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TEACHER QUALIFICATIONS AND STUDENT ACHIEVEMENT: A PANEL DATA ANALYSIS

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ABSTRACT: *Recent academic research suggests that teacher quality plays an important role in student achievement; however, empirical research on the efficacy of policies requiring teachers to obtain specific degrees is inconclusive, particularly in elementary education. This paper models a panel data production function with fixed effects using the Early Childhood Longitudinal Study (ECLS-K) to assess the relationship between different undergraduate and graduate majors and elementary student test scores. Specifically, we aim to discern if there is a difference in teacher efficacy within the different education related majors (e.g. early childhood education and elementary education) and between education and non-education related majors.*

JEL Classifications: *C23, I21*

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1. INTRODUCTION

Academics have analyzed nearly every aspect of education in the United States, with many early studies finding that observable educational inputs do not seem to matter for student achievement (see e.g. Hanushek (2003)). However, recent research suggests that teacher quality can play an important role in student achievement and that there is wide variation in teacher quality (see e.g. Rockoff (2004), Rivkin, Hanushek and Kain (2005), Aaronson, Barrow, & Sander (2007), Kane, Rockoff, & Staiger (2007), and Jepsen (2005)). Rivkin, Hanushek and Kain (2005) find that a one standard deviation increase in teacher quality is more beneficial to student achievement than a 10 student reduction in class size. Unfortunately, the teacher characteristics—experience and education level—included in Rivkin *et al.* (2005) account for very little of the variation in student achievement. Similarly, Aslam and Kingdon (2011), Aaronson *et al.* (2007) and Jepsen (2005) all find teacher quality to be an important determinant of student achievement, however, they find that the observable teacher characteristics explain very little of this variation[1]. Thus, the question remains: how can we ensure that we employ high quality teachers?

In an attempt to make sure that public school teachers are high quality, many states have altered their educational policies. For example, a number of states have begun requiring teachers

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to have specific educational backgrounds (e.g. pre-kindergarten through third grade teachers must complete at least 15 credit hours in early childhood education in South Carolina[2]; teachers must obtain a master's degree within 10 years of receiving their teaching certificate in Kentucky[3]). Some of the policy responses that have received attention in the academic literature include: requirements that teachers hold advanced degrees, requirements that teachers obtain teacher certification, requiring teachers to achieve minimum exam scores, and providing financial incentives to teachers for better performance.

Autonomy over educational policy in the United States is generally left to the states, resulting in a varying mix of statutes and regulations across the 50 states. Not surprisingly, the certification requirements placed on teachers vary greatly from state to state; however, the unifying feature is that some form of certification is required in every state. Goldhaber and Brewer (2000) investigated whether these certification requirements actually impact student achievement. They found that standard certification is positively associated with student achievement (as opposed to private school certification or no certification in the area taught), while students of teachers with emergency certification score no differently than students of teachers with standard certification[4]. Boyd, *et al.* (2006) find that teachers with reduced coursework, compared with typical university prepared teachers, provide smaller gains in student achievement in mathematics and English language arts. However, these differences are relatively small and disappear with teacher experience.

Goldhaber and Anthony (2007) and Clotfelter, *et al.* (2007) both find that teachers who obtained National Board for Professional Teaching Standards (NBPTS) certification in North Carolina were more effective teachers before certification when compared with other teachers who did not go on to get NBPTS certification. However, Harris and Sass (2009) find that teachers who receive certification from NBPTS are no more effective after certification than teachers who have not received this certification. Arias and Scafidi (2009) present a theoretical model, which concludes that teacher licensure only improves teacher quality if there is a vast difference in average quality between "traditional" teachers and "alternative" teachers. This difference is not found in the empirical literature.

Figlio and Kenny (2007), looking into the relatively new idea of "pay for performance," find increased student achievement in schools where financial incentives are offered to teachers for better performance. Unfortunately, their data cannot determine whether teacher incentives are offered at already high performing schools, or whether the incentives extract greater effort from the teachers, leading to better student achievement.

Similarly, Angrist and Guryan (2008) analyze the recently popular policy of requiring teachers to pass certain tests before earning their teaching certificate. They find that the testing requirement has little to no impact on teacher quality and they purport that this is evidence that testing proves to be more of a barrier to entry than a screen on low-quality teachers. The one positive result is that the testing requirement increased the probability that teachers teach a subject that was their major area of study. This leads to the question: do some majors better prepare teachers for educating students?

Goldhaber and Brewer (1997a) find that high school students of teachers with bachelor's or master's degrees in mathematics and reading score higher, on average, in mathematics and reading exams, respectively. Goldhaber and Brewer (1997b) find that tenth grade students of teachers with degrees and/or certification in mathematics score higher on mathematics exams. Similarly, Dee and Cohodes (2008) find that eighth grade students of subject-certified teachers score higher on standardized tests, but these gains are mostly limited to mathematics and social studies. Boyd *et al.* (2008) find that better teacher qualifications in New York City lead to enhanced student achievement. Ehrenberger and Brewer (1994) find that students of teachers with undergraduate degrees from more selective universities show higher test score gains in high school.

In contrast to the above-mentioned subject-specific studies, an abundance of research has found that teachers holding an advanced degree (e.g. master's and/or doctorates), in general, is not associated with any achievement gains in their students (e.g. Chingos and Peterson (2011), Rivkin, *et al.* (2005), and Summers and Wolfe (1977)). This leads to the possibility that advanced degrees are only beneficial in specific subjects, such as mathematics (see Wayne and Youngs (2003) for a review of this literature). That result, if accurate, leads to the implication that secondary education teachers in those subjects should obtain advanced degrees within their subject. However, this gives minimal guidance to policy makers in regards to elementary education, where one teacher often instructs students in all or most subjects.

