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Teacher Training, Teacher Quality, and Student Achievement

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TEACHER TRAINING, TEACHER QUALITY AND STUDENT ACHIEVEMENT*

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Abstract

We study the effects of various types of education and training on the ability of teachers to promote student achievement. Previous studies on the subject have been hampered by inadequate measures of teacher training and difficulties addressing the non-random selection of teachers to students and of teachers to training. We address these issues by estimating models that include detailed measures of pre-service and in-service training, a rich set of time-varying covariates, and student, teacher, and school fixed effects. Our results suggest that only two of the forms of teacher training we study influence productivity. First, content-focused teacher professional development is positively associated with productivity in middle and high school math. Second, more experienced teachers appear more effective in teaching elementary math and reading and middle school math. There is no evidence that either pre-service (undergraduate) training or the scholastic aptitude of teachers influences their ability to increase student achievement.

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I. Introduction

It is generally acknowledged that promoting teacher quality is a key element in improving primary and secondary education in the United States. Indeed, one of the primary goals of the *No Child Left Behind* law is to have a "highly qualified teacher" in every classroom. Despite decades of research, however, there is no consensus on what factors enhance, or even signal, teacher quality.[1]

We focus here on the relationship between teacher productivity and teacher training, including formal pre-service university education, in-service professional development, and informal training acquired through on-the-job experience. Previous research on teacher training has yielded highly inconsistent results and has fueled a wide range of policy prescriptions. Some studies find that formal education is important and these have been interpreted as support for strengthening existing teacher preparation programs in universities and increased expenditures on post-college training. Equally common, however, is the finding that formal education is irrelevant, leading others to argue for the elimination of colleges of education.

One reason for the uncertainty regarding the effects of teacher training is that past studies have been unable to overcome three methodological challenges in estimating the effects of training on teacher quality. First, it is difficult to isolate productivity, especially in teaching where a student's own ability, the influences of a student's peers, and other characteristics of schools also affect measured outcomes. The problem is exacerbated by the fact that assignment of students and teachers to classrooms is usually not random, leading to possible correlations between observed teacher attributes and unobserved student characteristics. Second, like in other

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[1] A related line of research looks at subjective evaluations by prinicipals and whether they are correlated with teacher quality. See Armour et al. (1976), Harris and Sass (2007), Murnane (1975) and Jacob and Lefgren (2005).

occupations, there is an inherent selection problem in evaluating the effects of education and training on teacher productivity. Unobserved teacher characteristics, such as “innate” ability, may affect the amount and types of education and training they choose to obtain as well as subsequent performance of teachers in the classroom. Third, it is difficult to obtain data that provide much detail about the various types of training teachers receive and even more difficult to link the training of teachers to the achievement of the students they teach. Addressing all of these issues in a single study presents significant data and estimation challenges.

In this paper we present new evidence on the effects of teacher university-based pre-service formal education and in-service professional development training on teacher productivity using a unique statewide administrative database from Florida. The Florida data allow us to tie student performance to the identity of their classroom teacher and in turn link teachers to their in-service training, their college coursework and their pre-college entrance exam scores. These extremely rich data also provide a unique opportunity to address the twin selection problems associated with teacher acquisition of training and assignment of students to teachers.

Our analysis proceeds in two steps. First, we estimate student achievement models that include a rich set of covariates that measure the time-varying characteristics of individual students, their classroom peers, and their school’s principal. In addition, we include multiple levels of fixed effects that control for unmeasured time-invariant student, teacher and school characteristics. This first-stage model includes detailed data on the quantity and characteristics of education and training teachers receive after they have entered the classroom, including both graduate education and workshops sponsored by schools and school districts (called “in-service” or professional development training). We also include measures of teacher experience, which represent informal on-the-job training. This first step yields estimates of the fixed effect for each teacher, which represents the teacher's contribution to student achievement or "value added" that does not vary over her career.[2] In the second step we take the estimated teacher fixed effect and regress it on characteristics of teachers' (time-invariant) undergraduate coursework, controlling for teacher pre-college cognitive/verbal ability with college entrance exam scores.

