

# Teacher Targeting and the Big-Fish-Little-Pond Effect\*

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## EXTENDED ABSTRACT

A burgeoning literature has convincingly shown that ordinal rank improves future student performance and other long-run outcomes such as college-going, health, major choice, and earnings (Murphy and Weinhardt, forthcoming; Denning et al., 2018; Elsner et al., 2018; Elsner and Isphording, 2018, 2017). The predominant mechanism put forth for this relationship is a behavioral response whereby students gain confidence when they are highly ranked in their local peer group. The increase in confidence in turn is hypothesized to improve non-cognitive skills and lower the cost of effort leading to better future performance for the student – a mechanism that has been called the ‘Big-Fish-Little-Pond’ effect.

This paper shows for the first time that the effect of ordinal rank on future performance is context-specific rather than an underlying feature of the education production function. Specifically, we show that changes to incentive environments faced by educators can completely *reverse* these ordinal rank effects. Indeed, when educators are rewarded for test score growth regardless of underlying student ability (e.g., value-added) our results are identical to those in the prior literature where ordinal rank positively affects future student performance. In contrast, switching to an incentive environment that disproportionately rewards educators for the performance of low-ability students results in ordinal rank *negatively* affecting future student performance.

To start, we follow the methodology from Murphy and Weinhardt (forthcoming) to isolate the effect of a student’s rank on future performance. Specifically, we use idiosyncratic variation in the distribution of test scores across classrooms to compare students with equivalent test scores but different classroom ranks. The thought experiment is to compare two

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students with the same test score but who are ranked differently within their classroom due to idiosyncratic variation in classmate quality. We also include classroom fixed effects to account for the fact that students with identical baseline test scores but different ranks might be in disparate school contexts.

We then apply the methodology using detailed administrative data from North Carolina that covers all third grade cohorts from 1997-98 to 2004-05. An advantage of our setting is that North Carolina administers a test at both the end *and* start of third grade, allowing us to calculate the ordinal classroom rank of students at the *start* of third grade. In addition, during our time frame there was a substantial change in the incentive environment faced by educators due to the introduction of the largest accountability reform ever implemented in the United States: the No Child Left Behind Act of 2001 (henceforth NCLB).

Before NCLB, North Carolina used a value-added incentive scheme which rewarded educators for student test score growth, regardless of underlying student ability. During this time period, we find that student performance on the end-of-third grade test is increasing in ordinal classroom rank at the start of third grade, consistent with results found in the prior literature (see the ‘pre-NCLB’ relationship between end-of-second grade rank and end-of-third grade test score in Figure 1). The introduction of NCLB, however, shifted the incentive environment in North Carolina as educators were now rewarded for having low-ability students exceed a proficiency threshold.<sup>1</sup> After NCLB, we find that the relationship between ordinal rank and future performance reverses: student performance on the end-of-third grade test is now *decreasing* in ordinal classroom rank at the start of third grade (see the ‘post-NCLB’ line in Figure 1). We find similar results when using end-of-fifth or end-of-eighth grade tests as the outcome (see Figure 2).

To explain the reversal in ordinal rank effects, we set out a theoretical model to explore the way teachers target students based on rank. The model features a flexible education production function, which depends on both innate student ability and teacher effort and features educators choosing student-specific effort given an incentive scheme. In addition, educators face a convex cost of effort, forcing them to focus their effort on particular students in the class where returns to effort are high. While the model makes basic predictions on the types of students teachers will target in a given environment, the exact educator response to a given incentive scheme crucially depends on the parameters of the education production function.

Given that we know the relationship between ordinal rank and future performance at

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<sup>1</sup>Specifically, NCLB rewarded schools for having a set proportion of their student body exceed a proficiency standard. In North Carolina, this proficiency standard was set quite low in the student ability distribution which led to schools targeting low-ability students (see Macartney et al. (2018), for instance).

