Are Good Schools Good for Everyone? An Examination of Heterogeneous School Effects

THESIS

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Abstract

I consider the possibility that school effectiveness is not a fixed characteristic, and that schools can have different impacts for different students. Two theories offer competing explanations for this trend. The Frog-Pond hypothesis argues that a student’s ranking relative to their peers is an important predictor of academic self-concept, so schools’ effectiveness for each student depends on their position relative to peers. School Specialization theory argues that schools adopt different practices in order to be most effective for the students that they serve. Using non-additive regression techniques, I find that the association between school quality and individual learning rate does indeed differ for students of different SES backgrounds, depending on whether the school serves predominantly high or low SES students. The observed patterns are most consistent with the specialization hypothesis. I discuss the implications for both scholars and education reformers.
Dedication

I would like to dedicate this thesis to my late stepfather, Jeff. You constantly sparked my intellectual curiosity from a young age. You encouraging me to read the Foundation novels, the Freakonomics books, and the emails you sent me encouraging me to pursue my academic interests set me on this path and I will be eternally grateful.
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Table of Contents

Abstract............................................................................................................................................... ii

Acknowledgments.............................................................................................................................. iv

Vita........................................................................................................................................................ vi

List of Tables ......................................................................................................................................... ix

List of Figures ...................................................................................................................................... x

Introduction.......................................................................................................................................... 1

Background......................................................................................................................................... 3

Heterogeneity in School Effects............................................................................................................ 3

Measures of School Quality & Out of School Time ........................................................................... 4

Frog-Pond Hypothesis............................................................................................................................ 8

School Specialization............................................................................................................................ 11

Data and Method................................................................................................................................. 14

Data...................................................................................................................................................... 14

Measures............................................................................................................................................. 15

Analytic Plan....................................................................................................................................... 17

Results.................................................................................................................................................. 19
Conclusions ......................................................................................................................... 23
Limitations .......................................................................................................................... 23
Discussion & Conclusion ...................................................................................................... 24
References .............................................................................................................................. 27
Appendix: Tables and Figures ............................................................................................... 31
List of Tables

Table 1. Descriptive Statistics of Model Variables .................................................................. 32
Table 2. School Impact by School SES .................................................................................. 33
Table 3: OLS Regression Predicting First Grade Learning Rate (Limited Sample) ........ 34
Table 4: OLS Regression Predicting First Grade Learning Rate (Expanded Sample) ..... 36
List of Figures

Figure 1. Models of School-Home Influence on Academic Outcomes ........................ 31
Figure 2. Differences in school impact coefficient by Family and School SES ............... 35
Introduction

Schools that serve predominantly white and high socioeconomic students tend to have more resources (Condron and Roscigno 2003) and better teachers (Kalogrides and Loeb 2013). Conventional wisdom and a lot of research would state that these schools are better overall, and that improving schools serving the disadvantaged should be an important goal. However, new and innovative measures of school quality (see Downey, von Hippel, and Hughes 2008) suggest that higher socioeconomic and white children do not necessarily enjoy greater math and reading gains due to school influence. Others have even found that public schools outperform better funded private ones (Lubienski and Lubienski 2013). If these new measures are indeed capturing school quality better than previous ones, why would schools serving high- socioeconomic and white children not exhibit better performance than schools serving disadvantaged children? Although there seems to be little relationship between measures of school quality and the socioeconomic composition of the study body (as Downey et al., 2008 find), my study considers whether these broad patterns apply similarly to different groups of students within schools. In other words, are good schools equally as good for students of different backgrounds?

Two theories offer different explanations for why schools may promote learning more among some groups versus others. The Frog-Pond hypothesis states that a student’s standing relative to his/her peers affects their academic self-image and educational outcomes. According to this perspective, students are better off, both academically and psychologically, in environments where they can develop a strong sense of academic
self-esteem (i.e., their own skills are better than most peers). An alternative theory is that schools specialize in teaching certain kinds of children. Schools serving high SES children, for example, may have the resources and skills best suited for promoting learning for children from high SES families. Yet they might struggle to handle the challenges associated with teaching children from disadvantaged families. Similarly, schools serving low SES children may be well-equipped to promote learning among children who begin school with few skills, but less positioned to promote learning among children who come to school already having strong skills.