We begin in section II by describing past literature on teacher training. Our methodology and data are discussed in sections III and IV, respectively. Our results, presented in section V, suggest that only two of the forms of teacher training influence productivity; content-focused teacher professional development is positively associated with productivity in middle and high school math and on-the-job training acquired through experience correlated with enhanced effectiveness in teaching elementary reading and elementary and middle-school math. The implications of our findings are discussed in section VI.

II. Previous Literature on the Effects of Teacher Training

In early work on teacher productivity, researchers estimated education production functions by regressing aggregate student achievement levels on measures of teacher training and various other controls using cross-sectional data (see review by Hanushek (1986)). A subsequent generation of studies used student-level two-year test-score gains and richer sets of teacher training variables to evaluate the impact of teacher training on student achievement. The state of the literature through the year 2000 has been extensively reviewed by Wayne and Youngs (2003) as well as by Rice (2003), Wilson and Floden (2003), and Wilson, et al. (2001). Rather than

[2] The term "value-added" has two rather different meanings in the education literature. Sometimes if refers to education production function models where the dependent variable is the gain in student achievement or student learning. The second meaning, which we use here, is simply the teacher's marginal product with respect to student achievement.

duplicate previous surveys we highlight new research findings over the last half-dozen years. Table 1 provides a summary of this recent work.

While some recent studies of the determinants of teacher productivity continue to employ the gain score approach (Aaronson, et al. (2007), Hill, et al. (2005), Kane, et al. (2006)), the bulk of recent research has shifted away from this methodology. The gain-score studies rely on observed student characteristics or "covariates" to account for student heterogeneity. However, they cannot control for unobserved characteristics like innate ability and motivation. There is evidence that better trained and more experienced teachers tend to be assigned to students of greater ability and with fewer discipline problems (e.g., Clotfelter et al. (2006), Feng (2005)). Given this positive matching between student quality and teacher training, the gain-score studies' inability to control for unobserved student characteristics would tend to upwardly bias estimates of teacher value-added associated with education and training.

The recent availability of longitudinal administrative databases has brought forth a new generation of studies that seek to ameliorate selection bias by controlling for time-invariant unobserved student heterogeneity via student fixed effects. In the last six years, eight studies of teacher productivity in the U.S. have employed this approach. An alternative method of avoiding selection bias is to either randomly assign teachers to students (as in the Tennessee class size experiment) or to exploit situations where there is an exogenous change in student assignments to teachers or in teachers to training. Five other recent studies exploit either experiments with random assignment, situations where there is "apparent random assignment" or "natural" experiments where assignment is based on exogenous factors.

No matter what the methodology, nearly all of the recent studies of teacher productivity include some measure of teacher experience, which serves as a proxy for on-the-job training.

Results for elementary math are about evenly split between positive and insignificant effects of teacher experience on student achievement. In contrast, all but one of the eight recent studies that separately analyze elementary reading find that student achievement is positively correlated with teacher experience. At the middle school level the findings are essentially reversed. Studies that include middle school consistently find positive effects of teacher experience on math achievement whereas the findings for the effects of experience on middle school reading achievement are evenly split between positive and insignificant correlations. The three studies of high school teachers yield conflicting results. Aaronson, et al. (2007) and Betts, et al. (2003) find no significant correlation between teacher experience and student achievement while Clotfelter, et al. (2007) find strong positive effects. One difference in these studies is that Clotfelter et al. utilize course-specific end-of-course exams while the other studies rely on more general achievement exams.

As discussed by Rockoff (2004) and Kane, et al. (2006), the estimated effects of experience may be biased if sample attrition is not taken into account. For example, less effective teachers might be more likely to leave the profession and this may give the appearance that experience raises teacher value-added when, in reality, less effective teachers are simply exiting the sample. Alternatively, selection could work in the opposite direction; more able teachers with higher opportunity costs may be more likely to leave the profession, leading to a spurious negative correlation between teacher experience and student achievement. One method of addressing the attrition issue is to include a teacher-specific effect, to control for unmeasured teacher ability, along with the experience measures. The teacher-specific effect should purge the influence of teacher time-invariant ability on experience, yielding unbiased estimates of the marginal product of experience.[3] While the recent gain score studies all include a teacher-specific effect, only two of the eight panel data studies, Hanushek et al. (2005) and Rockoff (2004), employ teacher fixed effects in addition to student fixed effects. Both of these studies analyze only a single school district. In our work we are able to include to include both student and teacher fixed effects using data for the entire state of Florida.