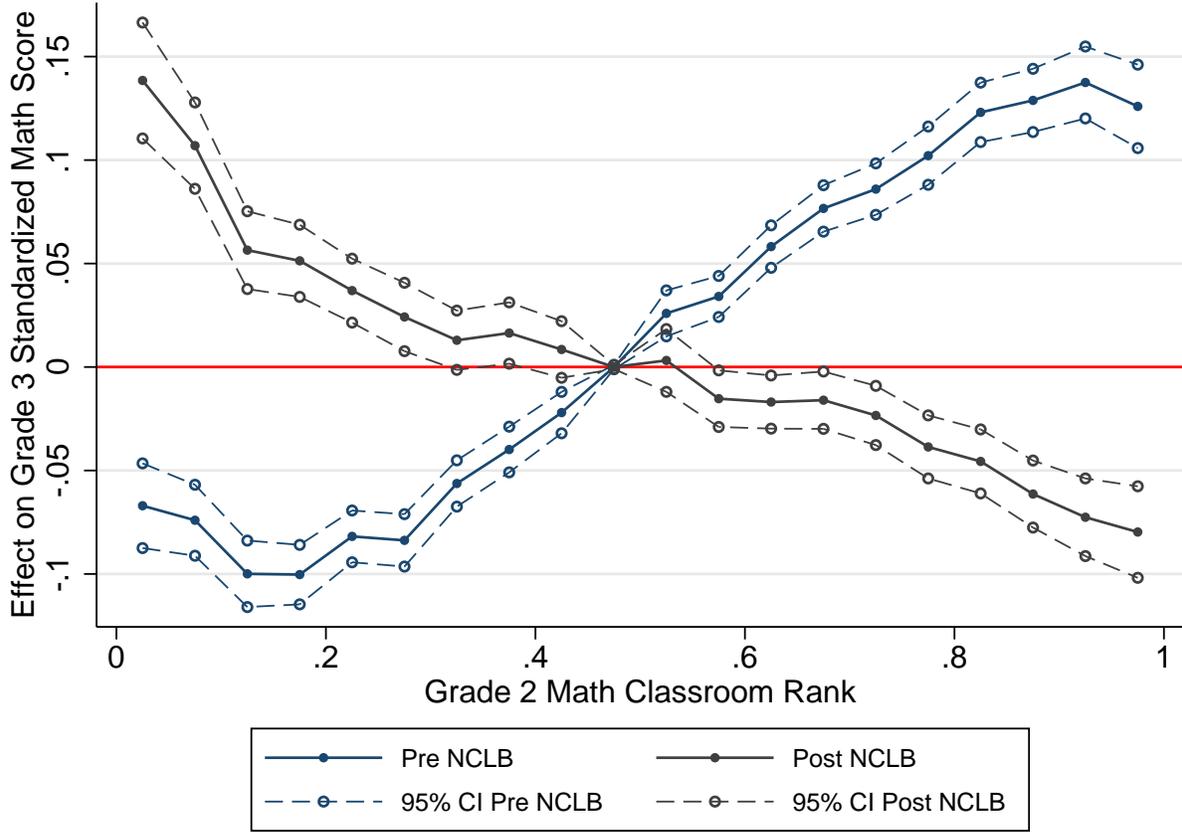
any point in time, we use changes to the educator incentive environment to estimate the parameters of the technology in a credible way. In particular, our structural model rationalizes the positive relationship between ordinal rank and future performance as being driven by a complementarity between teacher effort and student ability, making it so that returns to teacher effort are increasing in ordinal rank. An incentive scheme that targets low-ability students, however, reverses this relationship since it creates higher returns to teacher effort among lower ranked students within a given classroom.

