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**“Does teacher preparation matter?
pupil academic achievement and teacher’s college preparation”**

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Abstract

This study examines whether there is differential productivity associated with teachers trained within Florida Agricultural & Mechanical University’s college of education relative to teachers trained in other colleges and schools affiliated with the same university. We also examined whether there is differential productivity associated with alternative majors within and between the college of education and other academic units. We measure the productivity of a teacher by the educational achievement of pupils assigned to that teacher during a given year. We find that among pupils taught by recent graduates of FAMU, there is greater academic achievement among elementary school pupils taught by a teacher with a college major in elementary education than among elementary school pupils taught by a teacher with a college major in either secondary education or a non-education subject area. However, relative to secondary education and non-education majors, elementary education majors provide less value-added in middle school and high school.

JEL codes: I2, J15, J44, J45, J48

Key words: teacher quality, value-added model, historically black colleges and universities, HBCU, teacher productivity, education and value-added

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The K-12 educational system of the state of Florida must improve substantially; otherwise, children educated in the state of Florida will not be able to compete in the national or global economy. Among the 51 states and the District of Columbia, Florida ranks 49th in high school graduation rates (Greene, 2002). Ranking the states and the District of Columbia by the African American and Latino graduation rates, Florida is 32nd out of 39 and 26th out of 39, respectively. Florida citizens have expressed a desire to improve the state's education system.¹

Among other factors, Florida schools need improvements in teacher preparation. Discussions of teacher quality and school accountability have been animated by federal legislation, in particular, the No Child Left Behind Act of 2001. Among its many provisions, NCLB stresses the need for improvement in the academic achievement of disadvantaged pupils through high quality assessment systems, accountability systems, teacher training, and the alignment of curriculum and instruction. To those ends, Florida has implemented a statewide accountability system for public schools. This system includes performance measures such as adequate yearly progress, standardized testing, school grades, annual learning targets, and per pupil spending.

There is a shortage of teachers in the state of Florida and there is a shortage of African American teachers. Expanding the productive capacity and productive efficiency of Historically Black Colleges and Universities (HBCU) may ameliorate both teacher shortages. Nationally, HBCUs enroll more than 1/5 of all African American students attending 4-year universities and account for a similar number of bachelor's degrees attained by African American students (Provasnik and Shafter, 2004). More to the point, HBCUs account for 27.3 percent of African Americans graduating with a bachelor's degree in education, representing 30.2 percent of African American male graduates in education and 26.3 percent of African American female

graduates in education (Provasnik and Shafter, 2004, Table A – 22).

Florida Agricultural & Mechanical University (FAMU) is Florida's only public HBCU and it is one of the nation's largest HBCUs. New graduates of FAMU teach about 3.5 percent of all mathematics and reading pupils taught by new teachers in Florida and 17.5 percent of each year's reading and mathematics pupils taught by new African American teachers. As an important producer of teachers in Florida's K-12 education system, Florida A & M University is concerned about: (1) the quality and preparedness of its graduates, (2) evidence linking FAMU graduates to significant learning growth in Florida's education system, and (3) the contributions of its graduates toward realization of the NCLB's Title I provision – improving the academic achievement of the disadvantaged.

All Florida teachers must pass a series of certification examinations prior to their employment as teachers in Florida's public school system. These examinations insure minimal pedagogical and content competence. But, prior to certification, teacher preparation is not a homogenous process. For instance, Florida A & M University offers two approaches to teacher preparation. Specifically, some FAMU trained teachers enter the education profession via the traditional route of obtaining a degree within the college of education (EDU) and then passing the requisite certification examinations. This route places greater emphasis on the development of pedagogical skills and lesser emphasis on subject area content. Students may specialize in a variety of major areas of study, for example, mathematics education, English education, elementary education, and so forth.

Other FAMU trained teachers enter the education profession via the alternative route of obtaining a degree outside of the college of education (Non-EDU) and then passing the requisite certification examinations. This approach emphasizes the acquisition of subject area content and

places much less emphasis on the development of pedagogical skills. Students may specialize in the standard variety of major areas of study, for example, mathematics, English, business administration, art, and so forth.

Two empirical questions arise. Is the marginal effect of EDU status a statistically significant and substantively large determinant of pupil learning outcomes? Are there differential marginal effects of teachers' college majors within and between EDU and Non-EDU graduates? Theoretically, it is not immediately obvious that there should be a statistically significant effect associated with EDU status. Pupil achievement is a positive function of teaching skill, which consists of positive measures of both pedagogical and content knowledge. Suppose multiple combinations of pedagogical knowledge and content knowledge can be combined to produce a given level of pupil achievement. Suppose also that schools hire and release untenured teachers according to a teacher's productive contribution, as measured by pupil achievement. To the extent that these suppositions hold, the additional benefit of hiring another EDU teacher should be equal to the additional benefit of hiring another Non-EDU teacher. At the margin, EDU status should be statistically insignificant.

This study empirically investigates the effects of FAMU teacher preparation on pupil learning in Florida's K-12 educational system. Using value-added regression analysis, we seek to determine whether alternative (Non-EDU) and traditional (EDU) approaches to teacher preparation yield dissimilar effects on pupil learning. We use the Florida Comprehensive Assessment Test (FCAT) as our measure of pupil learning.

Limiting our analysis of elementary school to sixth grade, we find that there is no statistically significant effect for EDU status. At this very broad level, pupils with College of Education trained teachers have test scores that are neither greater than nor less than pupils with

teachers trained outside of the College of Education. Also, for middle school and high school, EDU status is statistically insignificant. When we capture teacher preparation by specific college major, rather than the broad category of EDU status, a more informative pattern emerges. Elementary school (grader 6) pupils with teachers who majored in elementary education have equal or higher academic achievement in reading and mathematics than elementary pupils assigned to teachers who majored in either a non-education subject area or a field within secondary education. For middle and high school pupils, for both mathematics and reading, we find statistically significant and positive effects for teachers who majored in non-education academic disciplines or who majored in a field within secondary education.

I. Literature Review

Pre-service training associated with the traditional path to becoming a teacher requires a bachelor's degree with an education major, passing a series of certification and licensing examinations, and student teaching. The education degree places greater emphasis on pedagogy and lesser emphasis on academic content than is encountered in a non-education major. The pre-service training associated with alternative paths to becoming a teacher requires a bachelor's degree but not necessarily an education major, possibly passing a series of certification and licensing examinations, and often little or no student teaching. Hence, alternative paths of entry into teaching tend to de-emphasize the value of pedagogical training. In addition to pre-service training, both traditional and alternative paths of entry utilize on-the-job training, that is, in-service training, for both novice and veteran teachers.

A burgeoning class of literature has emerged to evaluate the relative effectiveness of non-traditional paths of entry to education and in-service training. For example, Angrist and Lavy (1998) found that pedagogical training is an effective and efficient method for increasing student

achievement. They showed that on-the-job training for Jerusalem elementary school teachers lead to improved academic performance as measured by their students' standardized test scores in reading and mathematics. The in-service training was based on pedagogical methods developed in American schools. The students were in fourth grade during the 1994 academic year and their academic achievement was measured during 1994, 1995 (the year on-the-job training began), and 1996 (training continued at a new higher level). Angrist and Lavy found that in-service pedagogical training for teachers increased pupil test scores by 0.2 – 0.4 standard deviations: a more cost-effective approach to raising pupil academic performance than either reducing class size or increasing school hours.

One alternative for increasing the flow and diversity of college graduates entering teaching is to allow in-service training to substitute for some pre-service requirements. During the late 1990s New York City created alternative paths of entry by offering reduced pre-service coursework and experience requirements in favor of relatively more support (in-service training) and additional coursework during first year of employment (Boyd et al., 2006). The alternative certification programs included Teach for America, Teaching Fellows, individual evaluation, temporary license, and “other.”² The New York City alternative certification programs focused on individuals with a subject area bachelor's degree but no or little pedagogical training. Some alternatively certified teachers were recent college graduates and some were mid-career professionals (older and more likely to already have subject area graduate degrees).

Boyd et al. (2006) focus on a sample of pupils in grades 3 – 8 for 1998-1999 thru 2003-2004 academic years. English language arts and mathematics are the subject areas used to measure pupil academic achievement. Except for teachers who entered teaching via Teach for America, the math scores of pupils with teachers who entered by the traditional path were 0.01 or

0.02 standard deviations higher than the test scores of pupils with alternative pathway teachers. There was no statistically significant effect for Teach for America. The coefficients for English language arts were similar, with the productivity premium for traditionally trained teachers ranging from 0.01 to 0.03; however, the coefficient for the “individual evaluation” pathway (rather than Teach for America) is statistically identical to the traditional path. These mathematics and English affects are roughly 40 percent of the test score improvement of pupils of second year teachers relative to pupils of first year teachers.

Importantly, Boyd et al. also find that attrition rates vary by path of entry. Traditionally trained teachers, teaching fellows, and individual evaluation teachers have the lowest and similar attrition rates. Teach for America, temporary license, and other pathway teachers have much higher attrition rates. Boyd, et al. (2008) note that newly hired alternative pathway teachers tend to have stronger academic qualifications than traditionally trained teachers. In 2003, 5 percent of the new hired Teaching Fellows and Teacher for American teachers failed the Liberal Arts and Sciences certification examination, compared to 16.2 percent of newly hired traditional teachers and 32.5 percent of uncertified teachers. Given the relatively superior academic ability of alternative pathway teachers and the difference in attrition rates, Boyd, et al. (2006) may underestimate the relative productivity of traditionally trained for teachers.

Clotfelter, et al. (2007) examine the relationship between teaching credentials and academic achievement for North Carolina pupils in grades 3 – 5, while Clotfelter, et al. (2008) examine this issue for high school students. The state of North Carolina provides traditional teaching licenses, lateral entry teacher licenses, and “other” teaching licenses. Lateral entry teachers have a bachelor’s degree, subject area major in the subject they are teaching, and a 2.5 collegiate grade point average. They must complete additional prescribed coursework with a

college or university. Lateral entry licenses are issued for two years but may be extended for an additional year. Lateral entry teachers who remain in teaching eventually convert to a regular license. Teachers with “other” licenses have provisional, temporary, or emergency licenses.