In addition to experience, the other commonly measured aspect of teacher training is the attainment of graduate degrees. Nearly all of the recent panel-data and random-assignment studies include a measure of post-baccalaureate degree attainment, typically whether a teacher holds a master's degree. Except for positive correlations between possession of a masters degree and elementary math achievement found by Betts et al. (2003), Dee (2004) and Nye, et al. (2004), recent research indicates either insignificant or in some cases even negative associations between possession of graduate degrees by a teacher and their students' achievement in either math or reading.

In contrast to experience and possession of advanced degrees, the pre-service undergraduate training of teachers has received much less attention in the recent literature. Two studies, Aaronson, et al. (2007) and Betts et al. (2003) consider the effect of college major on later teacher productivity, but fail to find a robust relationship between undergraduate major and the impact of teachers on student achievement. Three studies, Kane et al. (2006), Clotfelter et al.

[3] While the inclusion of teacher effects greatly reduces the potential bias associated with teacher attrition, it does not necessarily eliminate it for two reasons. First, since multiple observations are required to compute teacher effects, elementary school teachers who leave after one year are necessarily excluded. This is not a significant problem for middle and high-school teachers, however, since they teach multiple classes within a single period (though it remains a problem for estimating the effects of experience, which can still only be done for teachers with two or more years in the classroom). Second, if there is an unobserved time-varying component of teacher productivity that is correlated with the likelihood of attrition, then this will not be fully captured by the teacher effect. For example, as noted by Murnane and Phillips (1981) and others, the presence of young children in the home may lower teacher productivity and also increase the likelihood of attrition. We test whether teacher-specific effects eliminate attrition bias in our empirical work below.

(2006, 2007a) consider general measures of the quality of the undergraduate institution attended and find little or no relationship to teacher productivity in elementary or middle school. A fourth study, Clotfelter, et al. (2007b) does find a positive and significant relationship between the prestige of the undergraduate institution and productivity of high school teachers. Kane et al. (2006) also analyze the relationship between undergraduate grade point average (GPA) and teacher productivity in elementary and middle school. As with the other measures of undergraduate education, they find no significant relationship between GPA and subsequent teacher performance.

There are at least two shortcomings of recent estimates of the impact of undergraduate education on teacher productivity. First, recent work has relied on relatively gross measures, like college major, which may obscure significant variation in college coursework.[4] Second, none of the recent studies that include measures of undergraduate training control for the pre-college ability of future teachers. Thus, for example, a positive observed correlation between undergraduate institutional prestige and future teacher productivity could mean that institutional quality enhances the productivity of future teachers or simply that more able students are accepted into elite institutions and individual ability is determinative of productivity as a teacher. In our work we consider the specific courses taken by teachers and control for pre-college ability with college entrance exam scores.

Jacob and Lefgren (2004) is the only prior study of the impact of in-service professional development on teacher productivity in the United States.[5] Jacob and Lefgren exploit a "natural experiment" that occurred in the Chicago public schools where the level of professional

[4] At least two of the older gain-score studies, Eberts and Stone (1984) and Monk (1994) do include detailed measures of courses taken.

[5] Angrist and Lavy (2001) analyze the effects of teacher professional development on teacher productivity in Israel.

development was based (exogenously) on prior school-level average test scores. Jacob and Lefgren are not able to distinguish the specifics of the professional development that teachers received, however. Like Jacob and Lefgren, we include in-service professional development in our analysis of teacher training. Further, we are able to distinguish between training that focuses on content and that which emphasizes pedagogy.

III. Econometric Model and Estimation Strategies

A. Measuring Teacher Productivity and Within-Career Education and Training

While the issue of measuring a teacher's output is controversial, particularly outside the economics literature, we shall simply define the relevant product as student achievement measured by standardized tests. Consequently, we view a teacher's productivity as their contribution to student achievement, holding other inputs constant. To empirically measure the impact of education and training on teacher productivity it is therefore necessary to first develop a model of student achievement. We begin with a general specification of the standard "educational production function" that relates student achievement to vectors of time-varying student/family inputs (X), classroom-level inputs (C), school inputs (S) and time-invariant student/family characteristics (γ):

$$A_{it} = \lambda A_{it-1} + \boldsymbol{\alpha}_1 \mathbf{X}_{it} + \boldsymbol{\alpha}_2 \mathbf{C}_{ijmt} + \boldsymbol{\alpha}_3 \mathbf{S}_{mt} + \gamma_i + \varepsilon_{it} \tag{1}$$

The subscripts denote individuals (i), classrooms (j), schools (m) and time (t).

