WORKING TITLE: An Analysis of Peer Effects & and Differential Attrition in Project Star

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1 Introduction

Imagine yourself as an elementary school teacher trying to manage an unruly group of students. Do you seat them across the classroom from each other, hoping that once separated they stop their disruptive behavior? Or does this choice mean that they'll simply find someone else to talk to, resulting in further disruption? Answering these questions may prove instrumental for the success of your students. There exists extensive empirical literature examining the effect of exogenous policy shifts on student achievement. A considerable portion on the current economics of education literature, however, is now centered around the estimation of peer effects: the unobserved, peer-to-peer spillovers from students both inside and outside the classroom. Studying these mechanisms through which student outcomes may be maximized or diminished has significant consequences for policymakers.

It is well documented in the literature that student-to-student peer effects do in fact exist and that such effects are, in part, influenced significantly by peer quality. It is also well known that both private schools provide a channel through which wealthier, high-ability students are able to leave the public school system. Many private schools have entrance exam requirements which deliberately select for high-achieving students. Given the existence of such rationing, it is perhaps the case that the act of exiting a school may have unobserved effects on peers in the classroom. That is, if the distribution of students that exit public schools for private schools consists primarily of high-achieving students, perhaps there exist negative or reduced positive peer effects from such withdrawal. My paper aims to analyze the effects of this attrition, especially in relation to the varying degree of these effects based on student ability.

Within the context of United States public education, private schools create both exclusionary and rivalrous conditions. In particular, Private schools create rivalrous conditions by introducing rationing through two distinct channels: tuition rationing and cream-skimming. Tuition rationing is the practice through which private schools select for students with high-income backgrounds by charging for seats – disallowing lower-income families from consumption without some form of subsidization. Cream-skimming is the practice through which private schools select for high-ability students by introducing entrance exam cutoffs as a requirement for admission. The practice can be seen as "skimming" the highest performing students from the public school system into private schools. Although, in some cases, private schools may "cross-subsidize" (i.e. high-income, low-ability students' tuition is used to provide scholarships for low-income high-ability students) it remains that the plurality of students that enter private-schools are likely to be of high-ability.

Utilizing evidence from Tennessee's Student/Teacher Achievement Ratio Project (Project STAR) – an experiment in which elementary school students and teachers were randomly assigned to different class sizes – my paper aims to estimate the peer effects of student attrition on academic achievement between the 1st and the 3rd grade. Given that students were randomized into class types, it is likely that measures of peer effects from Project STAR are not biased due to sorting. Additionally, as part of the experiment, a robust set of student, teacher, and school-level characteristics were collected and students were tracked individually throughout the experiment. My analysis draws upon subsequent data on graduation and dropout rates of the students involved in STAR as well as the identification of students that left the public school system in order to classify students who potentially left the experiment for private schools.

First, I examine attrition in Project STAR writ large. Though the identification of the proportion of students who either moved across classrooms or schools within the experiment and those that left the experiment entirely, I paint a picture of differential attrition that occurred.

Second, using this identification, I introduce a model of attrition which measures the effect of student ability, controlling for confounds, on the probability a particular student stayed in the experiment. I compare the results from this model on the schools in Project STAR with attrition data from schools in the control group and compare both. This model motivates the empirical strategy behind peer effects estimation in the paper.

Third, I consider how attrition across all students who left Project STAR may have impacted students by considering the effects of attrition on changes in their lagged test scores. I estimate these peer effects using a regression analysis to explore both changes in the magnitude of the effect based on class size.

Finally, I perform an empirical analysis aiming to isolate the peer effects from students who left the public school system entirely. I use information on public school testing data both during and after Project STAR to classify students who potentially left the public school system. In order to identify students who potentially left the experiment for private schools, I fit a clustering model aimed at sorting such students into ”similar” groups. Using these clusters, I undertake a sensitivity analysis to measure the robustness of my measurements to certain assumptions on attrition. I also undertake a short discussion of the limitations of measuring unobservables and how inconsistencies in randomization within Project STAR may bias my results.