For reading achievement among elementary school pupils, the marginal effect of lateral entry is positive but insignificant in Clotfelter et al.’s preferred equation. However, it is positive and significant in the annual gain model with school fixed effects (0.044 standard deviations) and in the lagged dependent variable model with school fixed effects (0.039 standard deviations). “Other license” has a negative and significant effect in all specifications, -0.01 to -0.02 for reading and -0.03 to -0.06 for mathematics. For mathematics achievement among elementary school pupils, the marginal effect of lateral entry is negative (-0.01 to -0.03) for all equations but it is negative and significant solely for the contemporaneous model (-0.03).

Clotfelter, et al. (2008) also find superior achievement for high school pupils of traditionally trained teachers. North Carolina 9th and 10th graders are given end-of-course examinations in algebra; economic, legal, and political systems; and English I, while 10th graders have end-of-course examinations in geometry and biology. Unlike high school exit examinations or minimum competency examinations, end-of-course examinations cover material from a specific course and the scores may be linked to a specific teacher. The examinations are statewide and hence external to the individual school. This study finds that high school pupils taught by a teacher with a lateral entry license have end-of-course test scores that are 0.06 standard deviations lower than the scores of otherwise identical pupils taught by a teacher with a regular license. Prior lateral entry teachers, that is, those teachers who moved from the status of lateral entry teachers to secure a regular license, are as productive as other regular license teachers. The latter finding may indicate two things: 1) the training provided to lateral entry

teachers does succeed in increasing their productivity; and, 2) attrition effects. Clotfelter, et al. found a very high attrition rate among lateral entry teachers; hence, those remaining as teachers likely were also the more effective teachers. The study also found that “other” license teachers have a negative effect (-0.0466) on pupil achievement in end-of-course examinations relative to regular license teachers.

Aaronson, Barrow, and Sander (2007) examine mathematics achievement among 9th graders in Chicago’s public schools. There is considerable diversity in the academic preparation of teachers. The distribution of bachelor’s degrees are: education (19 percent), mathematics (47 percent), science (8 percent), and “all else” (26 percent). In comparison to pupils taught by teachers with “all else” degrees, Aaronson, et al. found that pupils taught by teachers with college majors in mathematics and science score 0.05 – 0.06 and 0.06 – 0.08 grade equivalents higher, respectively, on standardized examinations. However, the marginal effect of teachers with education degrees is 0.08 – 0.10 grade equivalents higher.

The extant literature shows that newly hired traditionally trained teachers have superior value-added and lower attrition relative to newly hired alternatively trained teachers. However, the extant literature has not addressed the question of the relative value-added of different collegiate majors within and between traditional and alternative pathways into teaching. We examine this issue below.³

II. Model

Why should a school hire both EDU and Non-EDU teachers? At least since Adam Smith economists have known that specialization according to comparative advantage combined with voluntary exchange can make all parties better off.⁴ To the extent that college students select their major area of study according to their academic comparative advantage and interests, higher

quality teachers are produced by having alternative paths of entry into teaching. Students with an academic passion for specific area content become better teachers by majoring in a content based subject, while those with a passion for understanding the teaching process become superior teachers by majoring in an education specialty. Secondly, a diverse and complementary population of teachers, that is, a mixture of those with education and non-education degrees, may yield cross-pollination effects: pedagogical and academic content is exchanged among teachers according to their relative strengths; thereby, the collective productivity of the faculty is higher than it would be otherwise. Finally, a diverse population of teachers allows for superior pupil-teacher matches based on the needs of the pupil and the strengths of the teacher.

Consider the simple teacher-school coordination game presented in Figure 1. Suppose all new teachers for given grade levels and given specialties (for example, mathematics and reading) are paid an identical wage. A teacher's productivity can be measured by her effect on the mean academic achievement of her own pupils or by her effect on the mean academic achievement of all the school's pupils. Schools seek to hire a certain fraction (θ) of Non-EDU trained teachers and a certain fraction ($1-\theta$) of EDU trained teachers. Similarly, a certain fraction of new teachers (μ) specialize in Non-EDU training and a certain fraction of new teachers specialize in EDU training ($1-\mu$). If Non-EDU teachers are matched with Non-EDU school positions, pupil and school achievement is E . If EDU teachers are matched with EDU school positions, pupil and school achievement is S . If Non-EDU teachers are placed in EDU school positions, pupil achievement is "e" while the gain to the school is "s". Similarly, if EDU teachers are placed in a Non-EDU teaching position, pupil achievement is "s" and the school gain is "e". Coordinated teacher-school matches are more productive than uncoordinated teacher-school matches; hence, $E > s$ and $S > e$.

Figure 1. Teacher-School Employment Game

		School	
		Non-EDU (θ)	EDU ($1-\theta$)
Teacher	Non-EDU (μ)	E,E	e,s
	EDU ($1-\mu$)	s,e	S,S

The expected payoffs for college students selecting Non-EDU and EDU majors are:

$$E(A|\text{Non-EDU}) = \theta E + (1-\theta)e \quad \text{and}$$

$$E(A|\text{EDU}) = \theta s + (1-\theta)S.$$

The expected payoffs for schools seeking to hire Non-EDU and EDU teachers are:

$$E(A|\text{Non-EDU}) = \mu E + (1-\mu)e \quad \text{and}$$

$$E(A|\text{EDU}) = \mu s + (1-\mu)S.$$

For teachers seeking to optimize their abilities, $\theta(E-s) = (1-\theta)(S-e)$, the expected gain from specializing in a non-education degree equals the expected gain from specializing in an education degree. Similarly, for schools seeking to optimize the productivity of their faculty, $\mu(E-s) = (1-\mu)(S-e)$, the expected gain from hiring a Non-EDU teacher equals the expected gain from hiring an EDU teacher. Because teachers are hired or released from employment according to their productiveness, that is, student achievement, future teachers adjust their specialization activity and schools adjust their hiring activity according to the relative achievement gains of EDU and Non-EDU teachers. In equilibrium, both EDU and Non-EDU teachers are hired and there is no marginal effect associated with EDU status: the benefit of hiring an additional EDU teacher is exactly offset by the opportunity cost of not hiring a Non-EDU teacher, $\frac{\theta}{1-\theta} = \frac{S-e}{E-s}$

$$= \frac{\mu}{1-\mu}.$$

Our study relies on observational data to examine the null hypothesis of no marginal effect associated with EDU status. When using this type of data, severe endogeneity problems frustrate empirical efforts to attribute causal status to parameter estimates obtained from regressions of pupil standardized test scores on teacher preparation variables. A controlled experiment designed to evaluate the relative effectiveness of teacher preparation would meet the following criteria: i) teachers are drawn from universities of identical academic standards and resources; ii) on-the-job training is not correlated with EDU status; iii) college students in training to become teachers are randomly assigned to college majors (both between the college of education and other university colleges and between academic units within the college of education); iv) pupils are randomly assigned to schools; and, v) within a given school and a given grade level pupils are randomly assigned to teachers with respect to whether or not the teacher obtained a degree within the college of education or other academic college within a university.

Criteria i and ii are satisfied by our sample design. All of the teachers in our sample are bachelor's degree graduates of the same institution during the same timeperiod, viz., Florida A & M University during academic years 2001-2002 through 2005-2006. Each educator teaches within the state of Florida and, therefore, has passed an identical series of state administered certification examinations. Since all educators are new teachers (no teacher has more than 5 years of post-graduation experience), they were trained by a roughly similar set of teacher-educators and other collegiate faculty.

Given the short duration of their teaching career, on-the-job training effects (captured by years of experience) will not be confounded by attrition (Kane, Rockoff, and Staiger, 2006). Experience and attrition will have a positive (negative) correlation if professional attrition is

relatively higher (lower) among poor quality teachers. If experience varies by EDU status, then estimates of the marginal effect of teacher preparation on pupil learning will be inconsistent and inefficient because of the correlation of experience and attrition. Hence, given a sample of new teachers, on-the-job training and EDU status are uncorrelated.

Criteria iii, iv, and v are addressed via the specification of our empirical model. Consider pupil i potential achievement for grade g , where $A_{1,igt}$ is the pupil's year t potential achievement if the pupil's teacher entered teaching via a major within the college of education (EDU) and $A_{0,igt}$ is the pupil's year t potential achievement if the pupil's teacher entered teaching via educational training outside of the college of education (Non-EDU). Let $A_{i,g,t-1}$ represent pupil i actual achievement during the previous year. Hence, the potential annual achievement gain to each pupil is

$$\Delta A_{1,igt} = A_{1,igt} - A_{i,g,t-1} \text{ and}$$

$$\Delta A_{0,igt} = A_{0,igt} - A_{i,g,t-1} .$$

We need panel data to obtain these estimates and only one of the potential gains is actually observed. Note however that the difference in differences of potential achievement is

$$\Delta A_{1,igt} - \Delta A_{0,igt} = A_{1,igt} - A_{0,igt}, \text{ which may be estimated via cross-sectional data. In an}$$

appropriately designed experiment, where conditions i) – v) hold, the differences in achievement represent the value added by EDU teachers (the treatment group in the experiment) relative to Non-EDU teachers (the control group in the experiment). For any given pupil i , we observe either $A_{1,igt}$ or $A_{0,igt}$ (or, $\Delta A_{1,igt}$ or $\Delta A_{0,igt}$), but not both. We do however observe the average pupil's achievement according to the EDU status of the teacher and therefore we may state the observed difference in pupil achievement as $E(A_{1,igt}) - E(A_{0,igt}) = E(A_{igt}|EDU = 1) - E(A_{igt}|EDU = 0)$.

In a regression framework, this is

$$A_{ijgt} = \beta_0 + \beta_1 \text{EDU}_{ijgt} + \varepsilon_{it},$$

for student i and teacher j and where $\text{EDU} = 1$ if teacher has a EDU college major, but 0 otherwise. In a well designed experiment $\text{Cov}(\text{EDU}, \varepsilon) = 0$ and $\beta_1 = E(A_{igt}|\text{EDU} = 1) - E(A_{igt}|\text{EDU} = 0)$ is the mean value-added attributable to teachers having a EDU degree.

For observational data, it is likely that $\text{Cov}(\text{EDU}, \varepsilon) \neq 0$. Consistent and efficient estimation of the differential productivity effect of EDU training (β_1) is conditional on our ability to resolve this endogeneity problem via our sampling framework and empirical specification of the pupil achievement equation. As we have stated, all of the teachers included in this study will be new graduates of a single collegiate institution, FAMU; as such, each teacher received pre-professional training from a university of identical academic standards and resources and on-the-job training is not correlated with EDU status.