Equation (1) is a restricted form of the cumulative achievement function specified by Boardman and Murnane (1979) and Todd and Wolpin (2003) where the achievement level at time t depends on the individual's initial endowment (eg. innate ability) and their entire history of individual, family and schooling inputs. Although often not stated, there are a number of implicit assumptions underlying the education production function specified in (1). First, it is assumed that the cumulative achievement function does not vary with age, is additively separable, and linear. Family inputs are assumed constant over time, and the impact of parental inputs on achievement, along with the impact of the initial individual endowment on achievement, induce a (student-specific) constant increment in achievement in each period.[6] This allows the combination of these time-invariant inputs to individual achievement gains to be represented by the student-specific fixed component, γ_i. Third, the marginal impacts of all prior school inputs decay geometrically with the time between the application of the input and the measurement of achievement at the same rate. Thus lagged achievement serves as a sufficient statistic for all prior schooling inputs. A thorough discussion of these assumptions and the derivation of the linear education production function model can be found in Todd and Wolpin (2003), Sass (2006) and Harris and Sass (2006).

The vector of classroom inputs can be divided into four components: peer characteristics, $\mathbf{P}_{-ijmt}$ (where the subscript –i students other than individual i in the classroom), time-varying teacher characteristics (eg. experience and in-service training), $\mathbf{T}_{kt}$ (where k indexes teachers), time-invariant teacher characteristics (eg. innate ability and pre-service education), δ_k, and non-teacher classroom-level inputs (such as books, computers, etc.), $\mathbf{Z}_j$. If we assume that, except for teacher quality, there is no variation in education inputs across classrooms within a school, the effect of $\mathbf{Z}_j$ becomes part of the school-level input vector, $\mathbf{S}_m$. School-level inputs can be de-composed into those that vary over time and those that are invariant over the time period

[6] An observationally equivalent assumption is that the impact of home inputs is time invariant and the amount of home inputs change by a constant rate over time. If family inputs change over time (at a non-constant rate) and are correlated with variables in the achievement model, this will lead to biased estimates of the model parameters. For example, if parents compensate for an inexperienced teacher by spending more time with their child in learning activities at home, this would impart a downward bias on the estimated effect of teacher experience on student learning. There is little consistent evidence whether or not home inputs systematically vary over time with the quality of schooling inputs, however. Bonesronning (2004) finds that class size has a negative effect on parental effort in Norway, suggesting that school and home inputs are complements. In contrast, Houtenville and Conway (forthcoming) find that parental effort is negatively correlated with school-level per pupil expenditures on instructional personnel, implying that school resources and parental effort are substitutes.

of analysis. The time varying components we measure are the administrative experience of the principal, the principal's administrative experience squared, whether the principal is new to the school and whether the school is in its first year of operation. Time-invariant school inputs are captured by a school fixed component, ϕ_m. The achievement function can then be expressed as:

$$A_{it} = \lambda A_{it-1} + \boldsymbol{\beta}_1 \mathbf{X}_{it} + \boldsymbol{\beta}_2 \mathbf{P}_{-ijmt} + \boldsymbol{\beta}_3 \mathbf{T}_{kt} + \boldsymbol{\beta}_4 \mathbf{S}_{mt} + \gamma_i + \delta_k + \phi_m + \nu_{it} \tag{2}$$

Where ν_{it} is a normally distributed, mean zero error.