The literature suggests that a teacher's major area of study is certainly important for middle school and high school student achievement. Unfortunately, few studies have looked at this relationship between teacher preparation and student achievement in *elementary schools*. Chingos and Peterson (2011) and Croninger, *et al.* (2007) both find that elementary students of teachers with undergraduate majors in education do not score higher, on average, in standardized tests. However, the Chingos and Peterson (2011) study uses data beginning in fourth grade, while our paper uses data beginning in first grade and the Croninger *et al.* (2007) study only looks at education majors versus non-education majors. They do not control for the different majors within education. Education majors can choose from a variety of sub-fields, including, but not limited to: early childhood education and elementary education.

Given that undergraduate and graduate education majors can choose from a number of specialized educational fields, one would assume that these specializations better prepare teachers to instruct at the specific grade levels. Unfortunately, there is no research—that we know of—which supports this assumption. Boyd *et al.* (2009) look at aspects of teacher preparation programs in New York City and find a positive relationship between elementary student achievement and program experiences that link with the practice of teaching (oversight of student teaching and some form of a capstone experience). Harris and Sass (2010) find that teacher experience is positively associated with elementary student achievement in math and reading, but find no relationship between teachers' undergraduate training and elementary student achievement. Similarly, Betts *et al.* (2003) find that the number of college courses a teacher completed in a subject does not have any meaningful impact on elementary student achievement, especially relative to the impact of student absences, peer effects and class size.

We model a panel data production function with fixed effects using the Early Childhood Longitudinal Study (ECLS-K) to assess the relationship between different undergraduate and graduate majors and elementary student test scores. Specifically, we aim to discern if there is a difference between education related majors and non-education related majors and within the different elementary related majors (e.g. early childhood, elementary, etc.). Previous research has used prior releases of this data, but only kindergarten and first grade student test scores were utilized and only analyzed education majors versus non-education majors. This paper also includes third grade and fifth grade student test scores, which allows for more accurate student fixed effect estimation, and we will also attempt to differentiate among the different education related majors (e.g. early childhood education and elementary education). We find that a teacher holding a *graduate* degree in elementary education is shown to increase elementary achievement in *mathematics*, while holding an *undergraduate* degree in elementary education is beneficial for elementary student achievement in *reading*. However, the overriding implication of this paper is that no policy of requiring teachers to hold certain degrees is universally beneficial for all students. This does not mean that teacher education degrees hold no value. Our data and methodology do not allow us to answer that question. Our results simply imply that *forcing* teachers to obtain certain degrees will not, in itself, increase student achievement.

Section 2 discusses the methodology. Section 3 describes the data. Section 4 presents the results and Section 5 concludes.

2. METHODOLOGY

Given the panel nature of our data, the estimation can be specified as a fixed effects model or as a random effects model. The model is written as

$$y_{it} = x_{it}\,\beta + u_i + \varepsilon_{it} \qquad (1)$$

where y_{it} is a measure of student achievement for student i in year t, u_i is the unobserved effect for each student, x_{it} is a vector of teacher and school characteristics, and ε_{it} represents purely idiosyncratic shocks which are uncorrelated with the choice of inputs[5]. We estimate this model using both test score levels (a student's test score in a given testing cycle) and test score gains (the change in a student's test score between two testing cycles) as the dependent variable, y_{it}.

If (1) is estimated using a fixed effects estimator, then all time-invariant attributes of the student (e.g. ability, family background, etc.) are captured by u_i, and x_{it} only includes time-varying variables. If (1) is estimated using a random effects estimator, then u_i is relegated to the error term and time-varying and –invariant variables are included in x_{it}. The main difference between these two models is that the fixed effects model allows arbitrary correlation between u_i and the included variables (x_{it}), whereas the random effects model does not. We estimate both models and then perform a Hausman test to see which is more appropriate.

3. DATA

The data come from the Early Childhood Longitudinal Study, Kindergarten (ECLS-K) class of 1998-1999. The ECLS-K database contains student, teacher, parent, and school principal responses on background questionnaires, as well student achievement scores on mathematics and reading exams. The parent background questionnaires include information on the parents' educational backgrounds and the family's socio-economic status. The teacher background questionnaires include information on the teachers' age, experience, educational background and certification status as well as the number of students in their class. The main variables of interest in this study are those measuring the teachers' educational background. We include dummy variables for whether they majored in early childhood education (ECE), elementary education (EE), other education related major (OE), or a non-education related major (NE) in both undergraduate and graduate school[6]. The school principal background questionnaires include information on the racial composition of the school.

Following Croninger *et al.* (2007) we created a number of teacher and school specific control variables. These include: a teacher's ratio of math coursework to total coursework and reading coursework to total coursework, the school's average reading and math course ratios, the school's average years of teaching experience, an indicator for whether the school had a high percentage of certified teachers, an indicator for whether the school had a high percentage of teachers with advanced degrees, an indicator for whether the school had a high percentage of teachers with elementary education, an indicator for whether the school had a high percentage of minority students and the average socioeconomic status of a school's students. We also include the following teacher background variables: teacher's age, an indicator variable for teachers holding less than 2 years of experience, an indicator variable for teachers holding more than 5 years of experience, and an indicator variable equal to one if the teacher has a standard or alternative certification.