In this study, I test the effect of school impact on low socioeconomic students in predominantly high socioeconomic schools and likewise for high socioeconomic students in predominantly low socioeconomic schools with data from the Early Childhood Longitudinal Study – Kindergarten cohort (ECLS-K). The main advantages of this dataset are the large sample size and the seasonal data collection schedule (tests were given at the beginning and end of the school year), which enables the creation of a school ‘impact’ score (see Downey et al. 2008), a more valid measure of school quality than conventional achievement and learning rate measures (von Hippel 2009). Although Downey et. al (2008) found that impact was uncorrelated with the socioeconomic composition of the student body, I suspect that the relationship is more complex.
Background

Heterogeneity in School Effects

That schools have different effects for different populations is not a new idea. Morgan (2001) found that the Catholic students who are the least likely to attend Catholic schools (among all Catholic students) are the ones who would benefit the most academically from that type of schooling. In their groundbreaking study, Brand and Xie (2010) found heterogeneous returns to college by social background. They noted that the people who are least like to attend college are, on average, the ones who benefit the most. These studies all suggest that what we consider to be a good school needs to be more nuanced. What is a good school for a high-achieving student may not necessarily be a good school for a lower achiever. While these and other studies establish the possibility of heterogeneous effects, to my knowledge no study has examined heterogeneous school influence by socioeconomic status at the primary school level.

Another example of school effect heterogeneity comes from recent findings about the effectiveness of charter schools. The history of charter schools suggests that disadvantaged students may respond differently to the same educational stimuli as their more advantaged counterparts. Despite this emphasis on innovation and the implementation of best practices across contexts, there is little evidence that charter schools boost the academic outcomes of students more than traditional public schools at all and in some cases actually hamper the student’s learning (Center for Research on
Education Outcomes 2013). Why would these schools show a mixed success rate? There are a variety of possible reasons. One possibility is that the socioeconomic and academic composition of different schools affect students’ academic self-concept (Marsh 1987), as predicted by Frog-Pond models (see Davis 1966). Under this model, students’ relative standing to one another affects their academic outcomes in profound ways. At one school, a student may be an academic superstar, while at another they may be below average, etc. Socioeconomic differences in student body composition would alter how effective different schools are for different students. Another possibility is that schools are effective because they specialize in teaching certain types of students. Because charter schools are often created with the intent of duplicating success developed elsewhere (Renzulli and Roscigno 2005), they may uncritically apply practices that are best suited for a different student body. For example, extracurricular activities (EAs) are positively associated with a number of academic outcomes (Feldman and Matjasko 2007), but it is costly in both money and time to participate so the positive effects of EAs are likely limited only to those who can afford to participate. Similarly, providing free breakfast for all students would greatly benefit food-insecure, low SES students, but would have little to no impact on higher SES students. In other words, practices that are effective for a low SES school may not be as effective for a high SES school.

Measures of School Quality & Out of School Time

Under the No Child Left Behind Act, school quality is assessed through various tests (typically math and reading) that are administered regularly from grades 3-8 and once in high school. Although the criteria vary by state, schools are typically rated as
‘failing’ if a certain proportion of the student body does not meet state mandated proficiency requirements on standardized tests. While these tests are generally reliable (they produce consistent results), they are not a valid measure of school effectiveness (von Hippel 2009), as they award and penalize schools for factors that are outside their control. Students spend the vast majority of their time outside of school, and this outside-of-school time affects in-school performance in a meaningful way (Downey, von Hippel, and Broh 2004; Wallberg 1984). Many states are now recognizing this problem and have moved toward value-added models that estimate children’s learning rather than their skills at one point in time. While these growth models represent a move in the right direction, they are likely still biased in favor of schools serving high-SES children because, even during the growth period, children spend most of their time outside of school (Downey et. al 2008).

To address outside-of-school time and how it affects measures of school quality, Downey et. al (2008) conceptualized school quality differently. They developed a cross-over design similar to medical studies, where patients are observed before and after treatment and the causal effect of treatment is attributed to the change in outcomes across the two periods. Downey et. al (2008) compared children’s learning rates in the summer (off treatment) and during school (on treatment). They posited that a good school improves children’s rate of learning between these two periods. The logic is straightforward: summer provides an estimate of the counterfactual—how children would learn if not in school. The difference between summer and school-year learning, therefore, provides an estimate of how school matters versus the counterfactual world without schools.
With this conceptual strategy, Downey et al. (2008) found no association between school impact and the socioeconomic composition of the student body or the percentage of disadvantaged minority students among 287 schools in the Early Childhood Longitudinal Study—Kindergarten Cohort of 1998-99. Indeed, roughly seventy-five percent of schools that would typically be vulnerable to the “failing” label using traditional methods of evaluation (e.g., test scores at one point in time), were no longer among the poorest performing schools when gauged via “impact.” This result raises the possibility that many schools serving disadvantaged children are doing better than we thought.

But this conclusion may be too simplistic. Model 1 of Figure 1 shows a relationship where in school and out of school factors influence academic outcomes independently of one another. Advantaged students do well academically because they come from ‘good’ families and go to good schools while the opposite is true for disadvantaged students. Under this model, schools that serve disadvantaged populations simply need to mirror their more advantaged counterparts to replicate their success, or try to do what more advantaged schools do to a greater extent in order to offset the disadvantages their student population experiences out of school. School reform would effectively take a best practices approach, finding the best schools (by whatever measure) and implementing their practices on a large scale. Under a school choice, charter school, or busing system, parents can easily identify the best school, take the necessary steps to get their child into that school, and then be assured that their child will be getting a better education than they would have otherwise.