We include three measures of teacher education and training in the vector of time-varying teacher characteristics, $\mathbf{T}_{kt}$. Experience, representing on-the-job training, is captured by a set of indicator variables representing various levels of experience; the omitted category is teachers with zero experience. This specification allows for non-linear effects of teacher experience on student achievement and avoids perfect collinearity between experience and time that would result from a continuous linear measure of teacher experience. In-service training is measured by a vector of variables representing the number of hours spent in various types of professional development courses. Both current-year hours of training as well as the amount of training in each of the three prior years are measured separately to allow for delayed implementation of new teaching strategies, human capital depreciation and possible negative impacts of contemporaneous training on student achievement associated with absences from the classroom. Finally, attainment of post-baccalaureate degrees is included to capture the effects of additional formal education obtained after entering the teaching profession. The vector of coefficients on these time-varying teacher characteristics, $\boldsymbol{\beta}_3$, thus represents the impact of within-career education and training on teacher productivity.

Estimation of equation (2) by ordinary least squares (OLS) is problematic since the error term is correlated with lagged achievement, rendering biased estimates of the regression coefficients.[7] To avoid this bias we shall focus on estimating models where λ is assumed to equal one and thus the dependent variable is A_{it}-A_{it-1} or the student achievement gain:

$$A_{it} - A_{it-1} = \Delta A_{it} = \boldsymbol{\beta}_1 \mathbf{X}_{it} + \boldsymbol{\beta}_2 \mathbf{P}_{-ijmt} + \boldsymbol{\beta}_3 \mathbf{T}_{kt} + \boldsymbol{\beta}_4 \mathbf{S}_{mt} + \gamma_i + \delta_k + \phi_m + \nu_{it} \tag{3}$$

This implies that the decay rate on prior inputs is zero; school inputs applied at any point in time have an immediate and permanent impact on cumulative achievement.[8] This is of course a strong assumption; we therefore test whether changes in the assumed value of lambda affect our results.[9]

B. Computational Issues

Estimation of (3) is computationally challenging since it includes three levels of fixed effects: individual students (γ_i), teachers (δ_k) and schools (ϕ_m). Standard fixed effects methods eliminate one effect by demeaning the data with respect to the variable of interest (eg. deviations from student means). Additional effects must then be explicitly modeled through the inclusion of dummy variable regressors. Given our data includes tens of thousands of teachers and thousands of schools, such standard methods are infeasible.

We combine two different approaches to solve the computational problem associated with estimating a three-level fixed effects model. First, we utilize the "spell fixed effects" method proposed by Andrews, et al. (2004) and combine the teacher and school fixed effects into a single effect, $\eta_{km} = \delta_k + \phi_m$. This combined effect represents each unique teacher/school combination or "spell." The education production function thus becomes:

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[7] See Todd and Wolpin (2003) and Sass (2006).

[8] Thus, for example, the quality of a child's kindergarten must have the same impact on his cumulative achievement as of the end of the kindergarten year as it does on his achievement at age 18.

[9] It is important to note that while the dependent variable is the change in student achievement, equation (1) is a model of student achievement levels, not achievement growth. The lagged value of achievement on the left hand side serves to represent the cumulative effect of all prior schooling inputs on current achievement.

$$\Delta A_{it} = \boldsymbol{\beta}_1\mathbf{X}_{it} + \boldsymbol{\beta}_2\mathbf{P}_{-ijmt} + \boldsymbol{\beta}_3\mathbf{T}_{kt} + \boldsymbol{\beta}_4\mathbf{S}_{mt} + \gamma_i + \eta_{km} + \nu_{it} \tag{4}$$

The second approach is an extension of the iterative fixed effects estimator recently proposed by Arcidiacono, et al. (2005).[10] The essence of the Arcidiacono et al. method is to estimate the fixed effect for each individual by calculating each individual's error in each time period (ie. actual outcome minus the individual's predicted outcome) and then compute the mean of these errors for each individual over time. With each estimate the individual fixed effects are recomputed and the process is iterated until the coefficient estimates converge.