2 Literature Review

Since the publication of the Coleman Report in 1966[1] there has been suspicion that student unobservables have a significant impact on education production.[2] The classic education production function predicts that test scores can be represented as a function of class size and confounds[3]. Subsequent research has shown that such a relationship is likely identifying only a portion of what affects student achievement[4], especially when viewed in conjunction with the documented relationship between peer effects and achievement. Some, as first described by Lazear (2001), theorize that disruption in the classroom presents a tradeoff between learning and class size – a higher proportion of "better behaved students" leads

[1]A study commissioned by the US government and mandated by the Civil Rights Act of 1964 aimed at measuring educational opportunity in the United States.

[2]Dickinson, E. E. (2016).

[3]Lazear, E. P. (2001), p.777; Examples include: student's own ability, teacher experience, parental income, percentage of students in school on free and reduced lunch, demographic characteristics, etc.

[4]Hanushek (2008).

to a larger optimal class size.[5] That is, disruptive students may have a greater negative impact on smaller class-sizes than larger ones. Such negative spillovers from disruption can perhaps be best understood through the lens of peer effects. The channel through which one's own production results in spillovers or externalities on peers achievement is measured by peer effects. Subsequent literature has broadened this model of production to focus both on exogenous inputs to production (e.g. class size, curriculum, etc.) as well as inputs that cannot be controlled by policymakers (e.g. parental income, student's attentiveness, peer effects, etc.).[6]

Although there exists a vast literature on peer effects, papers analyzing the peer effects of attrition are somewhat limited, especially given the lack of longitudinal data of student-tracking across both the private and public school systems. One notable study is that of Dills (2005) which utilized the entry of a magnet school in Virginia to estimate the effect of the exit of high-ability students on the proportion of students scoring in the top quartile on a nationally-standardized exam. Dills finds that the loss of high-achieving students to the magnet school lowers the achievement of their lower-scoring counterparts who remained in public schools.[7] Key limitations of Dills' paper, though, include an inability to track individual students' test scores and a lack of demographic controls. Randomized experiments offer the best data to track peer effects given the elimination of selection bias due to peer sorting.

Within the context of Project STAR, papers such as Boozer (2001) focus on estimating the difference in peer-effects due to variation in class-size. Researchers have found that, especially for small classes, much of the effect of class-size on achievement is actually captured by the increased intensity of spillovers from peers in these settings.[8] Given missing data concerns in Project STAR, Sojurner (2011) develops a model for estimating peer effects with the caveat of missing peer data. Sojourner utilizes pre-assignment measures of student

[5] Lazear, E. P. (2001), p.779.
[6] Hanushek (2008).
[7] Dills (2005).
[8] Boozer (2001).

ability in conjunction with random assignment to estimate effects, finding that, on average, the effects of bring around high-achieving peers are positive and that peer-ability perhaps matters more for low-achieving students than for high-achieving students.[9] Key limitations of Project STAR include differential attrition and a lack of data on where students who left the experiment attended school after leaving. Rohlfs & Zilora (2014) exploit whether or not a student had public school testing records after the conclusion of Project STAR as a proxy for identifying if a student remained in the public school system. Such developments should assist in the estimation of peer effects of attrition and reduce the limitations the data impose.

3 Data

Project STAR was class-size randomization experiment across grades K-3 in Tennessee between 1985-1989. 11,600 students across 79 schools voluntarily participated in the study. Students and teachers were randomized into one of three class types at the start of the 1985 school year: small classes (13-17 students), regular-sized classes (22-25 students), and regular-sized classes with a teacher's aide (22-25 students in addition to a full-time teacher's aide). After being initially assigned to a class type, students were kept in that class for the duration of the experiment (i.e. 4 years, or between K-3rd grade). Among participating schools, each was required to have at least one of the three class types and randomization occurred within each school. Study administrators collected a variety of data on students from observable characteristics (e.g. race, age, gender, etc.) on both students, teachers, and schools as well as a variety of standardized test scores, administered at the end of each school year. Students who entered a participating school in the middle of the experiment were also randomly assigned to a class type upon entry. There are some limitations to the design, mainly that at the beginning of 1st grade, students in the regular and regular-aide classes were re-randomized across these types. Secondly, approximately 10 percent of stu-

[9] Sojurner (2011).

dents moved across small and regular-sized classes between grades.[10] Lastly, there exists evidence of differential attrition from the experiment by class type. As I work through my project, I may decide to exploit this to determine the severity of the peer effects from attrition based on a student's class type. It is important to note that identification of students who left the experiment, as noted by Rohlfs & Zilora, can only be separated into students who either changed class types, switched to another public school, or left he public school system entirely. Thus, I am unable to accurately identify among the students that left the public school system, which left to a private school. Further information about the experiment is well described in Krueger (1999).