1 It is not that the impact measure identifies all schools as operating well—there is more between-school variation in impact than in growth models—but rather that the variation in school quality is not distributed in the way we assume.
Perhaps what is needed is a more holistic conception of what out-of-school time really means, and how it affects the relationship between in-school factors and academic outcomes. Rather than out-of-school factors and in-school factors having independent effects on academic outcomes, out-of-school time may fundamentally change the way that students interact with schools, and the ability schools have to improve the academic outcomes of different students. This perspective is shown in Model 2 of Figure 1. Under this model, rather than asking what the best schools do and how these best practices can be implemented on a large scale, educational decision makers have to account for the fact that some policies that are not effective in schools serving high-SES children (i.e., school provided nutritional assistance), may be very effective in in a disadvantaged setting and vice versa. Under a school choice, charter school, or busing model, the decision becomes much more complicated. Parents now have to ask, will this school that appears to be effective, also be so for my child? The fit between the school’s resources and the child’s needs is what is important. Acknowledging this real world complexity is important because the interaction of out-of-school and in-school factors on academic outcomes complicates the extent to which parents have the ability to make informed decisions.

Measures that account for out-of-school time suggest that we need to think further about what constitutes a good school and for whom these schools are good. Schools in high socioeconomic communities are advantaged in numerous ways, such as having more resources at their disposal (Condron and Roscigno 2003) and more experienced teachers (Kalogrides and Loeb 2013). Achievement measures, like standardized test scores, show that, on average, these schools outperform their more disadvantaged counterparts. However, Downey et al. (2008) find that, when accounting for out-of-school-time, there
is little evidence that these higher SES schools have a larger impact on learning than lower SES schools. Somehow, despite their disadvantage in resources, this measure suggests that schools who serve lower SES students perform better than expected, likely via mechanisms that have not yet been identified. There are two main possibilities. One possibility is that when students are in lower SES environments, they are more able to stand out academically and build their academic and social self-concept in ways that they otherwise wouldn’t be able to. Another possibility is that there exist different mechanisms that boost academic outcomes in different settings.

While the fact that performance differences between low SES and high SES schools are small suggests that there may be different mechanisms that boost learning in different communities, it does not necessarily discount a best practices approach that could be beneficial for all types of students. Would more experienced teachers boost the academic outcomes of disadvantaged students the same way they do for advantaged students? Would better facilities have similar impact in low SES and high SES schools? In other words, while measures that consider out-of-school time, like impact, are a reasonable overall measure of school quality, they may hide important variation around the mean. A closer look may show that schools specialize in the learning of only a specific type of student.

**Frog-Pond Hypothesis**

One explanation for why schools could have different effects on different kids is the Frog-Pond hypothesis, which states that a student’s standing relative to his or her peers is a strong indicator of their later academic success. In his classic article, Davis
(1966) examined the career decisions of college-aged men. He found that students who had higher GPAs overall tended to go into more elite careers. However, when adding in school quality as a variable, Davis found that as a school became more competitive, the less likely the student was to choose an elite career. Davis famously cautioned parents against sending their children to elite colleges if there was a good chance that their child would be near the bottom of the graduating class, warning that “It is better to be a big frog in a small pond, than a small frog in a big pond” (Davis 1966:31). This theory has enjoyed sustained popularity since Davis’ original article and is still one of the predominant explanations of why school quality differs for different students (Crosnoe 2009; Espenshade, Hale, and Chung 2005; Goldsmith 2011; Seaton, Marsh, and Craven 2010).

Numerous articles have replicated Davis’ original findings in other educational areas. Some notable examples are the findings of Marsh (1987) and Marsh et al. (1995), respectively, that average school ability negatively affects academic self-concept, and that participation in gifted and talented academic programs also has a negative influence on academic self-concept. Similar to Davis’ original study, Espenshade et al. (2005) notes that high school quality has a negative effect on elite college admission when controlling for individual academic factors. Most recently, Seaton et al. (2010) found that the Frog-Pond effect remains robust even when controlling for SES, academic self-regulation, and academic motivation motive. Most of these and other Frog-Pond studies focus strictly on the academic quality of schools (average test scores, average GPAs, etc.) but the same general patterns extend to SES as well; Crosnoe (2009) finds that low
income students suffer both academically and psychosocially as the proportion of students in a school with middle to high income and college educated parents increases.

