: Evidence from a randomized experiment" Review of Economic Studies, 84, 2, pp 547-587.

Brown, G., Gardiner, J., Oswald, A., and Qian, J. (2008). Does wage rank affect employees wellbeing? Industrial Relations: A Journal of Economy and Society, 47(3):355–389.

Bursztyn, L. and Jensen, R. (2015). How Does Peer Pressure Affect Educational Investments? The Quarterly Journal of Economics, 130(3):1329–1367.

Carlson, N.R., Enzie, M. E., Buskist, W. and C. D. Heth, (2005) Psychology: the science of behaviour (3rd Canadian ed) Pearson Canada.

Carrell, Scott and Fullerton, Richard L. and West, James, "Does Your Cohort Matter? Measuring Peer Effects in College Achievement", *Journal of Labor Economics* 27, 3 (2009), pp. 439-464.

Carrell, S. E., Hoekstra, M., & Kuka, E. (2016). The long-run effects of disruptive peers (No. w22042). National Bureau of Economic Research.

Chetty, R., Hendren, N., and Katz, L. (2016) "The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment, American Economic Review, 106, 4, PP. 855-902

Chetty, R., Friedman, J., and Rockoff, J. (2014) "Measuring the Impacts of Teachers II: Teacher Value-Added and Student Outcomes in Adulthood", American Economic Review, 104, 9, pp2633-79

Chetty, R., Friedman, J., Hilger, N., and Saez, E., Schanzenbach, D.W. and Yagan, D (2011) “How does your kindergarten classroom affect your earnings? Evidence from Project STAR”, The Quarterly Journal of Economics, 126, 4, 1593-1660

Cullen, J. B., Long, M. C., & Reback, R. (2013). Jockeying for position: Strategic high school choice under Texas' top ten percent plan. Journal of Public Economics, 97, 32-48.

Elsner B. and Isphording, I. (2017a) "A Big Fish in a Small Pond: Ability Rank and Human Capital Investment", *Journal of Labor Economics*.

Elsner, B., & Isphording, I. E. (2017b). Rank, Sex, Drugs and Crime. *Journal of Human Resources*, 0716-8080R.

Genakos, C. and Pagliero, M. (2012). Interim Rank, Risk Taking, and Performance in Dynamic Tournaments. Journal of Political Economy, 120(4):782 – 813.

Greenwood, Michael J. "Internal migration in developed countries." Handbook of population and family economics 1 (1997): 647-720.

Hastings, J., Kane, T. J., & Staiger, D. O. (2009). Heterogeneous preferences and the efficacy of public school choice. NBER Working Paper, 2145, 1-46.

Hoxby, C. and Weingarth G. (2006) “Taking race out of the equation: School reassignment and the structure of peer effects” Working paper, Harvard University.

i Vidal, J. B. and Nossol, M. (2011). Tournaments without prizes: Evidence from personnel records. Management Science, 57(10):1721–1736.

Kendler, S. K,, Turkheimer, E., Ohlsson, H., Sunquist, J. and K. Sunquist, **„**Family environment and the malleability of cognitive ability: A Swedish national home-reared and adopted-away cosibling control study”, *PNAS,* March 23.Kremer, M. and Levy, D., "Peer effects and alcohol use among college students", *The Journal of Economic Perspectives* 22, 3 (2008), pp. 189-206.

Lavy, V., Silva, O., and Weinhardt, F. (2012). The Good, the Bad, and the Average: Evidence on Ability Peer Effects in Schools. Journal of Labor Economics, 30(2):367–414.

Luttmer, E. F. P. (2005). Neighbors as negatives: Relative earnings and well-being. The Quarterly Journal of Economics, 120(3):963–1002.

Marsh, H., Seaton, M., Trautwein, U., Ludtke, O., Hau, O’Mara, A., and Craven, R. (2008). The Big Fish Little Pond Effect Stands Up to Critical Scrutiny: Implications for Theory, Methodology, and Future Research. Educational Psychology Review, 20(3):319–350.

Murphy R. & Weinhardt F. (2014) “ Top of the Class: The Importance of Ordinal Rank” CESIFO Working Paper NO. 4815

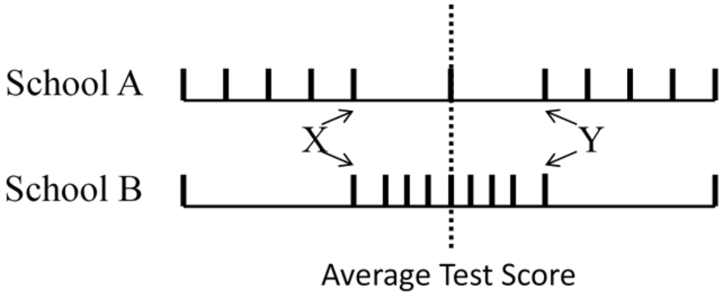
Sacerdote, B., "Peer Effects with Random Assignment: Results for Dartmouth Roommates", *Quarterly Journal of Economics* 116, 2 (2001), pp. 681-704.

Tincani, M. M. (2015). Heterogeneous peer effects and rank concerns: Theory and evidence. Mimeo, University College London.

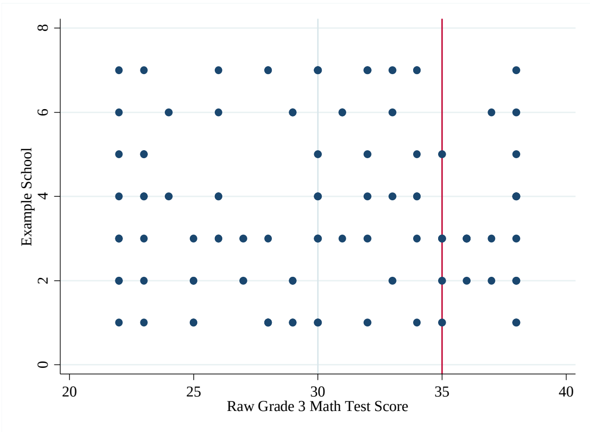
Whitmore, D., "Resource and peer impacts on girls' academic achievement: Evidence from a randomized experiment", *American Economic Review* P & P (2005), pp. 199-203.