To construct a regression model free of other endogeneity problems, we must further control for random assignment of college students across academic majors, random assignment of pupils to schools, and random matching of teachers and pupils within schools. We do so by adding the following vectors to our regression model: teacher characteristics (T), pupil's grade level and other characteristics (C), and school characteristics (S). In this case,

$\beta_1 = E(A_{ijkt}|\text{EDU} = 1, \text{grade}_{ijkt}, T_{ijkt}, C_{ijkt}, S_{ijkt}) - E(A_{ijkt}|\text{EDU} = 0, \text{grade}_{ijkt}, T_{ijkt}, C_{ijkt}, S_{ijkt})$ is the mean value-added attributable to teachers having a EDU degree, conditional on the characteristics of $i = 1, \dots, n$ pupils, $j = 1, \dots, J$ teachers, and $k = 1, \dots, K$ schools.

Equations (1) and (2) state that pupil learning outcomes (A_i) are a function of pupil ability and prior learning ($A_{i,t-1}$), EDU status, pupil grade level and peer effects, teacher characteristics (T), additional pupil characteristics (C), school fixed effects ($S = \sum_k \text{District}_k \delta_k$),

and ε is a random error term.

$$(1) A_{ijkt} = \beta_0 + \alpha A_{i,t-1} + \beta_1 \text{EDU}_{ijt} + \beta_2 \text{Grade}_{it} + \beta_3 \text{Peer Effects} + T_t \beta_4 + C_t \beta_5 + \sum_k \text{District}_{kt} \delta_k + \varepsilon_t,$$

and

$$(2) A_{ijkt} = \beta_0 + \alpha A_{i,t-1} + \sum_{p \in \text{PEU}} \text{EDUMajor}_{ijpt} \beta_{1,p} + \sum_{p \notin \text{PEU}} \text{NonEDUMajor}_{ijpt} \beta_{1,np} + \beta_2 \text{Grade}_{it} \\ + \beta_3 \text{Peer Effects} + T_t \beta_4 + C_t \beta_5 + \sum_k \text{District}_{kt} \delta_k + \varepsilon_t.$$

Pupil learning during a given period depends on a pupil's entire history of learning, as affected by previous socioeconomic status, past teachers, natural ability, developed ability, past peers, and so forth. Thus, $A_{i,t-1}$ is a baseline achievement measure, a sufficient statistic for all past unobserved educational inputs and a pupil's observed endowment of mental capacity. Todd and Wolpin (2003) show that baseline achievement ($A_{i,t-1}$) is endogenous, that is, $E(\varepsilon_t | A_{i,t-1}) \neq 0$. A contemporaneous specification of equations (1) and (2) is one approach to addressing this issue, but the contemporaneous requires that we assume $\alpha = 0$. A second identification strategy focuses on annual gain as the dependent variable. In this case, we assume $\alpha = 1$ and estimate (1') and (2') as follows.

$$(1') A_{ijkt} - A_{i,t-1} = \beta_0 + \beta_1 \text{EDU}_{ijt} + \beta_2 \text{Grade}_{it} + \beta_3 \text{Peer Effects} + T_t \beta_4 + C_t \beta_5 + \sum_k \text{District}_{kt} \delta_k + \varepsilon_t,$$

and

$$(2') A_{ijkt} - A_{i,t-1} = \beta_0 + \sum_{p \in \text{PEU}} \text{EDUMajor}_{ijpt} \beta_{1,p} + \sum_{p \notin \text{PEU}} \text{NonEDUMajor}_{ijpt} \beta_{1,np} + \beta_2 \text{Grade}_{it} \\ + \beta_3 \text{Peer Effects} + T_t \beta_4 + C_t \beta_5 + \sum_k \text{District}_{kt} \delta_k + \varepsilon_t.$$

A third identification strategy uses an instrumental variable approach. Per Todd and Wolpin (2003) we know that $E(\varepsilon_t | A_{i,t-2}) = 0$ and $E(A_{i,t-1} | A_{i,t-2}) \neq 0$. Hence, we can use the latter

conditional expectation to obtain a predicted baseline achievement measure $\hat{A}_{i,t-1}$ and thereby obtain consistent parameter estimates from the following equations.

$$(1'') A_{ijkt} = \beta_0 + \alpha \hat{A}_{i,t-1} + \beta_1 \text{EDU}_{ijt} + \beta_2 \text{Grade}_{it} + \beta_3 \text{Peer Effects} + T_t \beta_4 + C_t \beta_5 + \sum_k \text{District}_{kt} \delta_k + \varepsilon_t, \text{ and}$$

$$(2'') A_{ijkt} = \beta_0 + \alpha \hat{A}_{i,t-1} + \sum_{p \in \text{PEU}} \text{EDU}_{ijpt} \beta_{1,p} + \sum_{p \notin \text{PEU}} \text{NonEDU}_{ijpt} \beta_{1,np} + \beta_2 \text{Grade}_{it} + \beta_3 \text{Peer Effects} + T_t \beta_4 + C_t \beta_5 + \sum_k \text{District}_{kt} \delta_k + \varepsilon_t.$$

Ordinary least squares is used to estimate both equations. The standard errors are adjusted for clustering: pupils with the same teacher have correlated standard errors.

Our regression analysis is confined to an examination of mathematics and reading achievement of Florida public school pupils. The Florida Comprehensive Assessment Test (FCAT) provides our measures of pupil learning. The FCAT yields developmental scale scores for the Sunshine State standards (FCAT-SSS) as well as scores for a nationally comparative norm referenced test (FCAT-NRT). FCAT-SSS tests student mastery at each grade level. It is a criterion-based examination established by the State of Florida. School accountability, teacher promotion, and student graduation criteria are based on the FCAT-SSS. FCAT-NRT is a version of the Stanford-9 achievement test; hence, it represents a measure of learning outcomes that is well-known and permits comparisons across time and across state boundaries. Our presentation and discussion here is confined to the equations using the FCAT-SSS as the dependent variable. Mason (2010) also presents the results using the FCAT-NRT, but those equations have dramatically fewer observations than the ones presented here and they do not yield different results.

We wish to estimate the causal effect of teacher academic preparation and pedagogical

training. The quality of education provided to pupils may vary across college majors, both within the college of education and between the college of education and other major academic units. College students of greater ability or greater willingness to work may be disproportionately attracted to higher quality (more challenging) academic majors. Hence, the teaching ability of graduating teachers may vary both because of heterogeneity in the ability and effort of college students and because of heterogeneity in the quality of academic majors. Equation (1) presents a model whereby a teacher's college major is aggregated into one of two choices, either the teacher did or did not obtain an EDU degree. This equation is used to assess the relative effectiveness of EDU preparation. Equation (2) decomposes the choice of college majors: among the set of college majors some teachers choose a specific EDU area of study ($p \in \text{EDU}$), for example, elementary education, mathematics education, and so forth, and all other teachers major in a specific Non-EDU area of study ($p \notin \text{EDU}$), for example, business administration, history, English, and so forth. Equation (2) is used to assess the marginal effect of teacher's college education within and between EDU and Non-EDU graduates.

Parents select schools according to the quality of the school or other reasons. Given that a particular institution has been chosen by parents, school administrators allocate pupils to individual teachers. But, administrators may not allocate pupils in a random fashion. When there are multiple teachers for a given grade level pupils may be allocated to teachers according to the perceived ability of pupils. Some teachers are assigned high ability pupils while other teachers are assigned low ability pupils. If school administrators believe that EDU trained teachers are more (or less) able to teach low ability pupils, then EDU status will not be independent of pupil ability. Hence, again, to infer a casual relationship between observed differences in the academic achievement of pupils when those pupils have been taught by teachers who differ by EDU status,

we must control for pupil and school heterogeneity.

Consistent and efficient estimation of the effect of teacher preparation on student learning will not occur if teacher assignment by EDU status varies across schools of differing quality. School characteristics (S) are modeled as fixed effects, captured by a vector of binary variables representing the school districts in our sample. Mostly, our sample contains 1 school per school district. In addition to a pupil's grade level and peer's academic achievement, we also control for class size. Peer effects and class size capture school and classroom specific differences in the learning environments of pupils.

We capture a teacher's analytical skills, intellectual development, and work ethic prior to college entry by a vector of college entry examination scores, viz., scholastic achievement test (SAT) mathematics and verbal scores. The teacher characteristics vector also includes race and ethnicity, gender, age, experience, and whether a teacher has a graduate degree.

We control for pupil heterogeneity by including the race, ethnicity, and gender identity of the pupil. Additionally, we control for the English language learner status of pupils and whether or not a pupil is eligible for free or reduced price lunch.

We include FCAT scores for both mathematics and reading in grades 6-12. Harris and Sass (2006) note that for middle school pupils (grades 6-8 in their analysis) "it is easier to identify the relevant teacher and peer group for middle-school pupils than for elementary pupils." Typically, Florida's middle school pupils are not in "self-contained" classrooms, that is, they are likely to have subject specific teachers. On the other hand, elementary school pupils are more likely to receive their core academic instruction from a single teacher. Harris and Sass also note that 5 percent of elementary school pupils enrolled in self-contained classrooms have a separate mathematics course and 13 percent are enrolled in either special-education or gifted courses.

First, we test for the statistical significance and substantive educational importance of teacher's academic preparation. Specifically, for equation (1) our primary hypothesis is

$H_0: \beta_1 = 0$ and

$H_1: \beta_1 \neq 0$.

For equation (2) our primary hypotheses are

$H_0: \beta_{1,p} = 0$ for each p and

$H_1: \beta_{1,np} \neq 0$, where the comparative major is elementary education (the dominant EDU major for each educational cohort).

We test also whether the education process varies according to the nature of learning outcomes. In particular, does the value-added due to the EDU status of teachers vary according to whether our dependent variable is mathematics or reading outcomes?

Estimating the baseline achievement specification allows us test the validity of the contemporaneous and annual gain specifications.

Contemporaneous model test

$H_0: \alpha = 0$ and

$H_1: \alpha \neq 0$.

Annual gain model test

$H_0: \alpha = 1$ and

$H_1: \alpha \neq 1$.

Validity of the baseline achievement specification requires $0 < \alpha < 1$. The baseline achievement specification is econometrically less restrictive than the contemporaneous and annual gain specifications, but the baseline achievement specification requires three years of observations for each pupil while the annual gain and contemporaneous specifications require two years and one

year of observations, respectively.