How would the Frog-Pond model explain differentials in school effects based when factoring in both SES and school quality? The main mechanisms proposed in the literature are psychosocial and relate to academic self-esteem (Davis 1966) and some have found that these psychosocial outcomes affect academic performance (Crosnoe 2009). From this perspective, high-SES students should enjoy a relatively higher school impact when attending schools of predominantly low-SES students compared to a higher SES school. In contrast, low-SES students should be especially academically and socially worse off when attending a school of mostly high-SES children—they would be in an environment with a particularly threatening reference group.

While the above literature focuses on how the student body itself affects individual students via Frog-Pond mechanisms, but there is also some evidence that schools classify students via similar mechanisms. For example, Hibel et al. (2010) find that in elementary schools, a student’s SES relative to that of their peers is a predictor of whether or not that student is placed into special education. This introduces the possibility that the Frog-Pond theory operates from the bottom up (student body) and from the top down (institutional components of school).

Even though I cannot identify the specific mechanisms with the ECLS-K, I would expect patterns similar to those found by Crosnoe (2009) in high SES schools, mainly that lower SES students will not do as well in higher SES schools. Given what we know about class-based parenting patterns and education (see Calarco 2011; Lareau and Weininger 2008; Lareau 2003), lower SES students are isolated and at a cultural
disadvantage in these settings (see Ispa-Landa 2013) and will have worse psychosocial and academic outcomes (Crosnoe 2009).

_Hypothesis 1a: The school’s impact will be greater for high- versus low-SES students in schools serving predominantly low-SES students._

_Hypothesis 1b: The school’s impact will be greater for high- versus low-SES students in schools serving predominantly high-SES students._

_School Specialization_

A different way that school heterogeneity might matter is via school specialization. From this perspective, schools can have different effects for different students because schools specialize in teaching a particular type of student. The logic is similar to that of tracking (Carbonaro 2005; Hallinan 1994), which says that students learn best when their school environment provides developmentally appropriate challenges.

Schools serving high-SES children enjoy disproportionate numbers of children with high cognitive skills. This means that their classrooms have the luxury of emphasizing more advanced skills. They may have more honors classes, Advanced Placement courses, and guidance counselors with links to prestigious colleges. As a result of consistently working with highly skilled children, their teachers may become more specialized in challenging students with advanced skills.

In contrast, schools serving low-SES children may specialize in meeting the needs of children with lower level skills. They may be adept at promoting remedial skills and meeting the many non-academic needs that can derail learning. Perhaps the most
notable examples of schools who serve economically disadvantaged children are the Knowledge is Power Program (KIPP) and the Harlem Children’s Zone (HCZ). Both programs employ a more direct, high intensity approach than is seen in other schools. KIPP’s motto is ‘No Excuses’ and requires students and parents to sign behavioral contracts (Pondiscio 2013). Tough, who wrote about HCZ’s approach to schooling, titled his book ‘Whatever it takes’ (Tough 2009) to best capture the attitude of the school’s founder. These programs establish an extremely rigorous college-for-all approach, have longer school days, are in session almost year-round, and offer nutritious meals to students, among other things. HCZ even provides facilities for an on-site medical clinic (Otterman 2010). While these programs have been effective (Curto, Fryer Jr., and Howard 2011), would they have the same effect on all types of students? Does establishing a clear goal of college for all (as KIPP does), benefit students from families where there is already the expectation that they will go to college? Will an on-site medical clinic benefit students who likely already have access to medical care? How much does providing nutritious meals benefit students who are already food secure? The very factors that make these schools so effective are unlikely to have an equal effect across all populations, thus making it difficult to generalize their success to a larger audience.

An effective low-SES school would have the different characteristics of students (McCracken and Barcinas 1991) in mind when teaching students. Specifically in regards to primary schools an early education, low SES students often come into school academically and socially behind high SES students (Lee and Burkam 2002). Imagine a hypothetical scale of student ability (academic or social) that goes from 1 to 10. Low SES
students, on average, enter school with a score of 3, while high SES students enter with a score of 5. An effective low SES school will spend its time getting students to progress from a score of 3 to a score of 5 or 6. High SES students will still benefit somewhat, but because most of the school and teacher’s effort is spent on the majority of children, they only progress from a score of 5 to a score of 6. We could expect a similar pattern to occur in high SES schools too. As said above, this is very similar to the logic used by proponents of tracking.

While the specific mechanisms of specialization are not able to be identified with the ECLS-K, the overall patterns of school impact should be observable, mainly that schools will have the greatest impact on students that are part of the predominant SES category of that particular school’s student body.