Figure 1: Illustrative example of distributions in Texan Elementary Schools

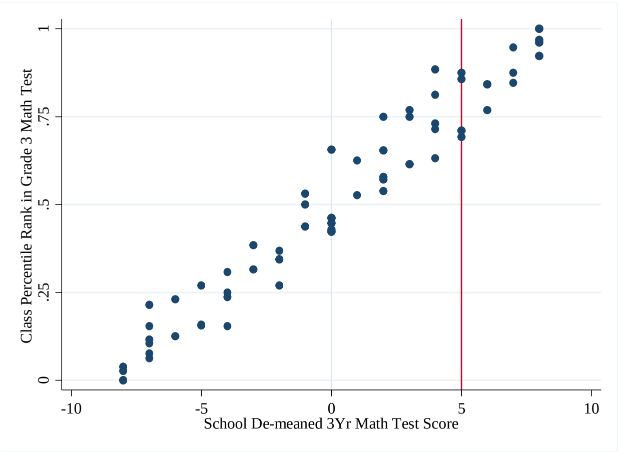
Panel A: Illustrative Example



Panel B: Test Scores distributions in schools with same mean, min and max

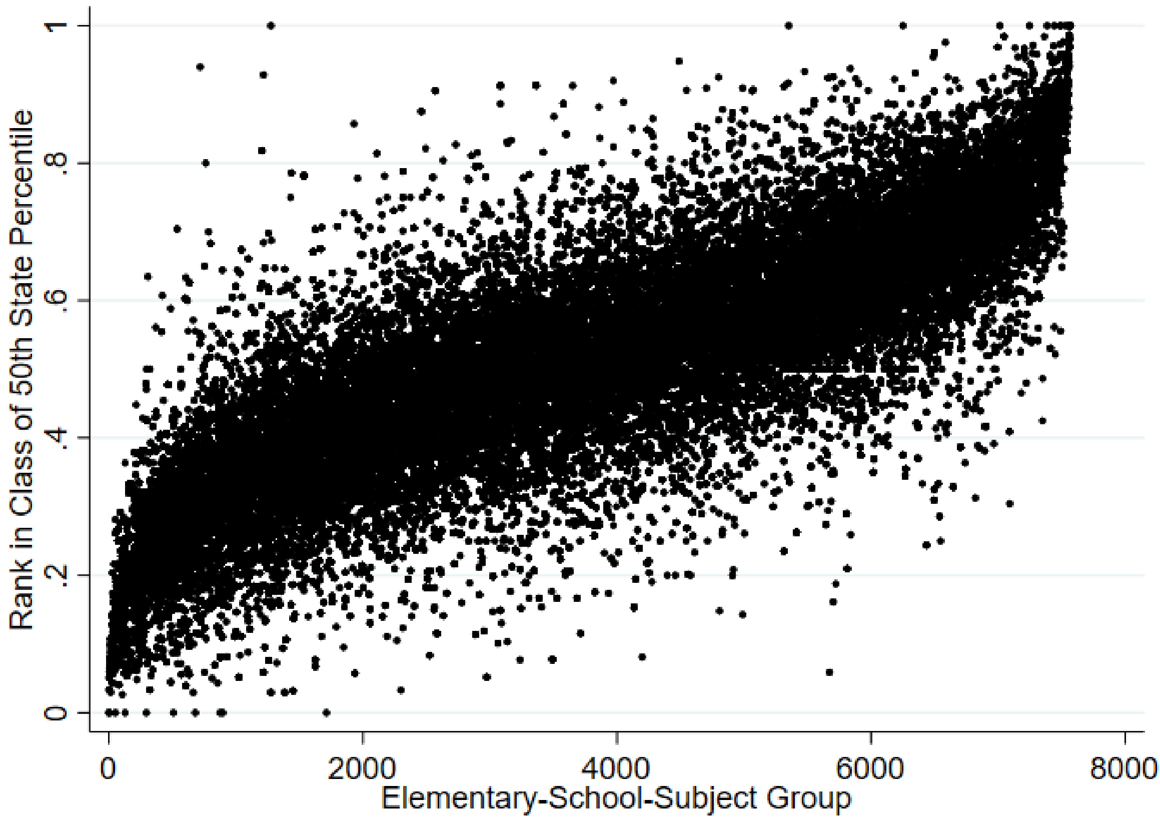


Panel C: Variation in class rank conditional on test scores



Notes: These figures are based on raw administrative data. This data has be perturbed in order to be FERPA compliant. This is showing the raw math scores in seven Texan elementary schools. Panel A is an illustrative example showing two classrooms with the same min, max, and mean scores where two students with the same achievement have different ranks. Panel B shows that such classrooms exist, presenting seven with the same mean, max, with students who have the same achievement having different rank . Panel C shows the different rank values these students with the same relative position within their classes have.

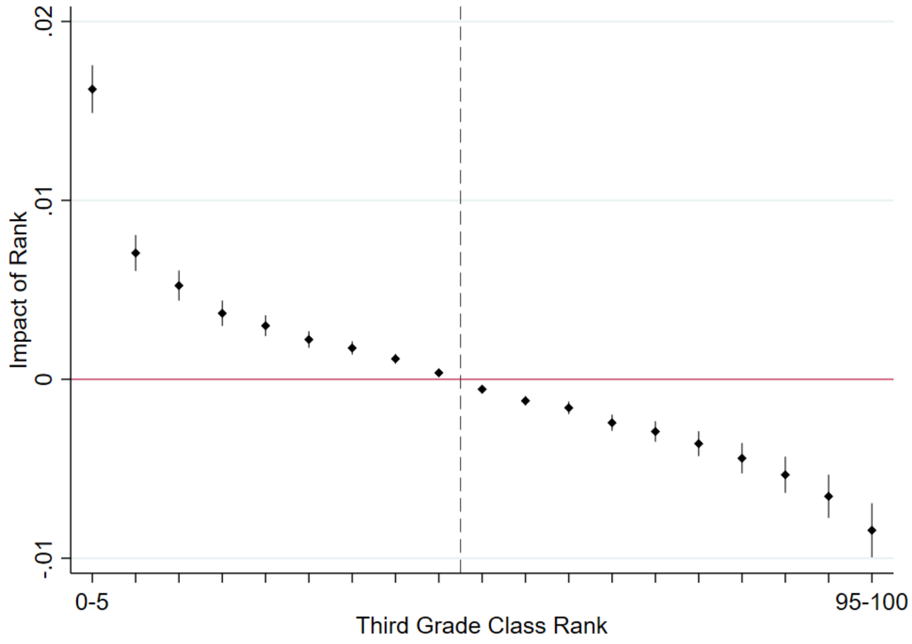
Figure 2: Common Support of Rank Conditional on Raw Math Test Scores