Our ability to uncover the mechanism underlying rank order effects can help policymakers and researchers alike understand the effect of classroom peers on the academic achievement of individuals. In general, a large literature in economics seeks to estimate peer effects by looking at the effect of plausibly exogenous changes in classmate quality on own achievement. Our research suggest that changes in classmate quality may have two independent effects that arise from: (i) direct peer effects, and (ii) changes to teacher targeting. While the impact of peer quality on own achievement is policy-invariant, teacher targeting is not. Given that teacher targeting depends on both the incentive environment and the distribution of students in the class, there are interesting policy opportunities where policymakers can adjust both the incentive scheme and classroom assignments to raise student achievement for at-risk students. We aim to investigate optimal policy along these two dimensions through counterfactual simulations that use the estimated parameters from our structural model.

## References

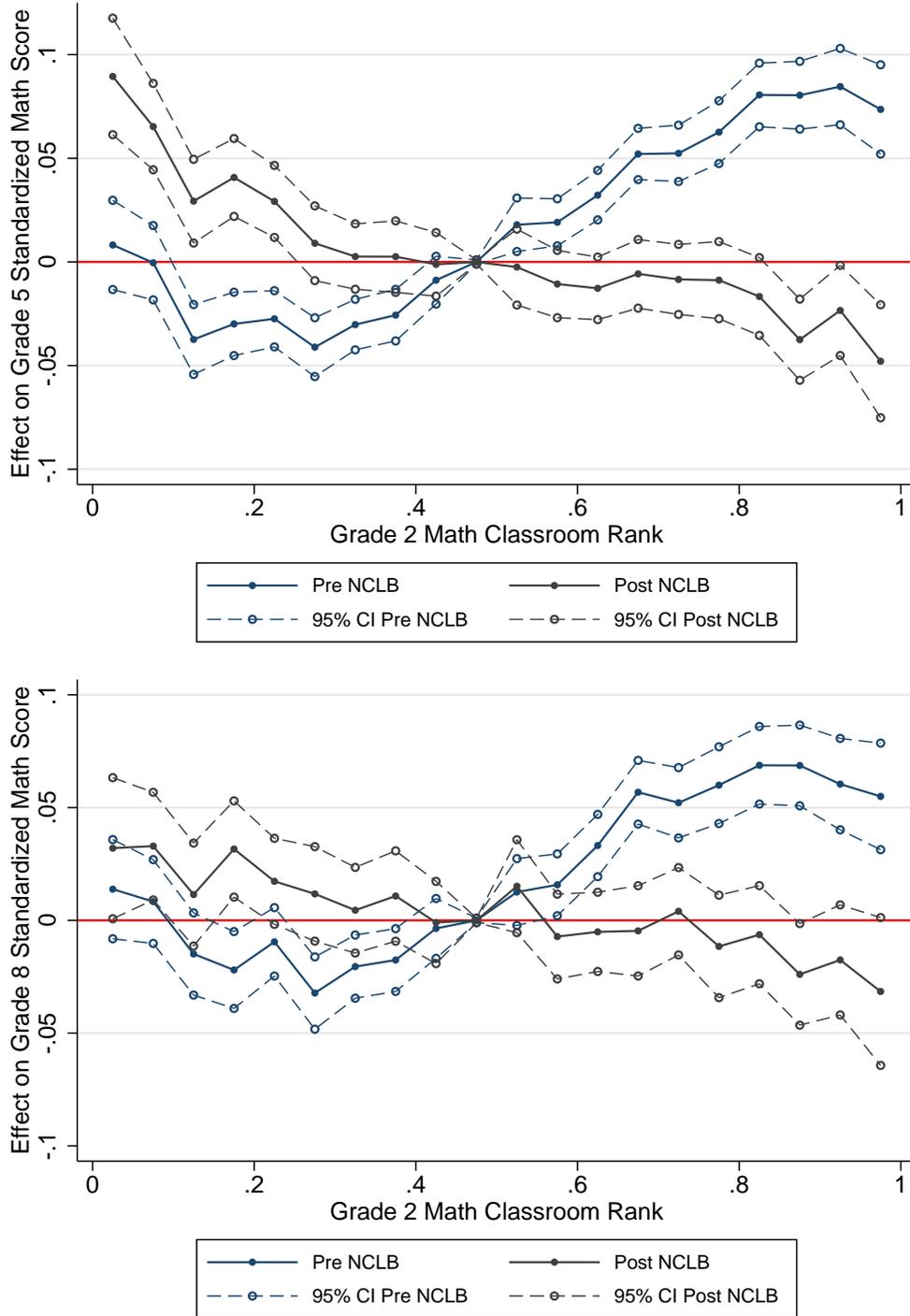
- Denning, Jeffrey T., Richard Murphy, and Felix Weinhardt (2018), “Class rank and long-run outcomes.”
- Elsner, Benjamin and Ingo E. Isphording (2017), “A big fish in a small pond: Ability rank and human capital investment.” *Journal of Labor Economics*, 35, 787–828.
- Elsner, Benjamin and Ingo E. Isphording (2018), “Rank, sex, drugs, and crime.” *Journal of Human Resources*, 53, 356–381.
- Elsner, Benjamin, Ingo E Isphording, and Ulf Zölitz (2018), “Achievement rank affects performance and major choices in college.” *University of Zurich, Department of Economics, Working Paper*.
- Macartney, Hugh, Robert McMillan, and Uros Petronijevic (2018), “Teacher performance and accountability incentives.” Working Paper 24747, National Bureau of Economic Research, URL <http://www.nber.org/papers/w24747>.
- Murphy, Richard and Felix Weinhardt (forthcoming), “Top of the class: The importance of ordinal rank.” *Review of Economic Studies*.