4 Empirical Framework

4.1 Identifying Attrition

Since the completion of Project STAR, subsequent studies have been commissioned in order to understand the long-run impacts of the experiment. As part of these studies, data is collected on the academic achievement of students who participated in Project STAR in grades 4 through 8. At the same time, students within the experiment were tracked. If a student moved within the experiment to another Project STAR school, that student's movement can be identified through the data. Utilizing this data, I am to reproduce Rohlfs & Zilora's identification of student status in the 3rd grade by their initial class assignment. Rohlfs & Zilora identify five types of attrition within Project STAR:

1. Students who were in a Project STAR school at time $t-1$, but who's school left the experiment at time t.

2. Students who changed class type within a school.

3. Students who left to another Project STAR school.

[10] Kruger (1999), p.499.

4. Students who left to another public school.

5. Students who left the public school system.

Identifying students who fall into attrition types 1-4 is easily seen through the data. Both students and schools are flagged for leaving the experiment. Though there may be some missing data concerns, subsequent identification of students who fall into categories 1 and 3 can be undertaking by examining whether or not there exists Project STAR testing data for these experiments both within the experiment's timeframe (i.e. grades K-3) or in the subsequent studies tracking the students post-experiment. Rohlfs & Zilora identify students who left the public school system as those who left Project STAR in 3rd grade and test scores do not exist for them in 4th grade. I strengthen this identification by checking if such students do not have public school records for both 4th and 5th grade. It is likely the case that if a student left Project STAR for a private school, they would not re-enter the public school system until after the 5th grade. This is due to the fact that private schools in certain geographic regions may only accept students between grades K-5. Thus, if a student left for a private school, it is likely that they do not have test score data for both grades 4 and 5. Another potential point of identification is to see which of these students perhaps re-entered the public school system in grades 6-8 (typically denoted as "middle school"). Students with access to only K-5 private schools may have perhaps been forced to re-enter the public school system for middle school. By identifying attrition types 1-5, I garner an understanding of the differences in attrition across class types – providing the opportunity to further identify the characteristics of students, namely ability, that are perhaps correlated with attrition.

4.2 Quantifying the Effect of Ability on Attrition

In order to quantify the effect of student ability on attrition, I turn to survival analysis. Within the context of Project STAR, attrition can be considered a survival observation of interest. That is, the act of a student leaving the experiment entirely (i.e. they fall into attrition categories 1,4, and 5) can be considered a "failure." Survival analysis allows for the identification of factors which may be correlated with the amount of time a stayed in the experiment (in other words, their time to failure). Here, I represent $T_{i,g,c,s}$ as the failure time (i.e. the number of years a student stayed in the experiment until they left) for each student i in grade g in classroom c at school s. It may be the case that due to missing data concerns or students leaving the experiment in one year and coming back in another, $T_{i,g,c,s}$ is unobserved (or, perhaps, not "completely" observed). Such observations are considered to be censored, with censoring time C_i. I model the data under the assumption that $T_i > C_i$ (i.e. the "survival time" is longer than the "censoring time"). Additionally, I assume that attrition in the experiment was constant across all years Project STAR took place. Thus, the hazard function of $T_{i,g,c,s}$ can be represented using an exponential distribution. I model the survival time through the following accelerated failure time (AFT) model:

$$log(T_i) = \beta_0 + \beta_1(TS_{i,g,c,s}) + \beta 2(CT_{i,g,c,s}) + \beta 3(X_{i,g,c,s}) + \epsilon_{i,g,c,s} \tag{1}$$

Where $TS_{i,g,c,t,s}$ is the test score for student i in grade g in classroom c in school s, $CT_{i,g,c,t-1,s}$ is a categorical variable for the class type student i was enrolled in upon entry to the experiment (e.g. small, regular-sized, or regular sized with teachers aide), and $X_{i,g,c,t-1,s}$ is a vector of controls for each student including observable student, teacher, and school data. Examples of this include student attendance, teacher's highest education level, student's race, percentage of school on free and reduced lunch, school geography (e.g. urban, rural, etc.), and others. The coefficients of this model have a multiplicative effect on time. That is, if $\beta_1 = 1$, then $exp(\beta_1) \approx 2.718$. Holding all other variables constant, an individual with $TS_{i,g,c,t,s}$ one unit greater than another is expected to stay in the Project STAR experiment 2.718 times longer than the other. In other words, the probability this individual "survived" to time $2.718t$ is the same as the probability that another individual has "survived" to time

t.