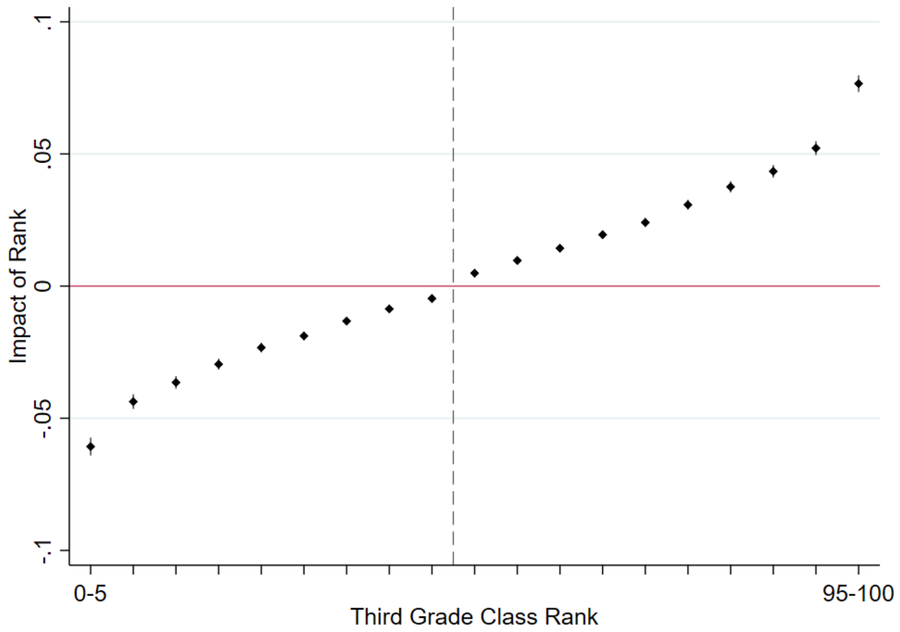
Notes: This figure is based on raw administrative data. This data has be perturbated in order to be FERPA compliant. This is showing the de-meaned by school and cohort math scores in all Texan elementary schools in our data.

Figure 3 – 3rd Grade Rank on K-12 Outcomes, 1

A. Repeat 3rd Grade



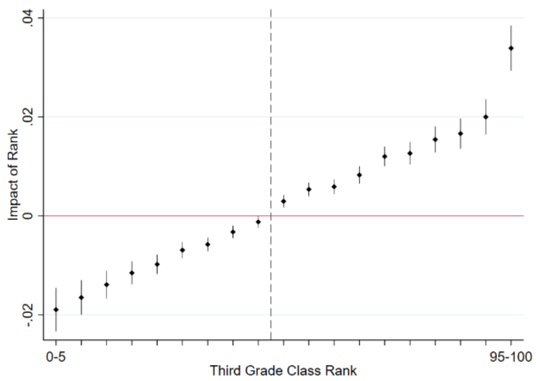
B. 8th Grade Test Scores



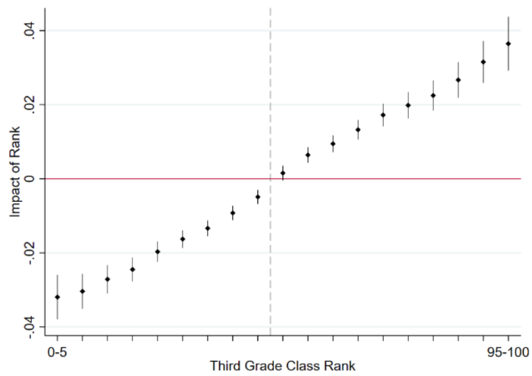
Note: These figures plot the coefficient for ventiles of class rank. The 45th-50th percentile is the omitted category. Estimates come from equation 2, which includes controls for race, gender, ESL status, and indicators for ventiles of student achievement. The mean retention rate is 1.6.