*Hypothesis 2a: The school’s impact will be greater for low- versus high-SES students in schools serving predominantly low-SES students.*

*Hypothesis 2b: The school’s impact will be greater for high- versus low-SES students in schools serving predominantly high-SES students.*

Note that Hypotheses 1b and 2b are the same. It is Hypothesis 1a and 2a that distinguish between the frog-pond and specialization explanations.
Data & Method

Data

*The Early Childhood Longitudinal Study – Kindergarten Cohort* (ECLS-K) is a nationally representative longitudinal study conducted by the National Center for Education Statistics. The first wave was collected in 1998-99 school year, when the cohort was in kindergarten, with major follow-ups conducted at the end of kindergarten, the end of first grade, the end of third grade, and the end of fifth grade. During the first wave of the study, while the respondents were in kindergarten, parents, teachers, and administrators were all surveyed and their responses linked to individual students and schools, respectively.

The original sample consists of 21,260 kindergarteners but only a subsample of roughly 5,000 students was randomly chosen for assessment in the fall of first grade—this subsample provides the leverage for seasonal analysis. The main variables I use in this analysis are reading theta scores from the end of kindergarten and the beginning and end of first grade, family SES (which the ECLS-K computes as an amalgam of parental income, education, and occupational prestige), race, gender, and family structure. Using multiple imputation to handle missing cases on independent variables, the final analytic sample is 4,565.

The ECLS-K is particularly useful for answering the question of heterogeneous school effects for a few reasons. First, students are given cognitive tests at multiple points during multiple school years. This allows me to create a school ‘impact’ score similar to
that produced by Downey et al. (2008). Another useful component of the ECLS-K is that students are nested in schools, which allows me to create school-level variables, like school ‘impact’. Finally, the sample size is large enough that I am able to observe students in a variety of student body configurations (high SES kids in predominantly low SES schools, and vice versa)

*Measures*

*Dependent Variable*

**First grade learning rate:** I measure this by the average daily learning rate for first graders during the school year. Learning rates are constructed by subtracting the beginning-of-year reading theta score from the end-of-year reading theta score.

For each student in the analytic sample, there is test data at three time points: the end of kindergarten (T1), the beginning of first grade (T2), and the end of first grade (T3) with corresponding dates for each test (T1d, T2d, and T3d, respectively). A formula for generating the daily in-school learning rate in first grade for student I is shown in the equation below:

\[ FGLR_I = \frac{T3 - T2}{T3d - T2d} \]

*Key Independent Variables:*

**School Quality:** Measured though school impact score. This score is the difference between average summer learning rate and average in-school learning rate. Compared to other measures of school quality, like raw achievement or overall learning rate, impact is best able to isolate the effect school has on academic outcomes from out of school factors.
The equation for calculating daily in-school learning rate is shown above. The equation to calculate summer learning rate is similar, but a bit more complicated. A crude summer learning rate would subtract T1 from T2 to get the overall gain in reading score and divide that by the difference in days $T_2 - T_1$. However, this would not account for any ‘overlap time’, or, the time that students are in school before or after the cognitive assessments are given. Such a measure would likely overestimate the overall summer learning rate, as it would include in-school time as well. To address this problem, I add the last day of kindergarten ($K_d$), and the first day of first grade ($F_d$) to the model. Then, I extend the first grade learning rate out to the beginning of first grade (FGLR$_i$), and extend the kindergarten learning rate\(^2\) (KGLR$_i$) out to the end of kindergarten to estimate what a child’s cognitive assessment score would be at the beginning of first grade and end of first grade, respectively. Finally, I divide the difference in these scores by the number of days the student was on summer break to generate the daily summer learning rate. The following equation shows this process.

$$Summer_i = \frac{\left(T_2 - (FGLR_i \cdot (T_2 - F_d))\right) - \left(T_1 + (KGLR_i \cdot (K_d - T_1))\right)}{(F_d - K_d)}$$

To generate the overall impact score of a school I subtract the mean summer learning rate for all students who would attend that school in the subsequent year from the mean first grade learning rate for the same school. (The construction of this measure is further documented in Downey et al. 2008).

\(^2\) Kindergarten learning rate calculated the same way as first grade learning rate
SES: Measured through the SES variable in ECLS-K. This variable is construction as an amalgamation of parental education, income, and occupational prestige. Rather than using these variables separately in the model, using the composite SES score allows for more simple classification of schools and easier interpretation. School SES is the average SES score of all students who attended that school.

Control Variables

Previous research has shown that sex (Adler, Kless, and Adler 1992; Thorne and Luria 1986), race (Moller et al. 2013; Renzulli, Parrott, and Beattie 2011), and family structure (Cavanagh and Fomby 2012; Raley, Frisco, and Wildsmith 2005) all affect academic outcomes in elementary school. I include the following variables to control for these influences.

Sex: Measured through a dummy variable indicating whether or not the respondent is female

Race: Dummy variables for white, black, Hispanic, Asian, and other racial categories, with white being the control group

Intact Family: A dummy variable indicating whether or not the student lives with both biological parents.