4.3 Identification of Differential Peer Effects From Attrition Across Class Size

I exploit the panel nature of the Project STAR data to use a fixed effects model to determine the differential peer effect from attrition across all students who left Project STAR based on class size. The dependent variable of interest is a measure of a student's test score, given by the testing data in Project STAR. I make use of lagged covariates to measure the effect of attrition in time $t-1$ on test scores in time t. Key to the estimation of peer effects within the context of education is the assumption that the test scores of student i depend on the background characteristics of student i's peers. For example, student i's learning is likely to be improved if student j's test scores are high. That is, I am primarily concerned with the endogenous peer effects of achievement. I include both school and year fixed effects to account for unobserved differences across both schools and time. There may be school-specific, time-invariant effects which these fixed effects pick up on (e.g. location, funding characteristics, etc.) which should aid in the robustness of my results. My model is outlined in equation (2):

$$\begin{aligned} TS_{i,g,c,t,s} = \beta_0 + \beta_1(L_{i,g,c,t-1,s}) + \beta_2(A_{i,g,c,t-1,s}) + \beta_3(\overline{CA}_{i,g,c,t-1,s}) + \beta_4(\overline{PA}_{i,g,c,t-1,s}) \\ + \beta_5(X_{i,g,c,t-1,s}) + \beta_6(CT_{i,g,c,t-1,s}) + \alpha_s + \gamma_{t-1} + \epsilon \end{aligned} \tag{2}$$

Here, $TS_{i,g,c,t,s}$ is the test score for student i in grade g in classroom c in school s at time t. $L_{i,g,c,t-1,s}$ is the proportion of students in student i's class that left for private schools at time $t-1$. $A_{i,g,c,t-1,s}$ is student i's ability, measured by their test score in time $t-1$. $\overline{CA}_{i,g,c,t-1,s}$ is classmate ability for student i. That is, the average test score of the students in student i's class that don't leave the experiment, measured by their test score in time $t-1$. $\overline{PA}_{i,g,c,t-1,s}$ is the peer ability for student i. That is, the average test score of the students in student

i's class that left the experiment in $t-1$. This is perhaps my main coefficient of interest as I am interested in how the leavers' ability affects students. $X_{i,g,c,t-1,s}$ is a vector of controls for each student including observable student, teacher, and school data. Examples of this include student attendance, teacher's highest education level, student's race, percentage of school on free and reduced lunch, school geography (e.g. urban, rural, etc.), and others. $CT_{i,g,c,t-1,s}$ is a categorical variable for the class type student i was enrolled in during time $t-1$ (e.g. small, regular-sized, or regular sized with teachers aide). Lastly, α_s is a school fixed effect, γ_{t-1} is a year fixed effect, and ϵ is the regression error term.

4.4 Identification of Peer Effects From Attrition to Private Schools

Given that I am unable to directly classify the students who left Project STAR for private schools, I estimate the potential negative effects of cream skimming by undertaking a two part procedure. First, utilizing clustering, I separate students who left the public school system entirely into distinct groups. Ranking these groups by average ability, I estimate the peer effects on achievement of each of these groups leaving, under the assumption that these students all left for private schools. Through this, I arrive at a range of parameter estimates for the potential peer effects from these students that left for private schools.