Figure 1: Classroom Math Rank Effects Before and After NCLB



Notes: We determine ordinal student rank in grade  $g$  according to the position of their math score in the distribution of scores at the classroom (school-grade-year-teacher) level. The rank measure used in the analyses is then given by equation (3) in Murphy and Weinhardt (2019) and ranges between 0 and 1. We group students into twenty bins (vingtiles) of the rank variable and regress future standardized (at the grade-year level) test scores on indicators for each possible bin, while leaving out the bin capturing students with a rank value of 0.45 to 0.5 as the omitted category. The solid-line profiles in each panel represent the estimated coefficients on these indicator variables and the dashed-line profiles represent 95% confidence intervals. Standard errors are clustered at the school level. Each regression also contains classroom fixed effects, an indicator variable for being the lowest ranked student in the classroom, an indicator for being the highest ranked student in the classroom, and a cubic function of the standardized math score earned in grade  $g$ . The sample consists of all third to fifth grade students from 1997-98 to 2004-05 and we track test future test scores up to eighth grade for all cohorts. NCLB took effect in the 2002-03 academic year.

Figure 2: Classroom Math Rank Effects Before and After NCLB



Notes: We determine ordinal student rank in grade  $g$  according to the position of their math score in the distribution of scores at the classroom (school-grade-year-teacher) level. The rank measure used in the analyses is then given by equation (3) in Murphy and Weinhardt (2019) and ranges between 0 and 1. We group students into twenty bins (vingtiles) of the rank variable and regress future standardized (at the grade-year level) test scores on indicators for each possible bin, while leaving out the bin capturing students with a rank value of 0.45 to 0.5 as the omitted category. The solid-line profiles in each panel represent the estimated coefficients on these indicator variables and the dashed-line profiles represent 95% confidence intervals. Standard errors are clustered at the school level. Each regression also contains classroom fixed effects, an indicator variable for being the lowest ranked student in the classroom, an indicator for being the highest ranked student in the classroom, and a cubic function of the standardized math score earned in grade  $g$ . The sample consists of all third to fifth grade students from 1997-98 to 2004-05 and we track test future test scores up to eighth grade for all cohorts. NCLB took effect in the 2002-03 academic year.