Model variables and descriptive statistics are shown in Table 1

Analytic Plan

After developing a school-level measure of “impact”, I assess the relationship between this measure and first-grade learning via an OLS regression. Model 1 uses School Impact to predict First Grade Learning rate. Model 2 introduces family SES as an independent variable. Model 3 introduces the interaction between school impact and
family SES, allowing me to test both the Frog-Pond and Specialization hypotheses. Finally Model 4 adds control variables of race, sex, and family structure, allowing me to test the overall robustness of my model. My models adjust standard errors due to clustering at the school level.

The analysis is conducted in four stages, with samples limited to schools in the lowest and highest school SES quintiles in the first two stages. In the second two stages I compare the processes in the two top SES quintiles of schools and the two bottom SES quintiles. Limiting the sample in this way allows me to test school effect heterogeneity in a variety of settings.
Results

Table 2 shows mean school impact scores by school SES quintile. Schools in the bottom 2 quintiles appear to be the highest impact schools. While this does not appear to be consistent with conventional wisdom, Downey et al.’s (2008) findings suggest that higher SES schools are not necessarily better at improving student outcomes than their lower SES counterparts. One possibility is that there is a ceiling effect at play—schools serving high-SES children struggle to improve their children’s already high skills. It is important to note, however, that the National Center for Education Statistics employed a routing test specifically designed to reduce ceiling effects. Students who performed well on the short routing test were giving a form of the longer test with a high ceiling. This strategy appears to have worked because the data do not show the classic signs of ceiling effects—i.e., clusters of students near the top of the distribution.

Table 3 shows results from OLS regression predicting first grade learning rate for students in the lowest and highest SES quintiles, respectively. Model 1 shows that school impact significantly predicts learning rates for first grade at the bivariate level, with a one unit increase in school impact being associated with a .414 unit increase in the daily learning rate for students in the lowest SES schools and a .509 unit increase for students in the highest SES schools and both associations are significant at the .001 level. Model 2 introduces SES as a predictor of first grade learning rate. In the sample limited to lowest SES schools, SES is not a significant predictor of first grade learning rate, while in the sample limited to the highest quintile SES it is. Model 3 introduces the interaction
between school impact and family SES. The coefficient for the interaction term is negative and statistically significant for students in the lowest quintile SES schools, meaning that in these schools, as family SES increases, school impact diminishes. Conversely, the coefficient for the interaction term is positive and statistically significant for students in the highest quintile SES schools, meaning that as family SES increases, school impact becomes a stronger predictor of first grade learning rate. Model 4 adds covariates for sex, race, and family structure and the interaction term remains robust.

Interaction terms can be difficult to interpret, especially when both variables are not in integer form. Table 3 shows that schools are the most effective for students in the predominant SES category of the school, but what is the practical significance of this relationship? Figure 2 shows what the school impact coefficient would be for students at the 75\textsuperscript{th} SES percentile, and for students at the 25\textsuperscript{th} SES percentile in both high and low SES schools. In high SES schools, the school impact coefficient for high SES students is .425 while the coefficient for low SES students is .221, meaning that the association between school impact and first grade learning rate for high SES students is almost double that of low SES students. In low SES schools, the school impact coefficient for high SES students is .129 while the coefficient for low SES students is .365, meaning that the association between school impact and first grade learning rate for low SES students is almost three times that of high SES students.

The patterns observed in Table 3 are consistent with what would be expected if Specialization mechanisms were present in schools; lowest SES schools that are high impact are most effective for lower SES students and vice versa. While the results support hypothesis 1b (as it is the same as hypothesis 2b), hypothesis 1a predicted that in
low SES schools, high SES students would do better than low SES students, but results show the exact opposite association. However, the previous analytic sample limits the interactions to only the highest and lowest SES schools where there is admittedly limited diversity. Analysis presented in Table 4 addresses this issue by expanding the analysis to schools in the lowest 2 and highest 2 SES quintiles while using the same modeling. Model 1 of Table 4 shows the bivariate relationship between school impact and first grade learning rate. The coefficients of .446 and .511 are similar to those presented in Table 3, and are both statistically significant. Model 2 introduces SES as a covariate, but is not statistically significant in either sample. Model 3 introduces the interaction between interaction between school impact and family SES and finds somewhat different results than Table 3. The coefficient for the interaction term in Model 3 is significant for lower SES schools, but not for higher SES schools, meaning that in lower SES schools, as family SES increases, school impact’s effect on first grade learning rate diminishes. However, this is not true for higher SES schools; school impact has the same effect on first grade learning rate for all students, regardless of SES. Model 4 introduces covariates for sex, race, and family structure and the results from the previous model remain unchanged.