Figure 4 – 3rd Grade Rank on K-12 Outcomes, 2

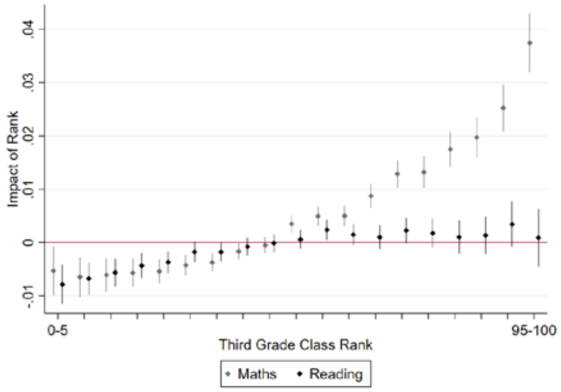
A. AP Calculus



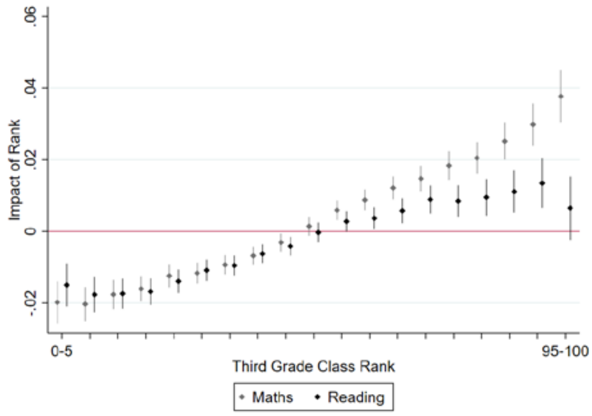
B. AP English



C. AP Calculus, subject-specific rank



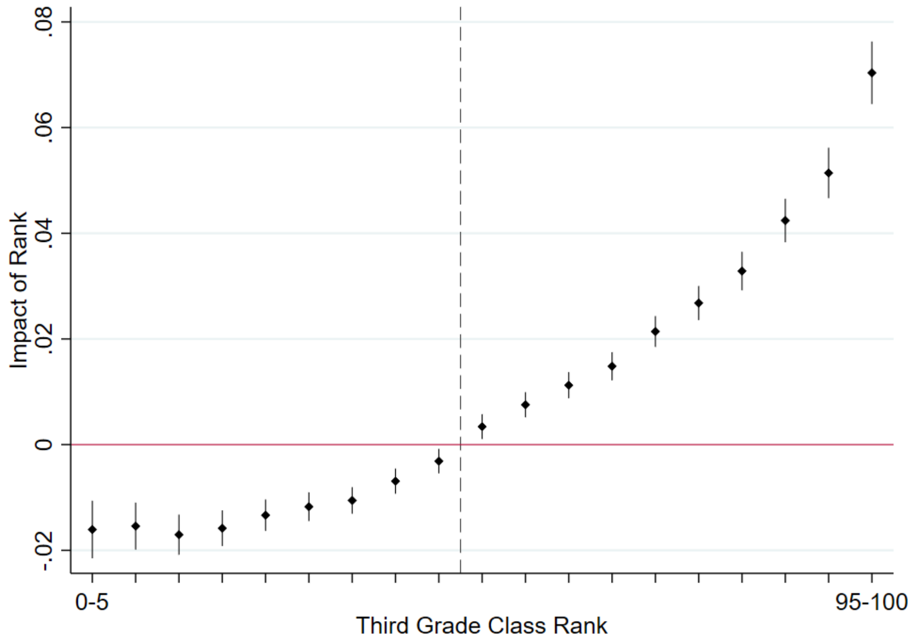
D. AP English, subject-specific rank



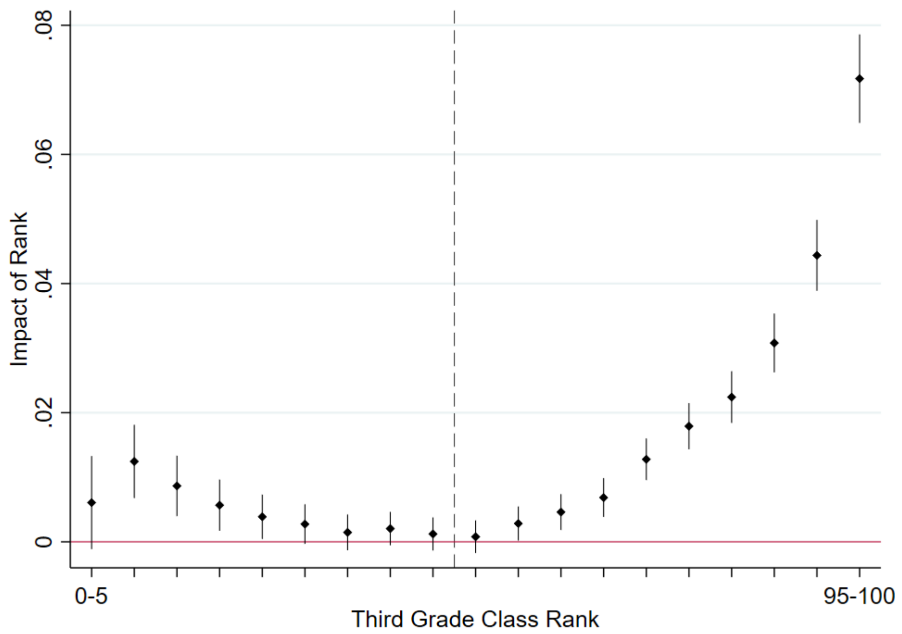
Note: These figures plot the coefficient for ventiles of class rank. The 45th-50th percentile is the omitted category. Estimates come from equation 2, which includes controls for race, gender, ESL status, and indicators for ventiles of student achievement.