These same students, their parents, teachers and school principals are then resurveyed and retested in 1st grade, 3rd grade and 5th grade. The original sample is approximately 19,000 students from kindergarten in 1998-1999, but the data has numerous observations with missing administrative data. We filter the sample to only include students with complete test score data, and teacher background information. We also limit our sample to students that attend public schools and are not enrolled in special education classes. After filtering, we are left with approximately 5,300 kindergarten students in 1999, 5,400 in first grade in 2000, 3,300 third grade students in 2002 and 3,500 fifth grade students in 2005. The smaller sample sizes in subsequent years are a result of a number of things: students leaving the country, students not being traceable, parents no longer giving consent to collect information on the children, missing information used in our study at the student-, teacher-, or school-level[7]. Unfortunately, the kindergarten surveys do not include the same teacher background questions and thus we must also exclude the kindergarten data from the test score levels model[8]. We are left with a main sample of 1,392 students with data from first, third and fifth grades. Additionally, we include sub-samples that only include first and third grade or only third and fifth grades. The sub-sample estimations are believed to be necessary because of the nature of teacher education variables. Generally speaking, an early childhood education major is trained to teach kindergarten through third grade.[9] Thus, we expect the results on the variables for early childhood education and elementary education majors to differ across these two sub-samples. The lower-grade sub-sample (first and third grades) has 1,810 students in each year, while the upper-grade sub-sample (third and fifth grades) has 1,626 students in each year[10].

Following Fryer and Levitt (2004), we re-scaled the overall sample test scores in each year to have a mean of zero and a standard deviation of one.

4. RESULTS

The results are broken into three sections. Section 4.1 presents the results using all of the students available at the appropriate grades. Sections 4.2 and 4.3 analyze sub-populations of the students, representing female students only versus male students only, and minority students only versus non-minority students only, respectively. Each section includes one table that analyzes test score levels and another that analyzes test score *gains* (the difference in test scores for a student from one tested year to the next) as the dependent variable[11,12].

It is important to analyze test score gains in addition to test score levels because it is possible that an analysis of test score levels will not capture all of the impact of certain variables. *For example*, one could find that students of teachers with an undergraduate major in early childhood education score higher,on average, than other students. However, it could be possible that this result is driven by within-school sorting—schools intentionally placing high-performing or low-performing students into separate classes. *If this were the case*, although students of teachers with a major in early childhood education score higher on average, they may have smaller test score *gains* than do students of teachers with a different academic background. We believe that our use of student fixed effects should eliminate (or at least minimize) this problem, but just to be sure we also include a model using test score gains as the dependent variable.

Ideally, our analysis would include the gain in test scores from one year to the next (e.g. first grade to second grade), however, that is not possible with the available data. Thus, our test score gains estimation could be biased by factors impacting student achievement in the years for which we do not have data. For example, a large test score gain between first grade and third grade for a particular student could be the result of teacher and school characteristics of the students' second grade year. However, our estimation would attribute that gain to characteristics of the students' third grade year. We do not have a way to correct for this limitation in the data. However, a finding of coefficient estimates with the same sign using both the test score gains variable and the test score levels variable should indicate that the results are robust to these potential biases.

Within the tables, we present the results using mathematics tests and reading tests using three different samples of students. Note that we use "main sample" to refer to the sample of first, third and fifth grade students, "lower-grade sub-sample" to refer to the sample of first and third grade students and "upper-grade sub-sample" to refer to the sample of third and fifth grade students. We will refer to the entire population of students (including male, female, minority and non-minority) as the "full population" and call the female-, male-, minority- and non-minority-only groupings of students as the "female-only sub-population," male-only sub-population," "minority-only sub-population," and "non-minority-only sub-population," respectively. For the sake of brevity, we only include the coefficient estimates for the teacher education variables. It is worth briefly mentioning that we find small and mostly insignificant coefficient estimates on our variables for teacher age, experience and certification. This is consistent with much of the existing literature. The full set of estimates is available upon request.

4.1. Full Population

Table 1 displays the results for the full population estimation using mathematics test scores and reading test scores for all three samples of grade combinations, while Table 2 displays the corresponding results using test score *gains* as the dependent variable. We find two variables that result in coefficient estimates that are statistically significant across the two models (test score levels and test score gains) using the main sample (students in grades 1-5) and the lower-grade sub-sample (students in grades 1-3), but no variables are statistically significant across both models using the upper-grade sub-sample (students in grades 3-5). The coefficient estimate on the dummy variable for teachers holding a graduate degree in elementary education (G-EE) is positive and statistically significant in *mathematics* for the main sample in both the test score levels and test score gains models. However, this coefficient estimate is not statistically different from zero in *reading* using either the test score levels model or the test score gains model. Interestingly, the coefficient estimates on G-EE are insignificant in both subjects for the upper-grade sub-sample and lower-grade sub-sample using both models.

Table 1
Fixed Effects Regression on Mathematics and Reading Test Scores

	1-5				*1-3*				*3-5*			
	Mathematics		*Reading*		*Mathematics*		*Reading*		*Mathematics*		*Reading*	
Variable	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*
UG-ECE	0.004	0.038	-0.018	0.039	-0.018	0.034	0.026	0.040	-0.023	0.031	-0.022	0.042
UG-EE	0.035	0.040	0.087*	0.050	0.036	0.050	0.061	0.049	0.010	0.032	0.112‡	0.036
UG-OE	-0.056	0.039	0.004	0.047	-0.024	0.040	-0.041	0.044	-0.029	0.030	-0.018	0.031
G-ECE	0.057	0.095	-0.086	0.102	0.122*	0.066	-0.013	0.069	-0.037	0.059	-0.016	0.067
G-EE	0.070†	0.031	0.015	0.041	0.025	0.033	0.051	0.037	0.027	0.029	0.017	0.036
G-OE	0.016	0.045	-0.023	0.049	-0.042	0.046	0.021	0.050	0.042	0.039	-0.069*	0.039
G-NE	-0.069	0.050	-0.055	0.067	-0.146	0.099	-0.273†	0.106	-0.037	0.044	-0.042	0.050

Note: ‡ means significant at the 1% level; † means significant at the 5% level; * means significant at the 10% level; G-NE means a graduate degree in a non-education related field; UG-ECE means an undergraduate degree in early childhood education; UG-EE means an undergraduate degree in elementary education; UG-OE means an undergraduate degree in an other education related degree; G-ECE is a graduate degree in early childhood education; G-EE is a graduate degree in elementary education and G-OE is a graduate degree in an other education related area; all standard errors are clustered at the school level.