Results from table 4 show that when the analytic sample is expanded, we gain a better understanding of the extent to which the specialization hypotheses receives support. The observed associations are consistent with the results expected if lower SES schools specialized. However, this is not the case for higher SES schools. How can this be reconciled with the results of Table 3? These findings suggest that different types of

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3 This is due to the fact that the sample is limited to schools that have a single predominant SES category, which dramatically decreases the variation in family SES. In models run on the entire sample, SES is indeed a significant predictor of first grade learning rate
schools specialize differently. High impact schools in both of the lowest SES quintiles tend to be better for lower SES students. On the other end of the SES spectrum, this is only true, however, for the highest quintile of SES schools, which suggests that the specialization mechanisms that make these schools better for high SES students are only present in these extremely high SES schools. Further analysis should look into identifying these mechanisms.
Conclusion

Limitations

This study has a few important limitations. First, the analysis presented is correlational, and cannot identify causal mechanisms. And as discussed in the previous section, more research needs to be done to identify what, specifically, produces different learning rates for different groups.

Another limitation is that the ECLS-K is structured in such a way that an impact score could only be generated for first grade. Different patterns may be observed for middle and high schools. It is likely that Frog-Pond mechanisms are stronger in later years of schooling (high school and college) when students are better able to assess themselves relative to their peers. The vast majority of studies examining Frog-Pond theories do so in a high school or college setting (see Davis 1966; Marsh et al.1987; Espenshade et al. 2005; Crosnoe 2009), though Frog-Pond mechanisms have been identified in Elementary school (Hibel, Farkas, and Morgan 2010). It is also likely that schools specialize to a greater extent in secondary and postsecondary years due to mechanisms like greater curricular differentiation. As such, my study does not provide a critique of the Frog-Pond hypothesis as much as it provides preliminary suggestive support for the idea that schools specialize.
Discussion

Returning to the original question of whether schools are universally effective or not, this study suggests that they are not. Multiple scholars have shown that schools often have heterogeneous effects for a variety of different groups (Brand and Xie 2010; Carbonaro and Covay 2010; Morgan 2001). My study adds to theirs in two main ways. First, I show that SES is a viable basis by which schools have heterogeneous associations with achievement. The socioeconomic gap in educational achievement has risen dramatically in recent years, even more than racial/ethnic gaps (Reardon 2011). My study suggests that we may need to rethink how schools affect lower SES students in order to close this gap. Second, I show that heterogeneous school effects exist as early as first grade. While these other studies have examined heterogeneous school effects in secondary school and in college, my study shows that heterogeneous effects (in regards to SES) exist early on.

What explains these heterogeneous school effects? The findings presented in this study are consistent with what those that specialization theory would predict if specialization mechanisms were operating. Frog-Pond models fail to explain the heterogeneous association between school impact score and first grade learning rate for different SES students in their respective schools. In contrast with what I would expect if Frog-Pond mechanisms were operating, high SES students in schools serving mostly low SES students enjoy less school “impact” than do low SES students (though, as noted above, it may be that Frog-Pond mechanisms are much stronger in later years of
schooling). This finding suggests that student body composition may not necessarily the
driver of these heterogeneous school-learning associations but rather that schools in
different socioeconomic environments specialize and cater to their predominant
socioeconomic group.

In light of these findings, my recommendation to scholars is twofold. First, there
needs to be more modeling of heterogeneous school effects. First, my study suggest that
schools matter differently for different students, but more work needs to be done to
identify the variables or basis by which schools have heterogeneous effects, the extent or
magnitude of these heterogeneous effects, and when, or at what grade levels, these
heterogeneous effects occur. For example, do heterogeneous school effects exist by race?
Are these differences large and practically significant? Do they occur more in primary or
secondary school? Second, more work needs to be done to identify the causal
mechanisms that produce specialized schools. Some mechanisms may be easily
identifiable (schools providing food assistance, counseling, or medical care), while others
may be more difficult to capture (the extent to which a school’s culture promotes learning
for a certain group (see Ispa-Landa 2013)). Understanding the mechanisms of
specialization is critical when applying findings like mine to practical topics like school
sorting, school choice, charter schools, etc. There may be mechanisms that produce
learning for low SES students that are not detrimental in any way for high SES students
and vice versa. Before any action is taken, scholars need to understand what is driving the
observed trends of school specialization.
With respect to school reform, the imitative practices of charter schools may not be as effective as many hope they are. The practices that make KIPP and HCZ effective might not be as effective for all types of students, and the practices of elite, private schools might not be generalizable either. Rather than looking to simply duplicate raw success in terms of achievement and learning, educational leaders should focus on what practices are effective for the type of students they currently serve or are aiming to serve in the future. This will require more research into the mechanisms that produce higher learning rates for different socioeconomic groups.