Figure 5 – 3rd Grade Rank on High School Graduation

A. Graduate High School



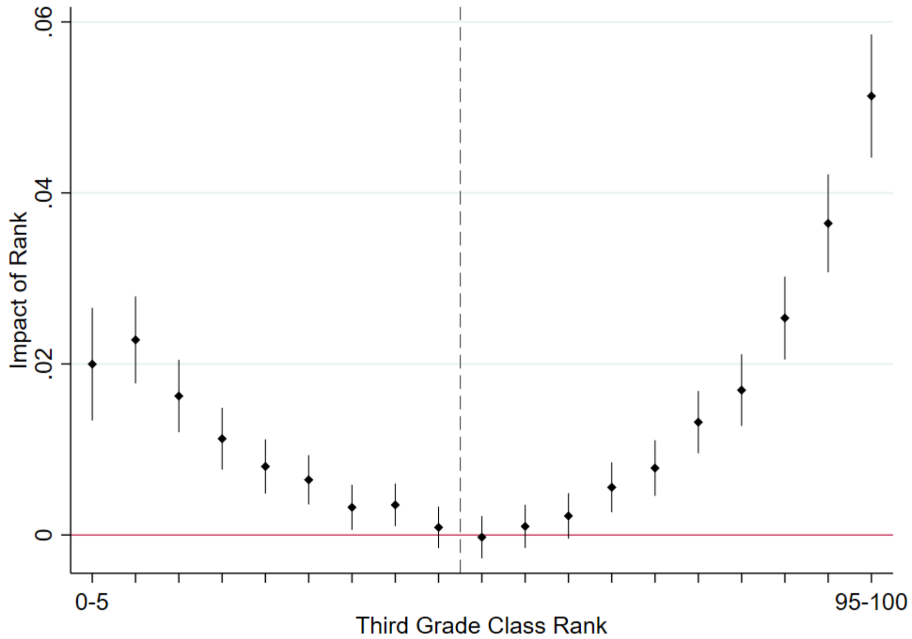
B. Enroll in College



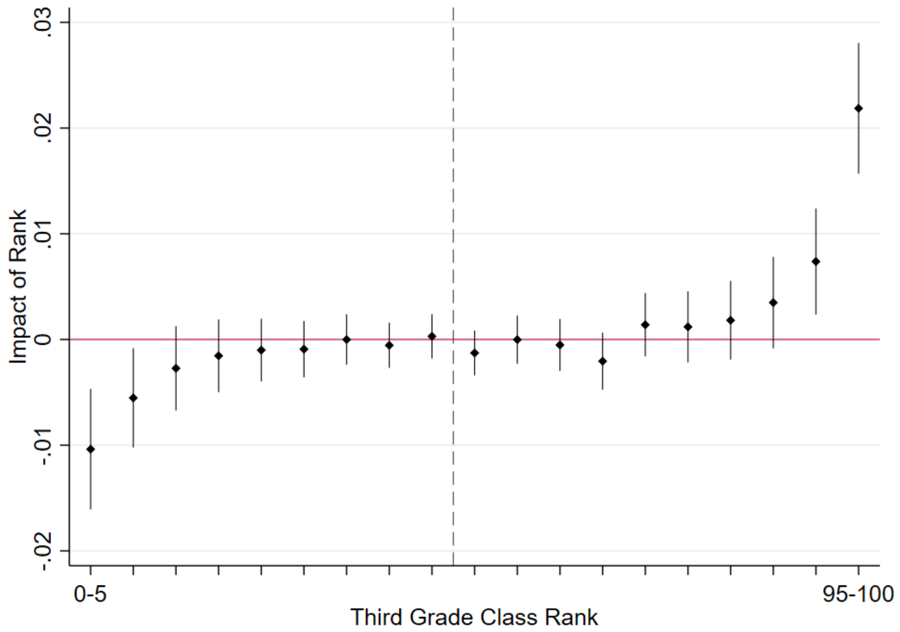
Note: These figures plot the coefficient for ventiles of class rank. The 45th-50th percentile is the omitted category. Estimates come from equation 2, which includes controls for race, gender, ESL status, and indicators for ventiles of student achievement. The mean high school graduation rate of 71 percent and a college enrollment rate of 47 percent.

Figure 6 – 3rd Grade Rank on College Enrollment

A. Enroll in Community College within 3 years of "on-time" high school graduation



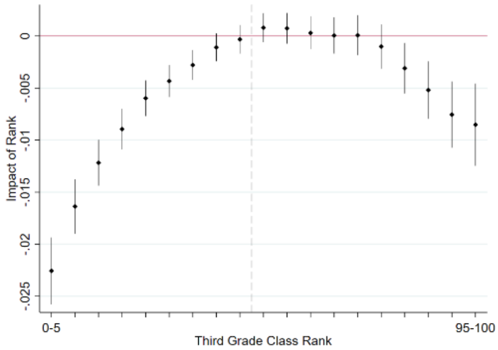
A. Enroll in 4 year within 3 years of "on-time" high school graduation



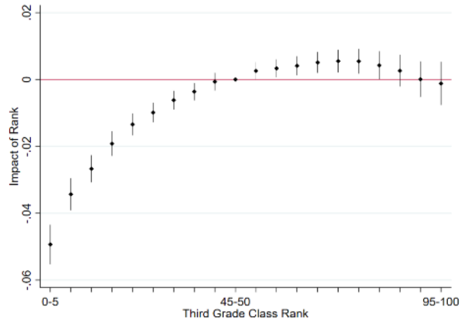
Note: These figures plot the coefficient for ventiles of class rank. The 45th-50th percentile is the omitted category. Estimates come from equation 2, which includes controls for race, gender, ESL status, and indicators for ventiles of student achievement. The mean 2-year college enrollment rate is 31 percent and the mean 4-year college enrollment rate is 23 percent. .

Figure 7 – 3rd Grade Rank on Bachelor's Degree Receipt

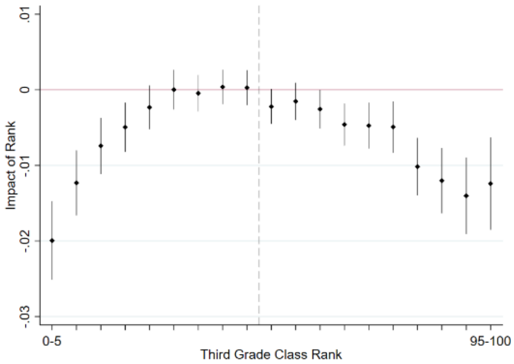
A. Grad 4yr in 4 years



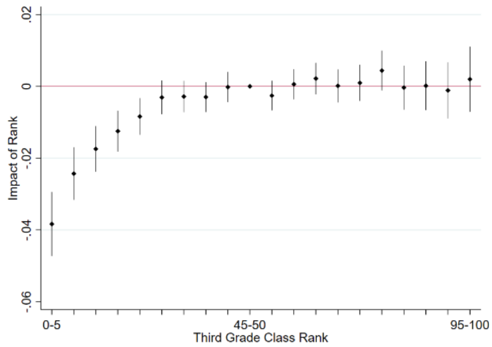
B. Grad 4yr in 4 years, w/ quality control



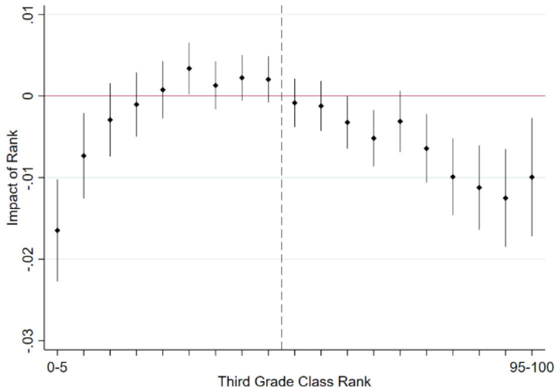
C. Grad 4yr in 6 years



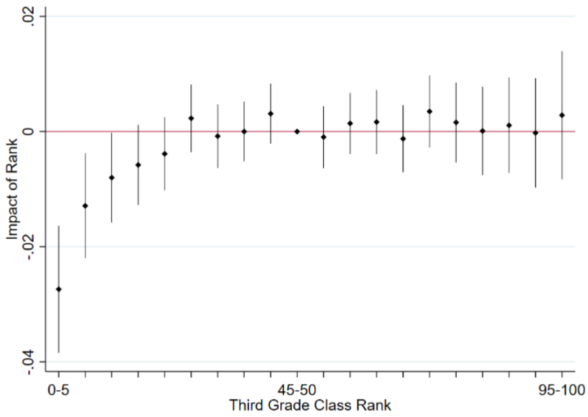
D. Grad 4yr in 6 years, w/ quality control