Table 2
Fixed Effects Regression on Mathematics and Reading Test Score *Gains*

	1-5				*1-3*				*3-5*			
	Mathematics		*Reading*		*Mathematics*		*Reading*		*Mathematics*		*Reading*	
Variable	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*
UG-ECE	-0.081	0.090	-0.079	0.125	-0.028	0.093	0.054	0.105	-0.021	0.080	-0.133	0.101
UG-EE	0.056	0.099	0.180†	0.090	-0.071	0.134	0.186	0.113	0.165†	0.081	0.133	0.105
UG-OE	0.059	0.095	-0.042	0.103	-0.095	0.100	-0.018	0.109	-0.009	0.077	-0.084	0.079
G-ECE	0.235	0.211	-0.194	0.191	0.388*	0.221	0.126	0.223	-0.013	0.158	-0.041	0.197
G-EE	0.221‡	0.072	0.147	0.091	0.070	0.116	-0.064	0.107	-0.027	0.064	0.027	0.088
G-OE	0.088	0.097	0.081	0.099	-0.091	0.160	0.061	0.152	0.071	0.104	-0.051	0.090
G-NE	0.045	0.109	-0.190	0.146	0.127	1.028	-0.786‡	0.148	-0.177	0.124	-0.281†	0.135

Note: ‡ means significant at the 1% level; † means significant at the 5% level; * means significant at the 10% level; all standard errors are clustered at the school level; see Table 1 for variable definitions.

The other main sample result that maintains the same sign across the two models is a positive and statistically significant coefficient estimate on the dummy for teachers holding an undergraduate degree in elementary education (UG-EE) in *reading*. However, this does not hold for reading in the lower-grade or upper-grade sub-samples, nor does it hold in mathematics in any of the samples.

In the lower-grade sub-sample, we find a positive and statistically significant coefficient estimate on the variable for teachers holding a graduate degree in early childhood education (G-ECE) in mathematics. However, again, this result does not hold in reading. Additionally, we find a negative and statistically significant coefficient estimate, in both models, on the variable representing teachers who hold a graduate degree with a concentration other than education (G-NE) in reading using the lower-grade sub-sample. These coefficients also happen to be of the greatest magnitude, meaning that the negative relationship between student achievement and teachers holding a graduate degree in a non-education major is greater that any of the positive relationships with any of the education related degrees. It is important to note here that none of the coefficient estimates on any of the undergraduate degree variables are statistically significant across both models using the lower-grade or upper-grade sub-samples.

In summary, our main sample results indicate that elementary students benefit in *mathematics* from teachers holding a graduate degree in elementary education and benefit in *reading* from teachers holding an undergraduate degree in elementary education; however, these benefits are quite small (less than 0.1 standard deviations in test score levels). It is possible that graduate programs in elementary education focus more on *mathematics*, while undergraduate programs focus more on *reading*. However, it is also possible that the teachers who choose to major in elementary education at the undergraduate level are simply better at helping students in *reading*, while those who choose a graduate major in elementary education are simply better at helping students with *mathematics*. Additionally, younger elementary students display increased achievement in *mathematics* when their teacher holds a graduate degree in early childhood education and decreased achievement in *reading* when their teacher holds a graduate degree in a field outside of education. This last result implies that students actually score higher on the achievement test with teachers that do not hold a graduate degree than they do with teachers holding a graduate degree in a non-education related subject.

This highlights one of the limitations of our study—mainly that we can not infer that a positive (negative) coefficient estimate on one of our teacher education variables means that particular degree-major combinations increase (decrease) teacher performance in the classroom. It simply means that students, on average, have higher (lower) achievement when their teacher has this degree-major combination. It is possible that the degree-major combinations are having meaningful impacts on teachers, but it is just as likely (especially considering this result on a graduate degree in a non-education related field) that teachers with certain abilities are *choosing* certain degree-major combinations. Thus our analysis does not provide any insight into the signal value versus human capital value debate. On the flip side, this analysis can provide insight to policy makers on the effectiveness of *requiring* certain degree-major combinations for teachers. For instance, a blanket policy that requires all teachers to obtain a graduate degree is not universally beneficial, given our result that teachers with a graduate degree in a non-education related field have a negative relationship with their students' achievement.

4.2. Gender Sub-Population

Table 3 displays the results for the female-only sub-population estimation using mathematics test scores and reading test scores for all three samples of grade combinations and Table 5 displays the corresponding results for the male-only sub-population. Tables 4 and 6 display the results using test score *gains* for the female-only and male-only sub-populations, respectively. The coefficient estimates on G-EE remain positive and statistically significant using mathematics test score levels and gains in the main sample estimations for the *male*-only sub-populations, but these estimates are both statistically *in*significant using the *female*-only sub-population.

Table 3
Fixed Effects Regression on Mathematics and Reading Test Scores
(Female Only)

	1-5				*1-3*				*3-5*			
	Mathematics		*Reading*		*Mathematics*		*Reading*		*Mathematics*		*Reading*	
Variable	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*
UG-ECE	-0.030	0.044	-0.006	0.056	0.023	0.043	0.034	0.053	0.006	0.046	0.050	0.054
UG-EE	-0.049	0.051	0.083	0.061	0.028	0.062	0.037	0.061	0.025	0.048	0.108†	0.051
UG-OE	-0.022	0.050	-0.003	0.054	-0.041	0.051	-0.002	0.060	0.011	0.040	-0.050	0.038
G-ECE	0.261†	0.115	-0.132	0.136	0.215†	0.091	0.077	0.097	-0.017	0.065	0.054	0.092
G-EE	0.032	0.036	-0.023	0.054	-0.004	0.042	0.003	0.051	0.033	0.039	0.034	0.049
G-OE	-0.033	0.062	-0.096	0.062	-0.081	0.058	-0.035	0.069	0.043	0.049	-0.024	0.055
G-NE	-0.088	0.069	-0.071	0.090	-0.199†	0.100	-0.424†	0.167	-0.009	0.054	0.001	0.060

Note: ‡ means significant at the 1% level; † means significant at the 5% level; * means significant at the 10% level; all standard errors are clustered at the school level; see Table 1 for variable definitions.