4.4.1 Clustering Analysis

In order to group students who left the public school system into "clusters" which will allow me to sort them by ability, I fit a variation of the k-means clustering algorithm. The usefulness of clustering is that it allows me to separate students into groups that "look" alike thus allowing me to perhaps infer or make assumptions about which students went to private school without the data needed to classify these students as private school students. K-means clustering is a technique through which for a given set of observations, these observations are separated into k sets such that some notion of "closeness" within the points in the set is minimized. To explain more rigorously:

Imagine we have a collection of N students who we know left the public school system $x_1, \ldots, x_n$ denoted by the set X. For each of these students there exists a $d \times 1$ vector $\vec{v}_i \in R^D$ where each row of the vector represents the value of each covariate for student x_i (i.e. row one is race, row two is gender, etc.). We denote the set of these vectors as $V = \{\vec{v}_1, \ldots, \vec{v}_n\}$. First, we take k random points in X and generate a set $M = m_1, \ldots, m_k$ of the mean Mahalanobis distances between all of the points each of the randomly selected initialization points. Then, we assign each x_i to the cluster with the closest mean: that is the cluster with the least squared Mahalanobis distance. This Mahalanobis distance is shown as follows:

$$D_m(\vec{v}_i, \vec{v}_j) = \sqrt{\sum_{i=1}^{p} (\vec{v}_i - \vec{v}_j)^T \Sigma^{-1} (\vec{v}_i - \vec{v}_j} \ , \ \forall i \neq j$$

We end up with k clusters which represent points that are "close" to one another. We then iterate this process multiple times, recalculating the means of the observations assigned to each cluster. We thus end up with k clusters of observations in X which we believe to be "similar" in some way.

4.4.2 Sensitizing Results & Regression

The regression analysis is very similar to that described in section 4.3. The equation is largely the same, with the main coefficient of interest being the average ability for each individual group which leaves. The equation is modeled as follows:

$$\begin{aligned} TS_{i,g,c,t,s} = \beta_0 + \beta_1(L_{i,g,c,t-1,s}) + \beta_2(A_{i,g,c,t-1,s}) + \beta_3(\overline{CA}_{i,g,c,t-1,s}) + \beta 4_{(}\bar{\delta}_{i,g,c,t-1,s}) + \beta_5(\overline{PA}_{i,g,c,t-1,s}) \\ + \beta_6(X_{i,g,c,t-1,s}) + \beta_7(CT_{i,g,c,t-1,s}) + \alpha_s + \gamma_{t-1} + \epsilon \end{aligned} \tag{3}$$

Here, $TS_{i,g,c,t,s}$ is the test score for student i in grade g in classroom c in school s at time t.

$L_{i,g,c,t-1,s}$ is the proportion of students in student i's class that left for private schools at time $t-1$. $A_{i,g,c,t-1,s}$ is student i's ability, measured by their test score in time $t-1$. $\overline{CA}_{i,g,c,t-1,s}$ is classmate ability for student i. That is, the average test score of the students in student i's class that don't leave the experiment, measured by their test score in time $t-1$. $\bar{\delta}_{i,g,c,t-1,s}$ is the cluster peer ability for student i. That is, the average test score of the students in student i's class that left the experiment and the public school system in $t-1$ who, through clustering, I treat as having left for private schools. This is perhaps my main coefficient of interest as I am interested in how the leavers' to private schools ability affects students. $\overline{PA}_{i,g,c,t-1,s}$ is the peer ability for student i. That is, the average test score of the students in student i's class that left the experiment in $t-1$ who *are not* included in the cluster δ. $X_{i,g,c,t-1,s}$ is a vector of controls for each student including observable student, teacher, and school data. Examples of this include student attendance, teacher's highest education level, student's race, percentage of school on free and reduced lunch, school geography (e.g. urban, rural, etc.), and others. $CT_{i,g,c,t-1,s}$ is a categorical variable for the class type student i was enrolled in during time $t-1$ (e.g. small, regular-sized, or regular sized with teachers aide). Lastly, α_s is a school fixed effect, γ_{t-1} is a year fixed effect, and ϵ is the regression error term.

In order to understand the sensitivity of my results to my assumptions I make regarding which students may perhaps "resemble" private school students, I aim to employ an analysis similar to that described in Emily Oster's 2016 paper: *Unobservable Selection and Coefficient Stability: Theory and Evidence*. Such methods allow me to see, under the assumptions of my model, how "non-randomly" would the data have to be selected in order to observe the range of parameter estimates I calculate. (Note for readers: I have not fully understood how to incorporate this into my paper yet, so I will focus my efforts on the effect of attrition writ large and the analysis of if ability affects attrition).

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