E. Grad 4yr in 8 years



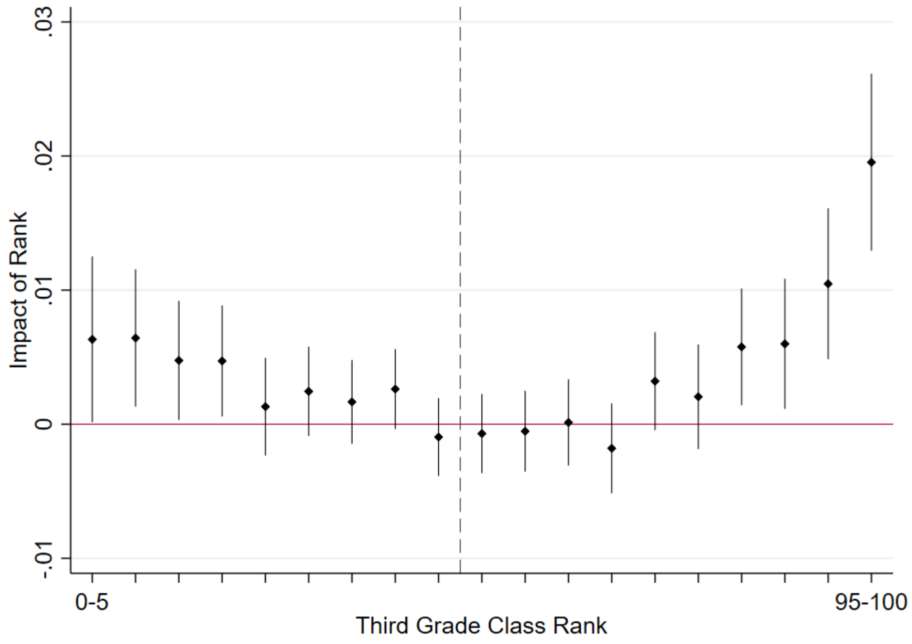
F. Grad 4yr in 8 years, w/ quality control



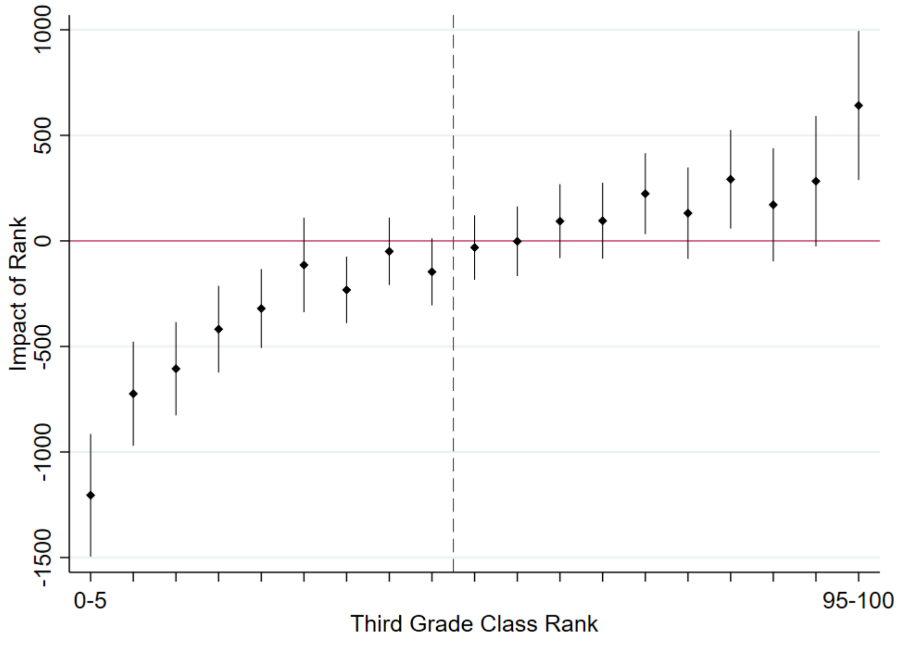
Note: These figures plot the coefficient for ventiles of class rank. The 45th-50th percentile is the omitted category. Estimates come from equation 2, which includes controls for race, gender, ESL status, and indicators for ventiles of student achievement.