We estimate 6 versions of each specification: i) basic, ii) district fixed effects, iii) district fixed effects and teacher characteristics, iv) district fixed effects with pupil and teacher characteristics, v) district fixed effects with teacher characteristics and teacher's collegiate SAT scores, and vi) district fixed effects with pupil and teacher characteristics and teacher's collegiate SAT scores. Also, separate equations are obtained for elementary (grade 6), middle (grades 7 and 8), and high school (grades 9 – 12). Finally, there are two versions of the dependent variable: FCAT – mathematics, Sunshine State standards and FCAT – reading, Sunshine State standards. For the basic specification, the explanatory variables include college major, peer effects, and binary variables for the pupil's grade level. Each of the additional specifications encompasses the basic specification.

III. Data

A. Description of variables

The data are provided by the K-20 Florida Education Data Warehouse and consist of multiple data groups. The data groups are identified by the academic year teachers received their bachelor's degree: 2001-2002 thru 2005-2006. Within each data group, there are two important sub-groups of variables: FAMU bachelor of arts (BA) degree recipients and pupils taught by a FAMU BA recipient. We refer to the former as "teacher" variables, while the latter are referred as "pupil" variables.

Teacher files contain data on FAMU bachelor's degree graduates. We limit the sample to teachers who graduated from college during the academic years 2001-2002 to 2005-2006; teacher experience ranges from 1 to 5 years. The teacher sample is limited to persons teaching mathematics or English courses. Pupil files contain only pupils in mathematics and English

courses taught by FAMU graduates during 2001-2002 to 2005-2006, though FCAT scores are often available for 1998-1999 to 2006-2007. Teachers and pupils are merged via a common course identification number. The composition of pupils varies across years, though a small number of pupils may be observed for multiple years if, coincidentally, a pupil is in 2 or more annual mathematics or English courses taught by recent FAMU graduates.

The elementary school sub-sample is limited to sixth graders. The complete elementary school sample contains no third grade pupils, just 2 fourth grade pupils, 31 fifth grade pupils, but 15,123 sixth grade pupils. Both fourth grade pupils are taught by a teacher with a mathematics education degree. Twenty-six of the fifth graders are taught by a teacher with an elementary education degree, 1 by a teacher with an English education degree, and 4 by a teacher with a natural sciences degree. Developmental scale scores rise with the pupil's grade level. There are only 33 observations for grades 3 thru 5 and 83 percent of these pupils are taught by a teacher with an elementary education degree and 87 percent of pupils are under the tutelage of an EDU trained teacher. So, lower grade status is nearly coincident with a teacher having an EDU degree. Including these observations in the sample would increase the likelihood of finding a negative and statistical significant effect for teachers with an EDU degree, confounding an EDU effect with a grade effect.

Tables 1a – 1c present descriptive statistics by educational cohort: elementary school (grades 6), middle school (grades 7 and 8), and high school (grades 9 – 12). Elementary education includes 88 teachers and 26 school districts. There are 23 districts and 66 middle school teachers and 20 districts and 58 high school teachers.

[Insert Tables 1a – 1c]

When we include the race and gender characteristics of the pupils, there are no

observations for 2005-06.

Persons with EDU degrees have majors in the following areas: elementary, English, mathematics, business, music, physical education, science, and social science. Elementary education (the omitted category) is the dominant EDU major. Fifty-nine percent of elementary pupils have EDU teachers, 49 percent of middle school pupils have EDU teachers, and 34 percent of high school pupils have EDU teachers.

Thirty-seven percent of elementary teachers are elementary education majors, while 7 percent and 12 percent of middle and high school teachers, respectively, have degrees in elementary education.⁵ This suggests that some teachers with elementary education college majors have passed state certification examinations allowing them to teach in middle and high school. Among elementary, middle, and high school teachers, 16 percent, 42 percent, and 21 percent, respectively, have English or mathematics education degrees. Less than 1 percent of elementary school teachers have a professional education college major, that is, a college major in business education or physical education, and just over 5 percent have a science education or social science education college major. Less than 1 percent of middle school teachers have a professional education college major and no teacher has a science education or social science education college major. Less than 1 percent of high school teachers have a professional education major and less than 1 percent have a science or social science major.

Among Non-EDU teachers, collegiate academic majors include:
engineering (electrical, industrial, mechanical, and civil),
natural sciences (mathematics, physics, and biology),
social scientists (psychology, criminal justice, economics, political science, and sociology);
humanities (drama, Spanish, English, history, music performance, philosophy and religion, and

African American studies); and, professional (journalism, magazine production, public relations, health administration, medical records administration, occupational therapy, business administration, computer science, agricultural business, accounting, health performance, graphic design, graphic arts, and social work).

Among Non-EDU elementary education teachers, individuals with professional degrees and social sciences degrees represent 22 percent and 10 percent of teachers, with humanities and natural science majors representing 1 percent and 8 percent, respectively, of all elementary teachers. Pupils with professional degrees also provide the dominant alternative path to middle school teaching, representing 17 percent of all teachers. Humanities majors are 10 percent of all middle school teachers, while natural and social science majors represent 11 percent, each, of all middle school teachers. Teachers with humanities and professional degrees are 28 percent and 18 percent, respectively, of all high school teachers, while natural and social science majors are about ½ percent and 9 percent, respectively, of all high school teachers.

Regardless of educational cohort, at least 90 percent of the teachers in our sample are African American. Teachers average about 2 years of teaching experience, are 26 years of age, and do not have an advanced degree. The minimum to maximum age range of these inexperienced teachers are 22 – 51 (elementary school), 22 – 51 (middle school), and 21 – 36 (high school). Nine percent, 4 percent, and 1 percent of elementary pupils have teachers with master's degrees from FAMU, Florida State University (FSU), and the University of Central Florida (UCF), respectively. Nine percent, 3 percent, and 2 percent of middle school pupils have teachers with master's degrees from FAMU, FSU, and UCF, respectively. Five and 2 percent, respectively of high school pupils have teachers with master's degrees from FAMU and UCF.

Elementary and middle school pupils have teachers with the highest level of pre-college ability. At 461 and 441, the SAT mathematics and verbal scores of high school teachers is lower than the SAT mathematics and verbal scores of elementary (467 and 484) and middle school teachers (465 and 478).

FAMU education graduates teach in schools with extremely high levels of pupil racial and ethnic segregation. African American males and females are 41 percent and 23 percent, respectively, of elementary pupils, while white males and females are 12 percent and 11 percent and Latinos and Latinas are 6 percent and 5 percent, respectively. African American males and females are 26 percent and 27 percent, respectively, of middle school pupils, while white males and females are 14 percent each and Latinos and Latinas are 11 percent and 9 percent, respectively. African American males and females are 32 percent each of high school pupils, while white males and females are 12 percent and 8 percent and Latinos and Latinas are 6 percent each.

B. Persistence in teaching

The data do not show evidence that persistence in the teaching profession varies by the college major of the teacher. Table 2 presents descriptive statistics on persistence in teaching for the mathematics and reading teachers included in our sample. However, given the small number of new entrants we cannot use the usual asymptotic tests of statistical significance. During 2001 two non-education majors and two education majors began their teaching careers in elementary school, 3 non-education majors and 3 education majors began their teaching careers in middle school, and 3 non-education majors and 5 education majors began their teaching careers in middle schools. Five years is the maximum potential measure of persistence for 2001-2002 new entrants who remained within the Florida public education system until the 2005-2006 academic

year. For 2001-2002 elementary school teachers, the mean lengths of persistence are 4.50 (non-education major) and 3.67 (education major), while the mean lengths of persistence for 2001-2002 middle school teachers are 2.33 and 4.00 years, respectively, and 4.00 and 5.00 years, respectively for high school teachers.

For all grade levels, mean persistence is greater among non-education majors who entered the profession during 2002-2003. But, for 2003-2004 new entrants mean persistence is higher among education majors teaching in elementary and high schools and nearly equal to non-education majors teaching in middle school. Finally, for 2004-2005, mean persistence is 1.50 years (non-education majors) and 1.60 years (education majors) for elementary school teachers.

[Insert Table 2]

C. Teachers' academic coursework⁶

Mason (2010) shows that non-education and education majors studied many similar language, literature, and reading courses. However, there are sometimes large differences in academic content and pedagogical courses taken by these differentially trained teachers. For example, 1.69 percent of elementary school teachers who were non-education majors completed a course in Language Arts for Middle and Secondary School and Children's Literature, respectively, while 12.35 percent and 60.49 percent of education majors completed these courses. Similarly, 5.48 percent and 1.37 percent of middle school teachers who were non-education majors completed a course in Language Arts for Middle and Secondary School and Children's Literature, respectively, while 25 percent and 31.82 percent of middle school teachers who were education majors completed college courses in these subjects. For high school teachers who were not education majors in college 8.62 percent and 1.72 completed these courses, while 23.68 percent and 31.58 percent of high school teachers who were education majors completed a

course in Language Arts for Middle and Secondary School and Children's Literature, respectively.

The fraction of non-education and education majors completing a course in Literature for Young Adults was 6.78 percent and 12.35 (elementary school), 13.70 percent and 27.27 percent (middle school), and 10.34 percent and 23.68 percent (high school), respectively.

Just over 5 percent of elementary school teachers who were non-education majors completed a course in the Foundations of Reading Instruction, nearly 8.5 percent completed a course in Developmental Reading in Secondary School, and none studied Diagnosing Reading. By contrast, 59 percent, 28 percent, and 49 percent, respectively, of elementary school teachers who were education majors completed these pedagogical courses. There were similar differentials among middle school and high school teachers.

There was substantial variation in the fraction of non-education and education majors completing at least 8 courses with an education prefix (Mason, 2010). Consider middle school teachers. Less than 1.5 percent of non-education majors but nearly 41 percent of educational majors studied Theory and Practice of Teaching I, while about 32 percent and 57 percent of non-education and education majors, respectively, completed the Introduction to Education course. Just under 7 percent and over 16 percent of non-education majors studied Educational Psychology and Foundations of Education, while nearly 30 percent and 50 percent of education majors completed these classes. Other course completion rates for non-education and education majors, respectively, are 25 percent and 68 percent (Educational Technology), 11 percent and 45 percent (Computer Applications in Education), 19 percent and 66 percent (General Methods in Secondary Education), and 4 percent and 41 percent (Internships, Practicums, and Clinical Practice).