Table 4
Fixed Effects Regression on Mathematics and Reading Test Score *Gains*
(Female Only)

	1-5				*1-3*				*3-5*			
	Mathematics		*Reading*		*Mathematics*		*Reading*		*Mathematics*		*Reading*	
Variable	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*
UG-ECE	-0.232†	0.123	-0.267	0.164	-0.042	0.126	-0.018	0.116	-0.043	0.103	-0.057	0.137
UG-EE	-0.051	0.123	0.335‡	0.120	-0.113	0.155	0.475‡	0.143	0.190*	0.106	0.191	0.132
UG-OE	-0.018	0.133	-0.096	0.116	-0.231	0.144	0.042	0.130	0.048	0.096	-0.042	0.103
G-ECE	0.626‡	0.222	-0.109	0.249	0.596†	0.263	0.198	0.285	0.448†	0.183	0.344	0.338
G-EE	0.144	0.093	0.134	0.123	0.119	0.162	-0.208	0.147	-0.019	0.086	0.086	0.127
G-OE	0.024	0.127	0.057	0.132	0.043	0.197	-0.042	0.195	0.109	0.112	0.004	0.127
G-NE	-0.130	0.155	-0.169	0.169					-0.196	0.142	-0.179	0.162

Note: ‡ means significant at the 1% level; † means significant at the 5% level; * means significant at the 10% level; all standard errors are clustered at the school level; see Table 1 for variable definitions.

Table 5
Fixed Effects Regression on Mathematics and Reading Test Scores (Male Only)

	1-5				*1-3*				*3-5*			
	Mathematics		*Reading*		*Mathematics*		*Reading*		*Mathematics*		*Reading*	
Variable	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*
UG-ECE	0.047	0.056	-0.037	0.056	-0.061	0.051	0.019	0.056	-0.041	0.044	-0.081	0.053
UG-EE	0.140†	0.062	0.119*	0.070	0.050	0.068	0.082	0.075	0.003	0.044	0.117†	0.054
UG-OE	-0.094*	0.051	0.022	0.072	-0.005	0.053	-0.074	0.061	-0.069*	0.039	0.026	0.050
G-ECE	-0.172	0.124	-0.019	0.143	0.039	0.094	-0.108	0.090	-0.060	0.103	-0.059	0.106
G-EE	0.115†	0.050	0.054	0.057	0.051	0.047	0.102†	0.051	0.015	0.037	-0.002	0.047
G-OE	0.072	0.055	0.062	0.065	-0.011	0.055	0.081	0.066	0.042	0.047	-0.112†	0.050
G-NE	-0.069	0.079	-0.050	0.093	-0.077	0.187	-0.099	0.122	-0.078	0.056	-0.096	0.074

Note: ‡ means significant at the 1% level; † means significant at the 5% level; * means significant at the 10% level; all standard errors are clustered at the school level; see Table 1 for variable definitions.

Table 6
Fixed Effects Regression on Mathematics and Reading Test Score *Gains* (Male Only)

	1-5				*1-3*				*3-5*			
	Mathematics		*Reading*		*Mathematics*		*Reading*		*Mathematics*		*Reading*	
Variable	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*
UG-ECE	0.109	0.134	0.089	0.145	0.037	0.140	0.099	0.155	0.033	0.112	-0.219*	0.126
UG-EE	0.217	0.132	0.039	0.157	0.152	0.201	-0.090	0.187	0.142	0.117	0.047	0.142
UG-OE	0.141	0.106	0.043	0.135	0.064	0.130	-0.045	0.175	-0.057	0.116	-0.136	0.121
G-ECE	-0.134	0.224	-0.234	0.263	0.115	0.308	0.112	0.275	-0.365*	0.214	-0.368*	0.220
G-EE	0.272‡	0.101	0.190	0.119	-0.028	0.149	0.075	0.153	-0.053	0.101	-0.034	0.106
G-OE	0.204	0.125	0.135	0.119	-0.100	0.223	0.159	0.241	0.043	0.137	-0.074	0.131
G-NE	0.168	0.163	-0.168	0.251	0.134	1.132	-0.754‡	0.198	-0.199	0.178	-0.379*	0.205

Note: ‡ means significant at the 1% level; † means significant at the 5% level; * means significant at the 10% level; all standard errors are clustered at the school level; see Table 1 for variable definitions.

The coefficient estimates on the variable representing teachers that have a graduate degree in early childhood education (G-ECE) are positive and statistically significant in mathematics across both models using both the main sample and the lower-grade sub-sample in the *female-only* sub-population[13]. Additionally, this coefficient estimate is positive and statistically significant in the test score *gains* model for the upper-grade sub-sample of female students in mathematics. There are no other statistically significant coefficient estimates across the test score levels and test score gains models with the same sign for any of the other degree variables in any of the sub-samples using the male-only or female-only sub-populations.

Thus, it appears that teachers who hold a graduate degree in *early childhood* education are beneficial to *female* students in mathematics, particularly younger female students. However, *male* students seem to perform better in mathematics when their teacher holds a graduate degree in *elementary* education. It is possible that graduate programs in early childhood education focus more on teaching *mathematics* to females, while graduate programs in elementary education focus more on teaching *mathematics* to males. However, it is also possible that the teachers who choose to major in early childhood education at the graduate level are simply better at helping female students with mathematics, while those who choose a graduate major in elementary education are simply better at helping male students with *mathematics*.