Figure 8 – 3rd Grade Rank on Labor Market Outcomes, 1

A. Positive Earnings, Age 23-27



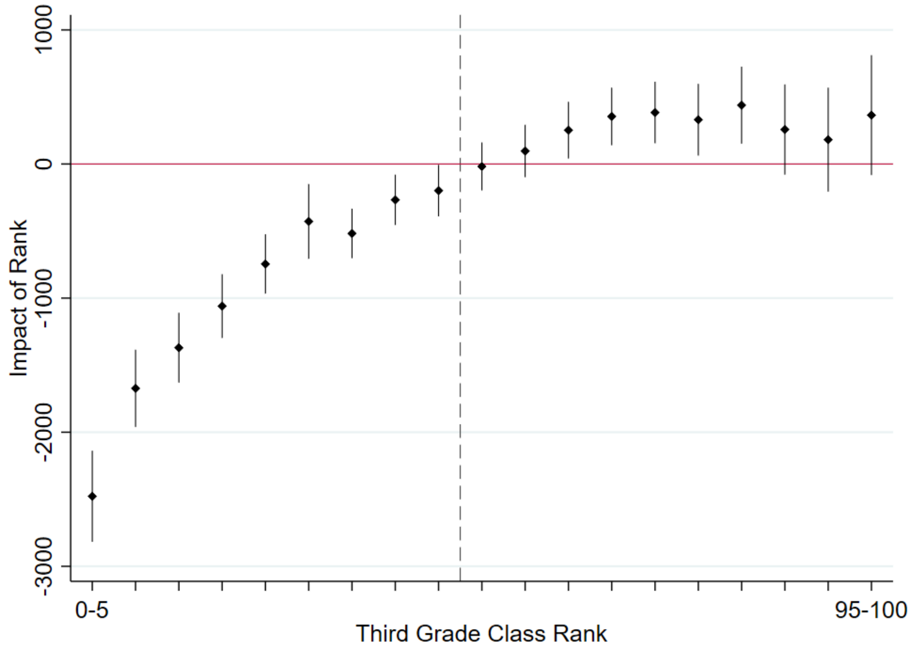
B. Average Earnings, Age 23-27



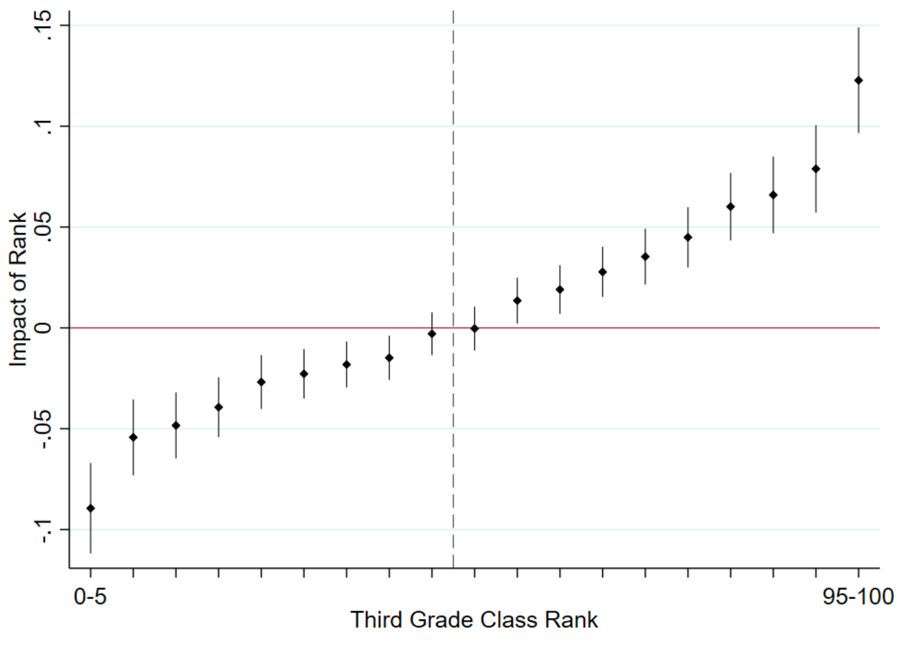
Note: These figures plot the coefficient for ventiles of class rank. The 45^{th}-50^{th} percentile is the omitted category. Estimates come from equation 2, which includes controls for race, gender, ESL status, and indicators for ventiles of student achievement. The mean positive earnings at ages 23-27 are $24,912 and mean earnings are $17,365.

Figure 9 – 3rd Grade Rank on Labor Market Outcomes, 2

A. Average Real Wages No Zeroes, Age 23-27



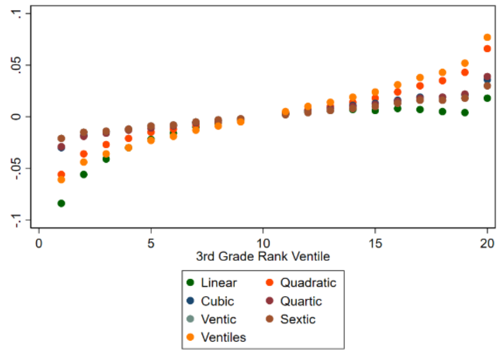
B. Log Average Wages, Age 23-27



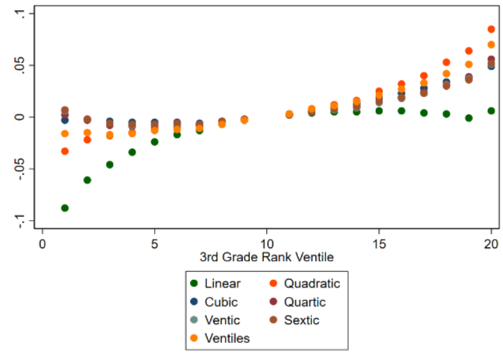
Note: These figures plot the coefficient for ventiles of class rank. The 45th-50th percentile is the omitted category. Estimates come from equation 2, which includes controls for race, gender, ESL status, and indicators for ventiles of student achievement. The mean retention rate is XXX.