Both non-education majors and education majors study a wide variety of mathematics courses, especially alternative algebra, geometry, and trigonometry courses. Nearly all college students have taken one or more of these courses as middle and high school pupils. Calculus however is generally reserved for college. Non-education and education majors differ considerably in their completion of an introductory calculus course, viz., Calculus for Business and Social Sciences I, Calculus I, and Calculus with Analytic Geometry II. These calculus courses are rough substitutes and whether a college student takes one or the other depends on high school preparation and college major. Among high school teachers who were not education majors, about 35.5 percent completed an introductory calculus course, while 18.4 percent of high school teachers who were education majors completed an introductory calculus course. (There are similar differences for elementary and middle school teachers). High school teachers who were education majors were much more likely to have studied courses in mathematics pedagogy; 29 percent and 13 percent completed Teaching Elementary School Mathematics I and Teaching Middle and Secondary School Mathematics. By comparison, 1.72 percent of non-education majors completed Teaching Elementary School Mathematics I and Teaching Middle and Secondary School Mathematics, respectively.

IV. Results

Tables 3 – 8 present alternative versions of equations (1) and (2). Tables 3 (elementary school), 4 (middle school), and 5 (high school) provide estimates of equation (1’), that is, a baseline achievement specification of the student academic achievement process. Although the results are not presented here, we have also estimated annual gain and contemporaneous specifications models of student academic achievement (equation 1’). We regard the baseline achievement model as the preferred specification. However, because it requires at least three

years of data, we also rely on the annual gain specification to establish the robustness of our results. The latter specification requires only 2 years of data on pupil test scores and, therefore, has more observations per regression.

A. Teacher preparation as a binary process

1. Elementary school

Table 3 present selected results for elementary school pupils for the baseline achievement specifications of equation (1). For all regressions, teacher preparation is modeled as a binary treatment where educational degree = 1 if the teacher obtained a professional education unit (EDU) degree and educational degree = 0 if the teacher has a Non-EDU degree.

p-values are included in brackets beneath the coefficient estimates. The predicted baseline achievement measures ($A_{i,t-1}$) are Mathss $_{t-1}$, Readss $_{t-1}$, Mathnrt $_{t-1}$, and Readnrt $_{t-1}$. Our estimates of pupil achievement persistence ($\hat{\alpha}$) is the coefficient on the baseline achievement measure. In each instance, we may reject the null hypothesis $\alpha = 0$, that is, the contemporaneous model of the pupil achievement equation is not supported by the data. Further, we reject at the 5 percent level of significance the null hypothesis $\alpha = 1$, that is, the annual gain model of the pupil achievement equation is not supported by the data.⁷ Accordingly, for elementary school pupils, the baseline achievement model is the empirically selected approach for modeling pupil academic achievement.

[Insert Table 3]

Table 3 shows that when the dependent variable is the pupil's mathematics score – Sunshine State standards, the coefficient on EDU degree is negative but statistically insignificant. Specifications (i) – (iii) have considerably more observations than specifications (iv) – (vi). Column (i) is the basic specification, where the explanatory variables include the

predicted value of the lagged test score, EDU status, mean peer score, and class size. All pupils are 6th graders. The second specification (dist) adds school district fixed effects to the list of explanatory variables, while the third regression (tchar) adds both school district fixed effects and teacher characteristics to the basic equation. The next specification (tcharstu) includes all of the explanatory variables in column (iii) as well as pupil characteristics. Hence, for specifications (i) – (iv) each regression encompasses the previous regression and specification (i) includes the least number of explanatory variables. The explanatory variables of the penultimate specification (tchar2), adds school district fixed effects, teacher characteristics, and teacher’s SAT scores to the basic equation. The final column presents the results of the most comprehensive regression (tcharstu2), the explanatory variables are identical to column (iv) except this specification also includes teacher’s SAT scores.

For the basic specification, elementary pupils with EDU trained teachers score about 11 points (0.0451 standard deviations) lower on the mathematics – Sunshine State standards portion of the FCAT than otherwise identical elementary pupils whose teacher has a Non-EDU degree. With district fixed effects (dist) this differential rises to 17 points, but if we include district fixed effects and teacher characteristics (tchar) to the basic equation the disadvantage of having a EDU trained teacher is about 16 points. Our most comprehensive specification (tcharstu2) adds district fixed effects, teacher and student characteristics, and teacher’s college entrance scores (SAT) to the regression. In this case, we find that elementary pupils with EDU trained teachers score 19 points (0.0779 standard deviations) lower on the mathematics – Sunshine State standards portion of the FCAT than otherwise identical elementary pupils whose teacher has a Non-EDU degree. Hence, limiting our analysis to sixth grade, the best point estimates show a 17 – 18 point disadvantage on the mathematics – Sunshine State standards portion of the FCAT for elementary

pupils with a EDU trained teacher. However, the estimates are not statistically significant.

The annual gain specifications (not shown) show a negative and statistically insignificant value-added effect for the mathematics – Sunshine State standards performance of pupils with EDU trained teachers, ranging from 29 – 55 points (0.1186 – 0.2254 standard deviations). Although our hypothesis tests show that this is not the appropriate specification, the annual gain model is able to take advantage of a larger number of observations. Similarly, the contemporaneous specification (not shown) has the largest number of observations and is also empirically rejected as the appropriate specification. The coefficient on EDU degree is statistically insignificant in all specifications of the contemporaneous model.

The baseline achievement model (Table 3) shows that when the dependent variable is the pupil’s reading score – Sunshine State standards, the coefficient on EDU degree is negative and statistically insignificant. The annual gain specifications sometime yield a statistically significant value-added effect associated with reading – Sunshine State standards performance of pupils with EDU trained teachers, ranging from -24 points to 173 points. However, this coefficient is insignificant in the preferred specification (tcharstu2). For the contemporaneous models the coefficient on EDU degree is statistically insignificant, mostly negative, and substantively small in all specifications.

Summing up, for elementary school pupils (6th grade), our best evidence suggests little or no marginal effect associated with EDU status.

2. Middle school

Tables 4 presents selected results for middle school pupils for the baseline achievement specifications of equation (1). In each instance, the data reject the null hypothesis $\alpha = 0$, that is, the contemporaneous model of the pupil achievement equation is not supported by the data.

Further, the data reject the null hypothesis $\alpha = 1$, that is, the annual gain model of the pupil achievement equation is not supported by the data.⁸ For middle school pupils, the baseline achievement model is the empirically selected approach for modeling pupil academic achievement.

Consider pupil's mathematics score – Sunshine State standards. When we include teacher's SAT scores as explanatory variables (tchar2), the baseline achievement specifications show the coefficient on EDU degree is statistically insignificant. Ignoring SAT scores, middle school pupils with EDU trained teachers score 15 points higher on the mathematics – Sunshine State standards portion of the FCAT than otherwise identical elementary pupils whose teacher has a Non-EDU degree. The contemporaneous specifications (not shown) have the opposite pattern: significantly significant effects (37 – 40 points) only for the regressions including SAT scores. The annual gain specifications (not shown) suggest a 25 – 32 point value added for EDU trained teachers.

[Insert Table 4]

The baseline achievement model shows that when the dependent variable is the pupil's reading score – Sunshine State standards, the coefficient on EDU degree is statistically insignificant. The annual gain specifications yields a statistically significant 24 - 41 point value-added effect associated with reading – Sunshine State standards performance of pupils with EDU trained teachers. For the contemporaneous specification the coefficient on EDU degree is statistically significant for the basic regression and for the regressions which include SAT score, suggesting that middle school pupils with a EDU trained teacher score 15 – 40 points higher on reading – Sunshine State standards of the FCAT than otherwise identical student.

The tcharstu2 specification of the baseline achievement model is our preferred equation.

This specification suggests no value-added differential associated with middle school pupils having a EDU or Non-EDU trained teacher.

3. High School

Table 5 presents selected results for high school pupils for the baseline achievement specifications of equation (1). The data reject the contemporaneous and annual gain models of the pupil achievement equation. For high school pupils, the baseline achievement model is the empirically selected approach for modeling pupil academic achievement.

The baseline achievement and contemporaneous specifications (not shown) show that a teacher's EDU status has a statistically insignificant effect on a high school pupil's mathematics – Sunshine State standards test scores. The annual gain specifications suggest a 12 – 14 point effect on high school pupil's mathematics – Sunshine State standards associated with a EDU degree.

[Insert Table 5]

When the dependent variable is the pupil's reading score – Sunshine State standards, the coefficient on EDU degree is statistically insignificant for the baseline achievement and contemporaneous specifications. For the annual gain specifications there is a 22 – 30 point increase in reading – Sunshine State standards test scores for high school pupils when their teacher has EDU college degree.

Using the preferred empirical specification, *tcharstu2* of the baseline achievement model, there is no statistically significant academic achievement differential associated with high school pupils having an EDU or Non-EDU trained teacher.

B. Teacher preparation as a multivariate process

1. Elementary school

Moving from a binary specification of teacher preparation to a multivariate approach to teacher preparation has no effect on our underlying statistical specification of pupil learning outcomes. In particular, our hypothesis tests continue to reject both the annual gain and contemporaneous specifications of pupil academic achievement. Given these results and data limitations (and to conserve space), we restrict our presentation and discussion of the multivariate approach to the baseline achievement model with FCAT-Sunshine State standards test scores as the dependent variable.

There are negative, statistically significant, and large effects on elementary pupil (grade 6) achievement (especially mathematics) when the teacher does not have an elementary education college degree (Table 6). Consider first mathematics – Sunshine State standards test score differentials associated with alternative majors within the college of education. For elementary school pupils taught by teachers with collegiate majors in either English education or mathematics education and for elementary school pupils taught by teachers with collegiate majors in professional educational disciplines (business education or physical education), test scores are 81 points and 170 points (0.33 and 0.70 standard deviations) less, respectively, than pupils taught by teachers with a specialty in elementary education.

There are negative, statistically significant, and large differentials for alternative Non-EDU majors. In comparison to 6th grade teachers who majored in elementary education, the mathematics – Sunshine State test score differentials for social science, humanities, and professional studies majors are -58 points (-0.24 standard deviations), -38 points (-0.16 standard deviations), and -12 points (-0.05 standard deviations), respectively.