4.3. Minority Sub-Populations

Table 7 displays the results for the minority-only sub-population estimations using mathematics test scores and reading test scores for all three samples of grade combinations and Table 8 displays the corresponding results for mathematics and reading test score *gains*. Tables 9 and 10 show the same results for the non-minority-only sub-population using test scores and test score *gains*, respectively. A couple of interesting results are worth noting. First, we find negative and statistically significant coefficient estimates on G-NE and positive and statistically significant estimates on UG-EE using the lower-grade sub-sample in reading for *non-minority*-only students using both the test score levels and test score *gains* models. Second, the coefficient estimates on G-EE, as in the full population and the male-only sub-population, are positive and statistically significant in mathematics in the main sample with the *non-minority*-only sub-population. Finally, none of the education variables maintain the same sign and statistical significance across both models using the minority-only sub-population.

Table 7
Fixed Effects Regression on Mathematics and Reading Test Scores (Minority Only)

	1-5				*1-3*				*3-5*			
	Mathematics		*Reading*		*Mathematics*		*Reading*		*Mathematics*		*Reading*	
Variable	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*
UG-ECE	-0.029	0.069	0.021	0.090	-0.062	0.066	0.045	0.069	-0.102	0.074	-0.123	0.076
UG-EE	0.049	0.070	0.107	0.076	0.056	0.070	-0.014	0.078	-0.101*	0.059	0.170‡	0.058
UG-OE	-0.133*	0.072	0.053	0.086	-0.051	0.071	-0.134*	0.080	0.008	0.057	0.079	0.056
G-ECE	0.079	0.215	0.126	0.172	0.196	0.136	0.026	0.109	-0.039	0.151	-0.016	0.164
G-EE	-0.029	0.081	-0.113	0.085	-0.041	0.069	0.026	0.066	0.008	0.053	-0.044	0.075
G-OE	-0.071	0.071	-0.083	0.100	0.032	0.071	0.147*	0.083	0.053	0.067	-0.105	0.084
G-NE	-0.157*	0.091	-0.170	0.164	-0.029	0.311	0.022	0.335	-0.071	0.077	-0.108	0.091

Note: ‡ means significant at the 1% level; † means significant at the 5% level; * means significant at the 10% level; all standard errors are clustered at the school level; see Table 1 for variable definitions.

Table 8
Fixed Effects Regression on Mathematics and Reading Test Score *Gains* (Minority Only)

	1-5				*1-3*				*3-5*			
	Mathematics		*Reading*		*Mathematics*		*Reading*		*Mathematics*		*Reading*	
Variable	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*
UG-ECE	-0.021	0.184	-0.309	0.249	0.215	0.188	0.011	0.209	-0.047	0.166	-0.375*	0.215
UG-EE	0.169	0.141	0.077	0.144	0.160	0.186	-0.119	0.185	0.172	0.151	0.116	0.234
UG-OE	-0.117	0.231	-0.154	0.199	-0.050	0.195	0.039	0.222	0.070	0.191	0.035	0.191
G-ECE	0.424	0.343	0.881‡	0.322	0.646	0.434	0.612*	0.338	-0.637†	0.266	0.169	0.382
G-EE	0.079	0.139	0.182	0.161	-0.094	0.238	0.295	0.186	-0.219	0.173	-0.099	0.166
G-OE	0.020	0.201	0.141	0.218	-0.326	0.257	0.277	0.266	-0.093	0.233	-0.042	0.237
G-NE	0.005	0.193	-0.251	0.286	2.042‡	0.273	0.454	0.277	-0.540†	0.226	-0.273	0.252

Note: ‡ means significant at the 1% level; † means significant at the 5% level; * means significant at the 10% level; all standard errors are clustered at the school level; see Table 1 for variable definitions.

Table 9
Fixed Effects Regression on Mathematics and Reading Test Scores (Non-minority Only)

	1-5				*1-3*				*3-5*			
	Mathematics		*Reading*		*Mathematics*		*Reading*		*Mathematics*		*Reading*	
Variable	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*
UG-ECE	0.023	0.040	-0.019	0.040	0.006	0.036	0.016	0.046	0.012	0.031	0.032	0.047
UG-EE	0.018	0.050	0.068	0.063	0.023	0.065	0.110*	0.063	0.051	0.040	0.072	0.044
UG-OE	-0.044	0.042	-0.015	0.055	-0.008	0.048	-0.010	0.053	-0.042	0.031	-0.055	0.036
G-ECE	0.037	0.100	-0.164	0.113	0.079	0.074	-0.046	0.087	-0.048	0.071	-0.057	0.070
G-EE	0.108‡	0.034	0.053	0.044	0.044	0.037	0.051	0.044	0.030	0.032	0.032	0.041
G-OE	0.041	0.052	-0.003	0.055	-0.072	0.055	-0.029	0.062	0.036	0.044	-0.056	0.043
G-NE	-0.028	0.058	-0.022	0.077	-0.158	0.121	-0.353‡	0.110	-0.032	0.049	-0.020	0.056

Note: ‡ means significant at the 1% level; † means significant at the 5% level; * means significant at the 10% level; all standard errors are clustered at the school level; see Table 1 for variable definitions.

Table 10
Fixed Effects Regression on Mathematics and Reading Test Score *Gains* (Non-minority Only)

	1-5				*1-3*				*3-5*			
	Mathematics		*Reading*		*Mathematics*		*Reading*		*Mathematics*		*Reading*	
Variable	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*	*Coef.*	*S.E.*
UG-ECE	-0.098	0.104	-0.024	0.123	-0.091	0.107	0.118	0.111	0.000	0.088	0.003	0.116
UG-EE	-0.036	0.129	0.208*	0.115	-0.256	0.172	0.416‡	0.155	0.158*	0.094	0.070	0.119
UG-OE	0.077	0.098	-0.010	0.116	-0.105	0.117	-0.061	0.133	-0.017	0.081	-0.058	0.089
G-ECE	0.188	0.233	-0.414†	0.184	0.288	0.233	-0.108	0.248	0.112	0.202	-0.122	0.212
G-EE	0.259‡	0.086	0.148	0.103	0.158	0.129	-0.261†	0.129	0.021	0.066	0.050	0.102
G-OE	0.114	0.121	0.064	0.121	0.068	0.172	-0.103	0.200	0.071	0.119	-0.061	0.100
G-NE	0.080	0.136	-0.166	0.183	-0.547	1.033	-1.243‡	0.213	-0.100	0.143	-0.306*	0.161

Note: ‡ means significant at the 1% level; † means significant at the 5% level; * means significant at the 10% level; all standard errors are clustered at the school level; see Table 1 for variable definitions.