Figure 10 – Flexible controls for Achievement

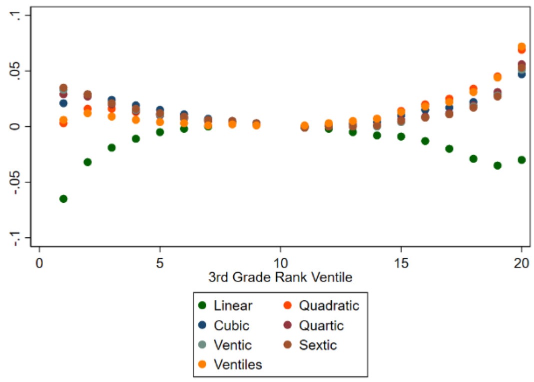
A. 8th Grade Test



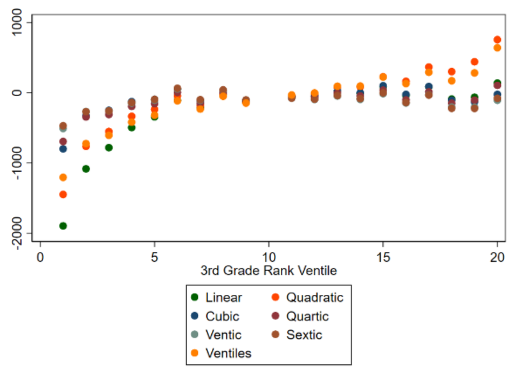
B. Ever Graduate HS



C. Any College



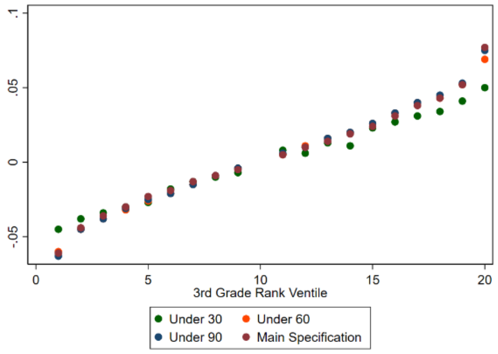
D. Real Wages Age 23-27



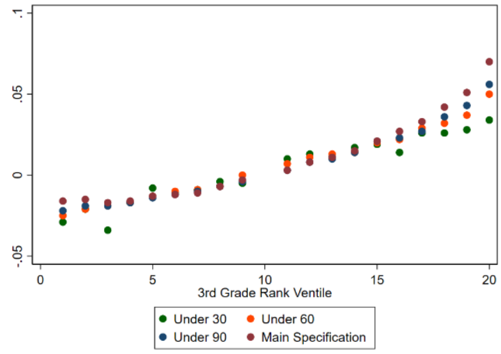
Note: These figures plot the coefficient for ventiles of class rank. The 45th-50th percentile is the omitted category. Estimates come from equation 2, which includes controls for race, gender, ESL status, and indicators for ventiles of student achievement.

Figure 11 – Results by Class Size

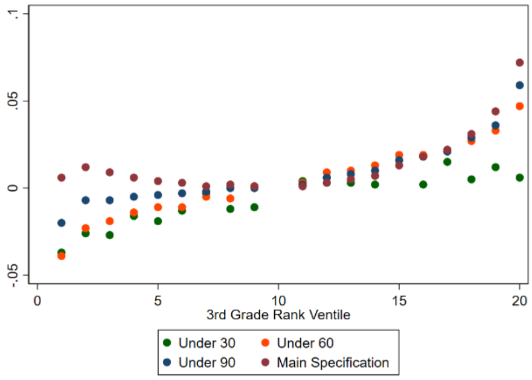
A. 8th Grade Test



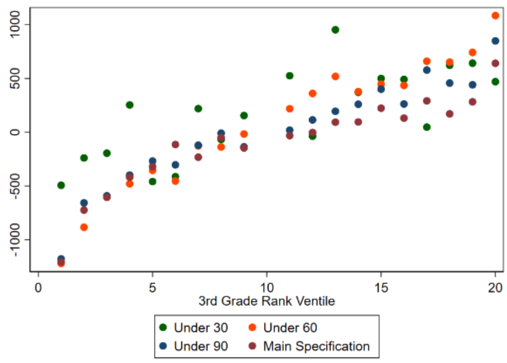
B. Ever Graduate HS



C. Any College



D. Real Wages Age 23-27



Note: These figures plot the coefficient for ventiles of class rank. The 45th-50th percentile is the omitted category. Estimates come from equation 2, which includes controls for race, gender, ESL status, and indicators for ventiles of student achievement.

Table 1 Summary Statistics

	Mean	Observations
Demographics		
Male	0.50	6,025,902
Economic Disadvantage	0.48	6,025,902
English as a Second Language	0.11	6,025,902
White	0.47	6,025,902
Asian	0.03	6,025,902
Black	0.15	6,025,902
Hispanic	0.35	6,025,902
Size of 3rd Grade SSC	92.6	6,025,902
Repeat 3rd Grade	0.004	6,025,902
Academic Outcomes		
State Test Percentile, 8th Grade	0.55	4,911,034
Ever Graduate High School	0.71	6,025,902
AP Calculus	0.07	6,025,902
Ap Science	0.07	6,025,902
AP English	0.19	6,025,902
Any College	0.47	6,025,902
Enroll, 4 yr college	0.23	6,025,902
Enroll, 2 year college	0.31	6,025,902
BA in 4 years	0.06	4,507,290
BA in 6 years	0.14	3,551,734
BA in 8 years	0.16	2,617,974
Labor Outcomes		
Non zero wages, Age 23-24	0.65	3,551,734
Real Wages, Age 23-24	15,249.3	3,551,734
Real Wages, Age 23-24 No Zeros	23,318.5	2,322,682
Non zero wages, Age 26-27	0.63	2,169,136
Real Wages, Age 26-27	20,139.2	2,169,136
Real Wages, Age 26-27 No Zeros	31,864.7	1,370,946
Non Zero Wages, Age 23-27	0.65	3,551,734
Real Wages, Age 23-27	17,365.0	3,551,734
Real Wages, Age 23-27 No Zeros	24,912.7	2,618,678

Note: This table contains summary statistics for the main estimating sample of third graders from 1995-2008. Some outcomes are only available for early cohorts which generates the differences in sample size. Enroll, 4yr college means enrollment within 3 years of "on-time" high school graduation and is similarly defined for 2-year colleges.

Table 2 The distribution of rank by School Value Added

Ventile	Average Class Rank	"Good"	"Bad"
1	0.047	0.035	0.073
2	0.104	0.074	0.143
3	0.158	0.112	0.203
4	0.21	0.152	0.257
5	0.261	0.188	0.306
6	0.31	0.228	0.353
7	0.356	0.267	0.402
8	0.403	0.306	0.449
9	0.449	0.348	0.497
10	0.496	0.391	0.542
11	0.542	0.437	0.585
12	0.587	0.485	0.626
13	0.635	0.536	0.671
14	0.686	0.594	0.718
15	0.722	0.633	0.75
16	0.779	0.697	0.802
17	0.82	0.753	0.84
18	0.869	0.82	0.881
19	0.924	0.89	0.929
20	0.958	0.941	0.961

Note: This table shows three things for each ventile of student achievement. The second column is the average class rank. The third column is the average class rank from someone in that ventile in a "Good" school—that is a school with Value Added 1 standard deviation above the mean. The last column is the average class rank by ventile of student achievement in a school with Value Added one standard deviation below the mean.