Considering reading-Sunshine State standards, Table 6 does not show statistically significant results for alternative majors within the college of education. Among majors outside

the college of education, pupils taught by teachers with majors in the social sciences and professional studies have test scores that are 108 points lower (-0.44 standard deviations) and 30 points higher (0.12 standard deviations), respectively, than the reading scores of pupils taught by teachers with an elementary education college major.

[Insert Table 6]

2. Middle school

The baseline achievement model presents strong evidence of greater mathematics achievement among middle school pupils assigned to teachers with college majors other than elementary education (Table 7). Contrarily, except for the social sciences, a teacher's collegiate major has no statistically significant effect on a middle school pupil's reading achievement. For mathematics – Sunshine State standards, middle school pupils enrolled in the class of a teacher who majored in English education or mathematics education score 85 points (0.41 standard deviations) higher than otherwise identical pupils enrolled in a class of a teacher who majored in elementary education. The marginal effect on a middle school pupil's mathematics – Sunshine State standards score for teachers with degrees in natural sciences, social sciences, and humanities is 95 points (0.46 standard deviations), 222 points (1.07 standard deviations), and 154 points (0.74 standard deviations), respectively.

For reading – Sunshine State standards, middle school pupils enrolled in the class of a teacher who majored in a social science score 131 points (0.49 standard deviations) higher than otherwise identical pupils enrolled in a class of a teacher who majored in elementary education.

Elementary education majors teaching middle school mathematics courses are not as productive as other college majors, both within the college of education and between the college of education and other academic units. Except for teachers majoring in a social science,

elementary education majors teaching middle school readings courses are equally productive as other college majors, both within the college of education and between the college of education and other academic units.

[Insert Table 7]

3. High School

The baseline achievement model presents statistically significant and substantively large evidence of greater mathematics and reading achievement among high school pupils assigned to teachers with college majors other than elementary education (Table 8). Within the college of education, for mathematics and reading – Sunshine State standards, high school pupils enrolled in the class of a teacher who majored in English education or mathematics education score 53 points (0.30 standard deviations) higher and 114 points (0.41 standard deviations) higher, respectively, than otherwise identical pupils enrolled in a class taught by a teacher who majored in elementary education. But, the mathematics effect is statistically insignificant.

Among Non-education majors, the respective marginal effects on a high school pupil's mathematics and reading – Sunshine State standards scores are: 34 points (0.19 standard deviations) and 89 points (0.32 standard deviations) for engineering majors; 0.23 points (insignificant) and 129 points (0.88 standard deviations) for natural sciences majors; 107 points (0.60 standard deviations) and 177 points (0.64 standard deviations) for social sciences; 29 points (insignificant) and 54 points (0.20 standard deviations) for humanities majors; and, 86 points (0.49 standard deviations) and 112 points (0.41 standard deviations) for professional studies majors.

[Insert Table 8]

Elementary education majors teaching high school mathematics and reading courses are

not as productive as other college majors, both within the college of education and between the college of education and other academic units.

V. Discussion

This study has examined whether there is differential productivity associated with teachers trained within Florida Agricultural & Mechanical University's College of Education (EDU) relative to other colleges and schools affiliated with the same university. We also examined whether there is differential productivity associated with alternative majors within and between the College of Education and other academic units. We measure the productivity of a teacher by the educational achievement of pupils assigned to that teacher during a given year.

Some weaknesses of the study include the following. We have no information on the productivity of new FAMU teachers employed outside the state of Florida or persons with education degrees who opted for careers outside of teaching. Also, we do not have a productivity measure for teachers of subjects other than reading and mathematics.

Considered broadly, at the level of major academic units such as colleges and schools, differences in teacher preparation do not appear to matter with respect to student academic achievement. There are no inter-college effects for teacher preparation for either mathematics or reading among elementary, middle, and high school pupils.

Statistically significant and substantively large effects emerge when we consider specific academic majors, rather than the broadly defined groups of education majors and non-education majors. When elementary pupil mathematics achievement is measured via the Sunshine State standards of the Florida Comprehensive Assessment Test, pupils whose teachers majored in English education or mathematics education or business education or physical education scored 0.33 or 0.70 standard deviations lower, respectively, than otherwise identical pupils taught by a

teacher who majored in elementary education. English and mathematics education, as well as business education, and physical education are components of FAMU's secondary education program.

In comparison to 6th grade teachers who majored in elementary education, the mathematics – Sunshine State test score differentials for social science, humanities, and professional studies majors are -0.24 standard deviations, -0.16 standard deviations, and -0.05 standard deviations), respectively. Additionally, pupils taught by teachers with majors in the social sciences and professional studies have test scores that are 0.44 standard deviations lower and 0.12 standard deviations higher, respectively, than the reading scores of pupils taught by teachers with an elementary education college major.

For middle school pupils, our best equation shows greater mathematics and reading achievement (as measured by the FCAT's Sunshine State standards) associated with teachers who did not major in elementary education in college. There is a 0.41 standard deviation increase in mathematics scores associated with teachers who were English education or mathematics education majors in college. Among non-education majors, relative to elementary education majors, the marginal effects measured in standard deviations are 0.46 (natural sciences), 1.07 (social sciences), and 0.74 (humanities). For reading – Sunshine State standards, middle school pupils enrolled in the class of a teacher who majored in a social science score 0.49 standard deviations higher than otherwise identical pupils enrolled in a class of a teacher who majored in elementary education.

When we measure high school pupil academic achievement by the FCAT's Sunshine State standards, our results suggest that pupils taught by teachers who were elementary education in college do not perform as well as students taught by secondary education majors and non-

education majors. In particular, for mathematics – Sunshine State standards, the value-added by teachers with an English education or mathematics education degree is 0.30 standard deviations. For high school pupil reading achievement – Sunshine State standards, the value-added effects are: English education or mathematics education (0.41 standard deviations), engineering (0.32 standard deviations), natural sciences (0.88 standard deviations), social sciences (0.64 standard deviations), humanities (0.20 standard deviations), and professional studies (0.41 standard deviations).

In conclusion, among students taught by recent Florida A & M University teachers, there is greater academic achievement among elementary school (grade 6) pupils taught by a teacher with a college major in elementary education than among elementary school pupils taught by a teacher with a college major in either secondary education or a non-education subject area. However, relative to secondary education and non-education majors, elementary education majors provide less value-added in middle school and high school. Future studies will attempt to determine the value-added of specific courses taken by education and non-education college majors.

Notes

¹ For example, during the 2002 elections citizens voted to limit class size. This is an important reform but certainly not the only needed reform.

² Teach for America (TFA) is a national program. According to its web site, TFA recruits “outstanding recent college graduates from all backgrounds and career interests to commit to teach for two years in urban and rural public schools (Teach for America, 2009).” TFA provides an intensive 5-week summer training program for incoming teachers as well as in-service training during the teacher’s 2-year commitment. Summer training includes practice teaching sessions and pedagogical guidance related to six broad themes: teaching as leadership; instructional planning and delivery; classroom management and culture; diversity, community, and achievement; learning theory; and, literacy development.

The New York City Teaching Fellows (TF) program is specific to that city. TF targets recent college graduates and mid-career professionals. TF participants receive introductory (usually summer) and in-service training. Training lasts for two years.

The New York City Department of Education and the City University of New York (CUNY) sponsors the Teaching Opportunity Plan (TOP). Participants must complete an intensive program run by CUNY, which includes coursework and experiences in NYC schools. Boyd, et al. (2006: 182) report that “TOP participants generally complete their requirements for certification and an master’s degree in two to three years, after which they are committed to teaching in NYC public schools for an additional two years.”

Teachers certified through individual evaluation undergo the same training as traditionally certified teachers (Boyd, et al., 2006: 180). However, the requirements are not

fulfilled at a single university and some requirements may be fulfilled via distance learning. If all requirements are successfully met, the State Department of Education provides certification for the individual teacher.

Teachers with a temporary license are the teacher of record for a class. They do not have permanent state certification. These teachers are allocated to schools experiencing a teacher shortage. Modifications to this program required temporary license teachers to have “completed at least twenty-seven credit hours of a preparation program and must be actively moving toward certification. In addition, they cannot teach in low-performing schools, and their licenses are valid only for one year and are currently set to expire following the 2004–5 school year (Boyd, et al., 2006: 180).”

³ Constantine, et al. (2009) is very much less sanguine regarding the productivity of traditionally certified teachers relative to alternatively certified teachers. This study reports: 1) no statistically significant difference in reading and mathematics achievement between students of traditional and alternatively certified teachers; 2) variation in the quantity of teacher training coursework has no effect on student academic performance; and, 3) the content of teacher coursework (either mathematics pedagogy, reading pedagogy, or fieldwork) has no significant effect on student test scores and there is no statistically significant effect associated with a teaching majoring in education. These claims have been vigorously challenged (Darling-Hammond, 2009; Corcoran and Jennings, 2009). Critics claim that the Constantine et al. study lacks internal validity, external validity, and an accurate interpretation of the results.

⁴ Of course, schools may also have Non-EDU teachers because there is a shortage of EDU trained teachers.

⁵ We are being a bit imprecise in our language. Since pupils are the units of analysis, it's 60 percent and 81 percent of middle school pupils have EDU teachers. The text trades off this cumbersome but precise language for language that is less cumbersome but a bit imprecise.

⁶ The teachers included here are all recent FAMU Bachelor of Arts degree graduates who are assigned Florida Education Data Warehouse employee identification number, rather than only those teaching reading and mathematics courses.

⁷ The p-values for specifications of the annual gain model are not presented here, but are available upon request to interested readers.

⁸ The p-values for specifications of the annual gain model are not presented here, but are available upon request to interested readers.