Some may interpret my findings as supporting socioeconomic segregation in schools, or that I advocate an approach that would have schools treat high and low SES students in fundamentally different ways, which would reproduce the class structure (Bowles and Gintis 2008). This would be a mistake. This analysis identifies that school impact is more strongly associated with learning rates for the children in the predominant SES group that the school serves but does not identify the mechanisms that produce this association. It may very well be that the practices that produce higher learning rates for low SES students can easily coexist with practices that produce higher learning rates for high SES students. In addition, my study focuses solely on how schools influence children’s acquisition of reading skills. There are a wide range of reasons to promote integration of students across socioeconomic status (e.g., greater appreciation for diversity) that have little to do with learning to read.
References


Appendix: Figures and Tables

Figure 1: Models of School-Home Influence on Academic Outcomes

Model 1: Independent Effects

Model 2: Holistic Conception
<table>
<thead>
<tr>
<th>Variable Name</th>
<th>Description</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>First Grade Learning Rate</td>
<td>Daily reading increase for while in during the first grade school year.</td>
<td>-0.161</td>
<td>0.138</td>
<td>0.006</td>
<td>0.027</td>
</tr>
<tr>
<td>School Impact</td>
<td>Average first grade learning rate subtracted from average summer learning rate by school</td>
<td>-0.125</td>
<td>0.183</td>
<td>0.003</td>
<td>0.021</td>
</tr>
<tr>
<td>SES</td>
<td>Student SES score</td>
<td>-3.230</td>
<td>2.785</td>
<td>0.057</td>
<td>0.769</td>
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<tr>
<td>School SES (Quintiles)</td>
<td>School SES score</td>
<td>0</td>
<td>4</td>
<td>2.175</td>
<td>1.758</td>
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<td>Female</td>
<td>Student sex (dummy variable)</td>
<td>0</td>
<td>1</td>
<td>0.492</td>
<td>0.500</td>
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<tr>
<td>Race</td>
<td>Student race (dummy variables)</td>
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<td></td>
<td></td>
</tr>
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<tr>
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<td>0.357</td>
</tr>
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<td>0.133</td>
<td>0.339</td>
</tr>
<tr>
<td>Asian</td>
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<td>1</td>
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<td>0.217</td>
</tr>
<tr>
<td>Other</td>
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<td>0</td>
<td>1</td>
<td>0.074</td>
<td>0.262</td>
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<tr>
<td>Intact Family</td>
<td>Student lives with two biological parents (dummy variable)</td>
<td>0</td>
<td>1</td>
<td>0.623</td>
<td>0.485</td>
</tr>
<tr>
<td>School SES (Quintiles)</td>
<td>School Impact</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>------------------------</td>
<td>---------------</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lowest</td>
<td>0.005</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Lower Middle</td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Middle</td>
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</tr>
<tr>
<td>Upper Middle</td>
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<td></td>
</tr>
<tr>
<td>Highest</td>
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Table 3: OLS Regression Predicting First Grade Learning Rate (Limited Sample)

<table>
<thead>
<tr>
<th></th>
<th>Students in Lowest SES Quintile Schools</th>
<th>Students in Highest SES Quintile Schools</th>
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<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
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<tr>
<td>School Impact</td>
<td>.414***</td>
<td>.414***</td>
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<td>SES</td>
<td>.000</td>
<td>.002</td>
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<tr>
<td>School Impact*SES</td>
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<tr>
<td>Female</td>
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<td>.004</td>
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<td>.005</td>
</tr>
<tr>
<td>Asian</td>
<td></td>
<td>.007</td>
</tr>
<tr>
<td>Other</td>
<td></td>
<td>.000</td>
</tr>
<tr>
<td>Intact Family</td>
<td></td>
<td>.001</td>
</tr>
<tr>
<td>N</td>
<td>679</td>
<td>679</td>
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</table>
Figure 2: Differences in impact score coefficient by School and Family SES

Note: Both interactions significant at the .01 level

Note: Sample Limited to Highest and Lowest SES Quintile Schools

Data: Early Childhood Longitudinal Study – Kindergarten Cohort
## Table 4: OLS Regression Predicting First Grade Learning Rate (Expanded Sample)

<table>
<thead>
<tr>
<th></th>
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<th>Schools</th>
<th>Students in Highest 2 SES Quintile</th>
<th>Schools</th>
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<td></td>
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<td>Model 2</td>
<td>Model 3</td>
<td>Model 4</td>
</tr>
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<td>School Impact</td>
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<td>.447***</td>
<td>.365***</td>
<td>.365***</td>
</tr>
<tr>
<td>SES</td>
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<td>-.000</td>
<td>-.000</td>
<td></td>
</tr>
<tr>
<td>School Impact*SES</td>
<td></td>
<td></td>
<td>-.140**</td>
<td>-.145**</td>
</tr>
<tr>
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<tr>
<td>Black</td>
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<td>Hispanic</td>
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<tr>
<td>Asian</td>
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<tr>
<td>Intact Family</td>
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<tr>
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