Thus, we do not find any uniform advantages to teachers holding a specific undergraduate or graduate degree for minority students. However, non-minority students appear to benefit in mathematics from teachers holding a graduate degree in elementary education. Additionally, younger non-minority students seem to gain from to teachers holding an undergraduate degree in elementary education, while they also appear to suffer from teachers holding a graduate degree in a concentration other than education.

4. CONCLUSIONS

The overriding implication of this paper is that no policy of requiring teachers to hold certain degrees is universally beneficial for all students. This does not mean that teacher education degrees hold no value. Our methodology does not allow us to answer that question. Our results simply imply that *forcing* teachers to obtain certain degrees will not, in itself, increase student achievement. Thus, states with laws requiring teachers to have such degrees are benefitting certain populations of students to the detriment of others.

We do, however, find that certain degrees are beneficial (detrimental) to certain sub-populations of students in certain subjects. We find that a *graduate* degree in elementary education is the only degree a teacher can obtain that is shown to significantly increase student achievement in *mathematics* for all elementary students using our full sample. This result also holds when we restrict our student population to male students and when we restrict the student population to non-minority students. However, we find that a teacher holding a graduate degree in elementary education does not provide a statistically significant benefit to female students or minority students. Female students are shown to benefit in *mathematics* from having a teacher with a graduate degree in early childhood education, while minority students are not shown to respond positively or negatively to teachers holding any education related degrees.

Alternatively, we find that an *undergraduate* degree in elementary education is the only degree a teacher can obtain that significantly increases student achievement in *reading* for all elementary students using our full sample. Surprisingly, this result only holds true in one of our sub-sample/sub-population combinations—young (first and third grade), non-minority students. Teachers holding a non-education related graduate degree were found to have a negative impact on student achievement in *reading* for young, non-minority students and the full population of young (first and third grade) students.

These results do not support the idea that teachers holding education related degrees are necessarily of a higher quality than teachers with non-education related degrees. Again, this does not mean that education related degrees are ineffective. Our results simply suggest that a policy that forces teachers to obtain certain education related degrees will not, by itself, lead to increased student achievement.

NOTES

1. Aslam and Kingdon (2011) and Aaronson *et al.* (2007) use middle school and high school data, respectively, whereas this paper utilizes elementary school data. While Jepsen (2005) also uses elementary school data, it does not account for specific undergraduate or graduate majors for teachers as we do in this paper.
2. *http://www.scteachers.org/cert/certpdf/TeacherCertificationManual.pdf*
3. *http://www.kyepsb.net/certification/certstandardroutes.asp*
4. It is worth noting here that Darling-Hammond *et al.* (2001) dispute some of the claims made in this article. Goldhaber and Brewer (2001) defend their original article in this rejoinder.
5. Our vector of teacher and school characteristics, xit, includes all of the teacher characteristics and school characteristics listed in tables of summary statistics in the appendix.
6. The same major may be labeled differently across states (e.g. one state may classify teacher preparation for grades K-5 as "early childhood education," while others may classify this as "elementary education"). This is not optimal; however, it is not extremely problematic either. If these variables really represent the same major, then our results will not be significantly different. To the extent that these majors are different, our method errs on the side of treating them differently.
7. Schooling is compulsory everywhere in the United States at least through the fifth grade, so there should not be any bias from students dropping out of school.
8. We can still include the test scores from these students in the test score gains model, as we only need the kindergarten data to calculate the difference in test scores for a given student between first grade and kindergarten.
9. This is not true in all states. For instance, Kentucky only considers kindergarten and first grade to be early childhood education.

10. The sample in this data set was designed to be a nationally representative sample of students in the United States in Kindergarten in 1998-1999. Thus, students were sampled from their schools; meaning not all students, nor all teachers from a school are included in this sample. The average class size of the students included in the full panel is 21.6 students per classroom, with a minimum of 10 and a maximum of 35.
11. The Hausman test that the coefficients in the random effects model are not correlated with the error term is rejected at the one-percent level in the majority of our models and sub-samples. Given this result and our doubt in the assumption of uncorrelated u and x in the random effects model, we present and discuss only the results from the fixed effects models. The random effects model results are available upon request.
12. Robust standard errors, clustered at the school level, are estimated following Wooldridge (2002).
13. It is important to note here that the lower-grade sub-sample of female-only students contains very few teachers that hold a graduate degree in an area outside of education, which results in G-NE being dropped from the test score *gains* model due to collinearity.