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Table 1a. Descriptive Statistics, Elementary School: 2001-2002 thru 2005-2006

	N	Mean	Std. Dev.	Min	Max
Teachers	88				
Districts	26				
FCAT - SSS, mathematics	7633	1581	244	770	2492
FCAT - SSS (reading)	7456	1561	294	539	2758
Class size	15123	11.42	3.74	1	22
Elementary education	15123	0.3653	0.4815	0	1
English education	15123	0.0951	0.2933	0	1
Mathematics education	15123	0.0678	0.2515	0	1
Business education	15123	0.0001	0.0081	0	1
Physical education	15123	0.0084	0.0913	0	1
Social science education	15123	0.0518	0.2216	0	1
Engineer	15123	0.0000	0.0000	0	0
Natural science	15123	0.0768	0.2663	0	1
Social science	15123	0.1049	0.3064	0	1
Humanities	15123	0.0120	0.1087	0	1
Professional	15123	0.2179	0.4128	0	1
Teacher, white	15123	0.0735	0.2609	0	1
Teacher, Hispanic	15123	0.0192	0.1371	0	1
Teacher, other race	15123	0.0197	0.1390	0	1
Teacher, male	15123	0.1197	0.3246	0	1
Experience	15123	2.45	1.24	0	5
Teacher, age	15123	25.95	2.99	22	51
Master's degree, FAMU	15123	0.0857	0.2799	0	1
Master's degree, FSU	15123	0.0382	0.1916	0	1
Master's degree, UCF	15123	0.0111	0.1048	0	1
SAT (mathematics)	8086	467	62.76	330	610
SAT (verbal)	8086	484	67.63	280	680
African American female	15123	0.2256	0.4180	0	1
White male	15123	0.1225	0.3279	0	1
White female	15123	0.1094	0.3122	0	1
Latino	15123	0.0565	0.2308	0	1
Latina	15123	0.0518	0.2216	0	1
Native American	15123	0.0016	0.0398	0	1
Asian American	15123	0.0098	0.0984	0	1
Mixed race	15123	0.0158	0.1247	0	1
Free or reduced lunch	11990	0.6590	0.4741	0	1
Limited English	11990	0.0389	0.1935	0	1
Limited English, but left LEP	11990	0.0797	0.2709	0	1
grade6	15123	1.0000	0.0466	0	1

Table 1b. Descriptive Statistics, Middle School: 2001-2002 thru 2005-2006

	N	Mean	Std. Dev.	Min	Max
Teachers	66				
Districts	23				
FCAT - SSS, mathematics	5794	1723	207	958	2572
FCAT - SSS (reading)	5823	1654	267	671	2767
Class size	11617	11.25	4.27	1	25
Elementary education	11617	0.0713	0.2573	0	1
English education	11617	0.3190	0.4661	0	1
Mathematics education	11617	0.1007	0.3010	0	1
Business education	11617	0.0000	0.0000	0	0
Physical education	11617	0.0033	0.0571	0	1
Social science education	11617	0.0000	0.0000	0	0
Engineer	11617	0.0230	0.1499	0	1
Natural science	11617	0.1067	0.3087	0	1
Social science	11617	0.1112	0.3144	0	1
Humanities	11617	0.0960	0.2946	0	1
Professional	11617	0.1689	0.3747	0	1
Teacher white	11617	0.0491	0.2160	0	1
Teacher Hispanic	11617	0.0290	0.1678	0	1
Teacher, other race	11617	0.0000	0.0000	0	0
Teacher, male	11617	0.1698	0.3754	0	1
Experience	11617	2.00	1.05	0	4
Teacher, age	11617	25.68	3.50	22	51
Master's degree, FAMU	11617	0.0925	0.2897	0	1
Master's degree, FSU	11617	0.0281	0.1652	0	1
Master's degree, UCF	11617	0.0168	0.1285	0	1
SAT (mathematics)	7483	465	72	230	610
SAT (verbal)	7483	478	80	240	630
African American female	11617	0.2687	0.4433	0	1
White male	11617	0.1401	0.3471	0	1
White female	11617	0.1393	0.3463	0	1
Latino	11617	0.1059	0.3077	0	1
Latina	11617	0.0879	0.2831	0	1
Native American	11617	0.0000	0.0000	0	0
Asian American	11617	0.0000	0.0000	0	0
Mixed race	11617	0.0000	0.0000	0	0
Free or reduced lunch	10634	0.5759	0.4942	0	1
Limited English 1	10634	0.0457	0.2088	0	1
Limited English 2	10634	0.1072	0.3094	0	1
Grade 7	11617	0.6070	0.4884	0	1
Grade 8	11617	0.3930	0.4884	0	1

Table 1c. Descriptive Statistics, High School: 2001-2002 thru 2005-2006

	N	Mean	Std. Dev.	Min	Max
Teachers	58				
Districts	20				
FCAT - SSS, mathematics	6042	1859	177	1068	2596
FCAT - SSS (reading)	6910	1777	275	772	2943
Class size	13028	9.78	4.45	1	24
Elementary education	13028	0.1200	0.3250	0	1
English education	13028	0.1024	0.3032	0	1
Mathematics education	13028	0.1031	0.3041	0	1
Business education	13028	0.0000	0.0000	0	0
Physical education	13028	0.0061	0.0781	0	1
Social science education	13028	0.0075	0.0864	0	1
Engineer	13028	0.1121	0.3156	0	1
Natural science	13028	0.0061	0.0776	0	1
Social science	13028	0.0881	0.2835	0	1
Humanities	13028	0.2772	0.4477	0	1
Professional	13028	0.1772	0.3819	0	1
Teacher white	13028	0.0290	0.1679	0	1
Teacher Hispanic	13028	0.0000	0.0000	0	0
Teacher, other race	13028	0.0061	0.0781	0	1
Teacher, male	13028	0.3009	0.4587	0	1
Experience	13028	2.17	1.14	0	4
Teacher, age	13028	25.76	2.58	22	36
Master's degree, FAMU	13028	0.0484	0.2145	0	1
Master's degree, FSU	13028	0.0000	0.0000	0	0
Master's degree, UCF	13028	0.0168	0.1286	0	1
SAT (mathematics)	8073	461	110	230	660
SAT (verbal)	8073	441	96	240	610
African American female	13028	0.3169	0.4653	0	1
White male	13028	0.1162	0.3205	0	1
White female	13028	0.0860	0.2803	0	1
Latino	13028	0.0805	0.2721	0	1
Latina	13028	0.0792	0.2701	0	1
Native American	13028	0.0000	0.0000	0	0
Asian American	13028	0.0000	0.0000	0	0
Mixed race	13028	0.0000	0.0000	0	0
Free or reduced lunch	8704	0.4324	0.4954	0	1
Limited English 1	8704	0.0609	0.2391	0	1
Limited English 2	8704	0.1127	0.3163	0	1
Grade 9	13028	0.4695	0.4991	0	1
Grade 10	13028	0.3350	0.4720	0	1
Grade 11	13028	0.1352	0.3420	0	1
Grade 12	13028	0.0602	0.2378	0	1

Table 2. Persistence for math and reading teachers by year of entry, grade, & college major

Year	Non-Education Major			Education Major		
	New Entrants	Length	Potential Maximum	New Entrants	Length	Potential Maximum
Elementary School						
2001	2	4.50	5.00	2	3.67	5.00
2002	6	3.17	4.00	10	2.60	4.00
2003	9	2.11	3.00	13	2.23	3.00
2004	21	1.50	2.00	10	1.60	2.00
2005	15	1.00	1.00	11	1.00	1.00
Middle School						
2001	3	2.33	4.00	3	4.00	4.00
2002	11	2.18	3.00	8	1.88	3.00
2003	11	1.64	2.00	11	1.63	2.00
2004	21	1.00	1.00	7	1.00	1.00
High School						
2001	3	4.00	4.00	5	2.40	4.00
2002	4	2.75	3.00	3	2.33	3.00
2003	15	1.71	2.00	4	2.00	2.00
2004	19	1.00	1.00	6	1.00	1.00

Table 3. Binary education treatment: baseline achievement specification, elementary school pupils

	Mathematics-Sunshine State standards						Reading-Sunshine State standards					
	basic	Dist	tchar	tcharstu	tchar2	tcharstu2	basic	dist	Tchar	tcharstu	tchar2	tcharstu2
Educdegr	-10.75	-17.21	-7.12	-9.24	-15.87	-18.78	-6.92	-10.1	-3.1	-6.38	-8.28	-5.24
	[0.190]	[0.025]	[0.472]	[0.465]	[0.126]	[0.146]	[0.343]	[0.228]	[0.771]	[0.606]	[0.523]	[0.727]
Mathsss _{t-1}	0.75	0.76	0.78	0.78	0.78	0.78						
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]						
Readsss _{t-1}							0.86	0.86	0.86	0.86	0.88	0.89
							[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
peer_masss	0.44	0.42	0.4	0.38	0.4	0.37						
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]						
peer_resss							0.33	0.3	0.29	0.25	0.26	0.17
							[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.001]
Observations	6092	6092	6092	4806	3201	2425	6263	6263	6263	5007	3286	2556
R-squared	0.542	0.548	0.552	0.547	0.57	0.549	0.563	0.567	0.568	0.563	0.577	0.577

Table 4. Binary education treatment: baseline achievement specification, middle school pupils

	Mathematics – Sunshine State standards						Reading – Sunshine State standards					
	Basic	Dist	tchar	tcharstu	tchar2	tcharstu2	basic	dist	tchar	tcharstu	tchar2	tcharstu2
Educdegr	8.22	14.36	14.75	15.03	-5.84	1.02	6.82	8.08	5.36	2.85	21.45	-5.17
	[0.059]	[0.019]	[0.022]	[0.028]	[0.646]	[0.940]	[0.232]	[0.313]	[0.521]	[0.755]	[0.169]	[0.767]
MathsssT1	0.72	0.73	0.73	0.71	0.81	0.79						
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]						
ReadsssT1							0.75	0.76	0.76	0.74	0.79	0.78
							[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
peer_masss	0.4	0.31	0.26	0.28	0.37	0.43						
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]						
peer_resss							0.41	0.4	0.37	0.34	0.3	0.38
							[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	4728	4728	4728	4377	3069	2853	4600	4600	4600	4216	2967	2717
R-squared	0.513	0.521	0.524	0.549	0.557	0.58	0.481	0.489	0.49	0.513	0.471	0.495

Table 5. Binary education treatment: baseline achievement specification, high school pupils