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Appendix

Table A.1
Full Population Summary Statistics

Variable	*Number of Observations*	*Mean*	*Standard Deviation*
Students Test Scores			
Reading	2784	0.000	1.000
Mathematics	2784	0.000	1.000
Teacher Characteristics			
Teacher Age	1369	42.033	11.243
No Experience	1369	25.42%	0.436
Experience	1369	56.39%	0.496
Certified	1369	92.33%	0.266
UG-ECE	1369	15.27%	0.360
UG-EE	1369	80.93%	0.393
UG-OEM	1369	12.20%	0.327
G-ECE	1369	3.87%	0.193
G-EE	1369	26.22%	0.440
G-OEM	1369	12.34%	0.329
G-NE	1369	3.58%	0.186
Reading Ratio	1369	43.32%	0.154
Math Ratio	1369	31.30%	0.105
School Characteristics			
School High Certification	300	82.51%	0.282
School Advanced Degree	300	48.12%	0.397
School EE	300	73.59%	0.346
School Minority	300	29.78%	0.436
School Any EE	300	85.83%	0.218
School Years Experience	300	8.068	4.108
School Reading Ratio	300	43.14%	0.078
School Math Ratio	300	31.41%	0.055
School SES	300	0.004	0.492

Note: UG-ECE means an undergraduate degree in early childhood education; UG-EE means an undergraduate degree in elementary education; UG-OE means an undergraduate degree in an other education related degree; G-ECE is a graduate degree in early childhood education; G-EE is a graduate degree in elementary education and G-OE is a graduate degree in an other education related area; G-NE means a graduate degree in a non-education related field.

Table A.2
Male Only Sub-Population Summary Statistics

Variable	*Number of Observations*	*Mean*	*Standard Deviation*
Students Test Scores			
Reading	1369	-0.085	1.034
Mathematics	1369	0.094	1.029
Teacher Characteristics			
Teacher Age	929	41.896	11.144
No Experience	929	24.76%	0.432
Experience	929	56.30%	0.496
Certified	929	92.47%	0.264
UG-ECE	929	14.75%	0.355
UG-EE	929	83.53%	0.371
UG-OEM	929	11.30%	0.317
G-ECE	929	3.34%	0.180
G-EE	929	26.59%	0.442
G-OEM	929	11.30%	0.317
G-NE	929	3.66%	0.188
Reading Ratio	929	42.93%	0.152
Math Ratio	929	31.16%	0.105
School Characteristics			
School High Certification	239	83.96%	0.267
School Advanced Degree	239	47.29%	0.388
School EE	239	74.50%	0.343
School Minority	239	29.90%	0.440
School Any EE	239	86.71%	0.210
School Years Experience	239	8.165	3.991
School Reading Ratio	239	43.35%	0.079
School Math Ratio	239	31.15%	0.056
School SES	239	0.018	0.483

Table A.3
Female Only Sub-Population Summary Statistics

Variable	*Number of Observations*	*Mean*	*Standard Deviation*
Students Test Scores			
Reading	1415	0.082	0.959
Mathematics	1415	-0.091	0.962
Teacher Characteristics			
Teacher Age	922	42.285	11.327
No Experience	922	26.03%	0.439
Experience	922	56.51%	0.496
Certified	922	92.08%	0.270
UG-ECE	922	14.43%	0.352
UG-EE	922	79.83%	0.402
UG-OEM	922	12.15%	0.327
G-ECE	922	3.47%	0.183
G-EE	922	26.25%	0.440
G-OEM	922	13.12%	0.338
G-NE	922	4.01%	0.196
Reading Ratio	922	43.56%	0.151
Math Ratio	922	31.51%	0.105
School Characteristics			
School High Certification	240	81.73%	0.290
School Advanced Degree	240	49.70%	0.399
School EE	240	72.80%	0.356
School Minority	240	27.19%	0.429
School Any EE	240	85.67%	0.223
School Years Experience	240	8.222	3.960
School Reading Ratio	240	43.52%	0.078
School Math Ratio	240	31.57%	0.057
School SES	240	0.021	0.497

Table A.4
Minority Only Sub-Population Summary Statistics

Variable	*Number of Observations*	*Mean*	*Standard Deviation*
Students Test Scores			
Reading	764	-0.425	1.072
Mathematics	764	-0.459	1.088
Teacher Characteristics			
Teacher Age	540	41.354	11.053
No Experience	540	25.74%	0.438
Experience	540	53.52%	0.499
Certified	540	91.30%	0.282
UG-ECE	540	14.81%	0.356
UG-EE	540	74.07%	0.439
UG-OEM	540	10.19%	0.303
G-ECE	540	2.78%	0.164
G-EE	540	20.19%	0.402
G-OEM	540	10.56%	0.308
G-NE	540	3.52%	0.184
Reading Ratio	540	42.63%	0.165
Math Ratio	540	31.16%	0.116
School Characteristics			
School High Certification	149	81.04%	0.291
School Advanced Degree	149	37.47%	0.380
School EE	149	69.14%	0.374
School Minority	149	51.87%	0.478
School Any EE	149	81.92%	0.254
School Years Experience	149	7.483	3.746
School Reading Ratio	149	42.88%	0.084
School Math Ratio	149	31.42%	0.060
School SES	149	-0.134	0.508

Table A.5
Non-Minority Only Sub-Population Summary Statistics

Variable	*Number of Observations*	*Mean*	*Standard Deviation*
Students Test Scores			
Reading	2020	0.161	0.921
Mathematics	2020	0.174	0.906
Teacher Characteristics			
Teacher Age	1061	42.685	11.288
No Experience	1061	24.22%	0.429
Experience	1061	58.91%	0.492
Certified	1061	92.93%	0.256
UG-ECE	1061	14.99%	0.357
UG-EE	1061	84.45%	0.363
UG-OEM	1061	11.97%	0.325
G-ECE	1061	4.15%	0.199
G-EE	1061	28.93%	0.454
G-OEM	1061	12.72%	0.333
G-NE	1061	3.96%	0.195
Reading Ratio	1061	43.63%	0.145
Math Ratio	1061	31.45%	0.097
School Characteristics			
School High Certification	249	83.06%	0.283
School Advanced Degree	249	51.94%	0.395
School EE	249	76.57%	0.337
School Minority	249	16.46%	0.345
School Any EE	249	88.42%	0.194
School Years Experience	249	8.475	4.121
School Reading Ratio	249	43.57%	0.078
School Math Ratio	249	31.23%	0.054
School SES	249	0.108	0.443