	Mathematics-Sunshine State standards						Reading-Sunshine State standards					
	basic	Dist	tchar	tcharstu	tchar2	tcharstu2	basic	dist	tchar	Tcharstu	tchar2	tcharstu2
Educdegr	12.2	13.54	12.4	13.05	2.55	14.36	9.56	9.06	6.68	5.2	24.85	5.6
	[0.149]	[0.184]	[0.229]	[0.290]	[0.870]	[0.512]	[0.294]	[0.401]	[0.583]	[0.719]	[0.175]	[0.785]
MathsssT1	0.68	0.69	0.69	0.68	0.77	0.75						
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]						
ReadsssT1							0.7	0.7	0.71	0.69	0.73	0.72
							[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
peer_masss	0.36	0.3	0.28	0.29	0.29	0.3						
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]						
peer_resss							0.36	0.33	0.32	0.3	0.29	0.28
							[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	4680	4680	4680	4337	3050	2840	4567	4567	4567	4195	2956	2712
R-squared	0.528	0.537	0.54	0.565	0.573	0.594	0.497	0.504	0.506	0.528	0.488	0.51

Table 6. Multivariate education treatment: baseline achievement specification, elementary school pupils

	Mathematics-Sunshine State standards						Reading-Sunshine State standards					
	Basic	Dist	tchar	tcharstu	tchar2	tcharstu2	basic	dist	tchar	Tcharstu	tchar2	tcharstu2
Engmatheduc	6.28	18.08	0.4	-24.04	-36.03	-80.51	12.45	23.9	23.99	32.77	7.18	6.44
	[0.636]	[0.041]	[0.971]	[0.024]	[0.031]	[0.000]	[0.348]	[0.024]	[0.126]	[0.062]	[0.769]	[0.843]
Profeduc	-4.05	20.55	0	0	-39.89	-170.1	53.72	70.72	22.55	29.52	0	0
	[0.493]	[0.015]	[.]	[.]	[0.231]	[0.000]	[0.000]	[0.000]	[0.424]	[0.442]	[.]	[.]
Libarteduc	4.03	60.22	151.41	0	0	0	-16.91	106.88	-132.27	30.85	0	0
	[0.517]	[0.032]	[0.000]	[.]	[.]	[.]	[0.041]	[0.000]	[0.000]	[0.176]	[.]	[.]
Engineer	0	0	0	0	0	0	0	0	0	0	0	0
	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]
Naturalsci	-2.67	11.16	-26.94	-14.18	-16.86	-7.23	-6.91	11.38	-5.99	34.65	-13.35	-18.88
	[0.755]	[0.279]	[0.085]	[0.386]	[0.193]	[0.595]	[0.554]	[0.223]	[0.608]	[0.027]	[0.381]	[0.215]
Socialsci	19.46	26.48	19.58	21.78	-46.42	-58.13	10.08	11.11	10.99	19.09	-94.1	-108.48
	[0.259]	[0.017]	[0.118]	[0.029]	[0.020]	[0.005]	[0.361]	[0.446]	[0.584]	[0.412]	[0.012]	[0.016]
Humanity	-32.13	-11.53	-27.22	-53.71	-28.18	-37.93	-18.09	-9.46	-12.61	-9.13	0.56	19.22
	[0.001]	[0.244]	[0.018]	[0.000]	[0.020]	[0.044]	[0.189]	[0.602]	[0.454]	[0.397]	[0.962]	[0.316]
Profess	17.51	31.03	11.86	-11.64	6.37	-12.37	16.29	22.15	22.51	32.54	27.32	29.7
	[0.079]	[0.003]	[0.197]	[0.264]	[0.395]	[0.084]	[0.082]	[0.041]	[0.095]	[0.023]	[0.054]	[0.034]
peer_masss	0.44	0.41	0.4	0.38	0.39	0.35						
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]						
peer_resss							0.32	0.28	0.29	0.24	0.24	0.14
							[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.004]
Mathsss _{t-1}	0.75	0.76	0.78	0.78	0.78	0.78						
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]						
Readsss _{t-1}							0.86	0.86	0.86	0.86	0.89	0.89
							[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	6092	6092	6092	4806	3201	2425	6263	6263	6263	5007	3286	2556
R-squared	0.543	0.549	0.554	0.548	0.572	0.552	0.564	0.568	0.569	0.564	0.579	0.58

Table 7. Multivariate education treatment: baseline achievement specification, middle school pupils

	Mathematics-Sunshine State standards						Reading-Sunshine State standards					
	basic	Dist	tchar	tcharstu	tchar2	tcharstu2	basic	dist	tchar	tcharstu	tchar2	tcharstu2
engmatheduc	18.41	8.62	4.31	43.84	29.39	84.68	-17.46	-27.09	26.58	-98.43	199.13	20.07
	[0.094]	[0.671]	[0.909]	[0.200]	[0.043]	[0.000]	[0.362]	[0.188]	[0.502]	[0.052]	[0.384]	[0.486]
profeduc	-6.3	-10.5	-27.16	-29.16	0	0	43.87	49.42	67.67	-60.43	0	0
	[0.402]	[0.621]	[0.481]	[0.325]	[.]	[.]	[0.017]	[0.022]	[0.096]	[0.189]	[.]	[.]
libarteduc	0	0	0	0	0	0	0	0	0	0	0	0
	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]	[.]
engineer	-3.01	-10.52	-26.5	-14.7	0	0	-33.8	-38.85	-23.13	-135.14	139.4	0
	[0.707]	[0.601]	[0.486]	[0.597]	[.]	[.]	[0.078]	[0.095]	[0.584]	[0.005]	[0.509]	[.]
naturalsci	2.63	-7.35	-16.1	23.31	-35.97	94.56	-11.72	-17.8	25.82	-101.16	243.14	35.48
	[0.780]	[0.774]	[0.694]	[0.496]	[0.203]	[0.003]	[0.586]	[0.479]	[0.504]	[0.036]	[0.350]	[0.617]
socialsci	-2.71	-15.5	-27.32	25.62	77.53	222.2	-29.62	-54.32	-10.96	-124.64	349.21	130.94
	[0.840]	[0.619]	[0.487]	[0.420]	[0.000]	[0.000]	[0.194]	[0.050]	[0.765]	[0.008]	[0.169]	[0.026]
humanity	14.76	0.04	-2.02	45.81	98.43	153.82	-14.63	-17.71	39.99	-70.24	229.3	73.08
	[0.125]	[0.998]	[0.960]	[0.195]	[0.000]	[0.000]	[0.428]	[0.399]	[0.328]	[0.153]	[0.332]	[0.124]
profess	3.63	-5.41	-5.84	22.55	-32.84	-11.79	-31.18	-46.77	13.46	-119.92	140.92	-45.34
	[0.732]	[0.802]	[0.873]	[0.499]	[0.080]	[0.618]	[0.134]	[0.041]	[0.722]	[0.013]	[0.547]	[0.343]
peer_masss	0.35	0.29	0.28	0.29	0.27	0.29						
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]						
peer_resss							0.35	0.32	0.31	0.29	0.27	0.27
							[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Mathsss _{t-1}	0.68	0.69	0.69	0.67	0.78	0.76						
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]						
Readsss _{t-1}							0.70	0.70	0.71	0.69	0.74	0.72
							[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	4680	4680	4680	4337	3050	2840	4567	4567	4567	4195	2956	2712
R-squared	0.529	0.537	0.54	0.566	0.58	0.604	0.498	0.505	0.507	0.529	0.491	0.513

Table 8. Multivariate education treatment: baseline achievement specification, high school pupils

	Mathematics-Sunshine State standards						Reading-Sunshine State standards					
	basic	Dist	tchar	tcharstu	tchar2	tcharstu2	basic	dist	tchar	tcharstu	tchar2	tcharstu2
engmatheduc	41.34	46.07	14.87	4.98	36.79	52.74	31.27	43.35	15.19	38.58	30.2	113.83
	[0.039]	[0.009]	[0.093]	[0.716]	[0.206]	[0.105]	[0.113]	[0.003]	[0.336]	[0.004]	[0.126]	[0.005]
Profeduc	16.53	16.91	8.46	-5.36	0	0	-19.15	-25.33	-29	-10.49	0	0
	[0.398]	[0.211]	[0.328]	[0.685]	[.]	[.]	[0.198]	[0.026]	[0.059]	[0.508]	[.]	[.]
Libarteduc	45.07	55.44	82.16	-44.55	0	0	9.82	3.86	26.6	136.7	0	0
	[0.027]	[0.003]	[0.000]	[0.019]	[.]	[.]	[0.762]	[0.821]	[0.243]	[0.000]	[.]	[.]
Engineer	18.82	14.68	7.38	3.7	21.98	33.68	2.2	-6.77	-8.36	33.08	9.67	88.79
	[0.327]	[0.278]	[0.376]	[0.712]	[0.290]	[0.057]	[0.891]	[0.574]	[0.563]	[0.054]	[0.634]	[0.001]
Naturalsci	36.08	18.62	-6.39	-3.98	18.35	0.23	-18.78	0.76	-20.3	-40.59	0.27	128.73
	[0.081]	[0.248]	[0.518]	[0.802]	[0.651]	[0.993]	[0.345]	[0.954]	[0.133]	[0.009]	[0.990]	[0.008]
Socialsci	41.83	42.75	44.31	31.6	76.15	106.76	26.47	33.17	29.75	54.11	91.09	177.47
	[0.042]	[0.004]	[0.000]	[0.017]	[0.076]	[0.024]	[0.176]	[0.044]	[0.123]	[0.004]	[0.020]	[0.006]
Humanity	37.35	34.54	12.64	7.16	15.33	29.36	21.37	36.84	17.17	28.86	10.33	54.27
	[0.067]	[0.039]	[0.252]	[0.639]	[0.431]	[0.257]	[0.242]	[0.040]	[0.373]	[0.142]	[0.434]	[0.036]
Profess	24.89	42.03	19.56	17.3	42.69	85.91	12.95	36.16	27.89	39.13	16.21	111.89
	[0.194]	[0.005]	[0.013]	[0.185]	[0.210]	[0.018]	[0.428]	[0.013]	[0.035]	[0.001]	[0.646]	[0.030]
peer_masss	0.24	0.21	0.18	0.19	0.17	0.19						
	[0.000]	[0.000]	[0.000]	[0.000]	[0.015]	[0.000]						
peer_resss							0.37	0.33	0.33	0.28	0.28	0.23
							[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Mathsss _{t-1}	0.66	0.66	0.66	0.63	0.69	0.65						
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]						
Readsss _{t-1}							0.76	0.76	0.76	0.8	0.76	0.8
							[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]
Observations	4821	4821	4821	3442	3138	2185	5639	5639	5639	3494	3580	2254
R-squared	0.519	0.524	0.529	0.564	0.544	0.581	0.514	0.519	0.521	0.611	0.523	0.629