Taking deviations from the teacher-school spell means, the achievement equation becomes:

$$(\Delta A_{it} - \overline{\Delta A}_{km}) = \boldsymbol{\beta}_1(\mathbf{X}_{it} - \overline{\mathbf{X}}_{km}) + \boldsymbol{\beta}_2(\mathbf{P}_{-ijmt} - \overline{\mathbf{P}}_{km}) + \boldsymbol{\beta}_3(\mathbf{T}_{kt} - \overline{\mathbf{T}}_{km}) + \boldsymbol{\beta}_4(\mathbf{S}_{mt} - \overline{\mathbf{S}}_{km}) + (\gamma_i - \bar{\gamma}_{km}) + \nu_{it} \tag{5}$$

where the overbar and km subscript denote the mean of the relevant variable over all students and all time periods covered by teacher k at school m. Subtracting the de-meaned student effect from both sides yields:

$$(\Delta A_{it} - \overline{\Delta A}_{km}) - (\gamma_i - \bar{\gamma}_{km}) = \boldsymbol{\beta}_1(\mathbf{X}_{it} - \overline{\mathbf{X}}_{km}) + \boldsymbol{\beta}_2(\mathbf{P}_{-ijmt} - \overline{\mathbf{P}}_{km}) + \boldsymbol{\beta}_3(\mathbf{T}_{kt} - \overline{\mathbf{T}}_{km}) + \boldsymbol{\beta}_4(\mathbf{S}_{mt} - \overline{\mathbf{S}}_{km}) + \nu_{it} \tag{6}$$

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[10] Arcidiacono et al derive their estimator in the context of a model with only fixed effects and no other covariates. However, it is straightforward to extend their approach to models with covariates. Details of the derivation are available upon request. Arcidiacono, et. al. (2005, p.9) demonstrate in simulations that their estimator is unbiased, regardless of the number of observations per student. Their approach does introduce a small bias in a model with so-called "peer fixed effects," but that is not relevant here. A refined procedure which yields unbiased estimates in the presence of peer fixed effects is discussed in Arcidiacono, et al. (2007). We demonstrate in Appendix Table A1 that the Arcidiacono, et al. (2005) iterative estimator produces estimates that are extremely close to the standard OLS estimates.

Equation (6) is estimated by ordinary least squares (OLS), using initial guesses for the individual effects. This produces estimates of β_1, β_2, β_3 and β_4 which are then used to calculate predicted outcomes for each individual and in turn update the estimated individual effects. The process is iterated until the coefficient estimates converge. Standard errors are obtained by bootstrapping.[11]

C. Measuring the Effects of Pre-Service Education on Teacher Productivity

In order to gauge the effects of teacher ability and college preparation on future productivity we follow a two-step estimation procedure first proposed by Dickens and Ross (1984). In the first step we calculate the estimated teacher-school effects from the estimation of equation (4). The predicted teacher-school spell fixed effect can be expressed as the difference between the average achievement gain for all students in group km minus the product of the estimated coefficients and the group averages of the explanatory variables:

$$\hat{\eta}_{km} = \overline{\Delta A}_{km} - \hat{\bar{\gamma}}_{km} - \hat{\boldsymbol{\beta}}_1 \overline{\mathbf{X}}_{km} - \hat{\boldsymbol{\beta}}_2 \overline{\mathbf{P}}_{km} - \hat{\boldsymbol{\beta}}_3 \overline{\mathbf{T}}_{km} - \hat{\boldsymbol{\beta}}_4 \overline{\mathbf{S}}_{km} \tag{7}$$

These teacher-school effects can be decomposed into three time-variant components: the part of teacher effect due to the education they receive as undergraduates, the portion of the teacher effect due to pre-college ability, and the school effect. In the second step we gauge the impact of pre-service education on later teacher productivity by regressing the estimated teacher-school

[11] The standard errors from the bootstrap procedure do not account for clustering of students within a classroom or classrooms within a school. This is partly compensated for by the fact that we include classroom peer measures and teacher fixed effects (which correspond to a common average error for all students a teacher ever teaches). Unfortunately, a procedure to account for clustering of errors at multiple levels within a bootstrap framework is not currently available. Cameron, Gelbach and Miller (2006a) derive corrected standard errors for the case where clustering occurs at multiple levels (eg. students in a class, classes within a teacher, teachers within a school), but there is not complete nesting (over time students switch teachers and teachers switch schools). However, this is method is based on OLS regressions and is not applicable to our iterative model. Cameron, Gelbach and Miller (2006b) derive a bootstrap procedure for determining the corrected standard errors when there is clustering at a single level, but the authors have not yet worked out a bootstrap procedure for the case of multi-way clustering.

effects on a vector of pre-service education variables for teacher k, $\mathbf{U}_k$, their entrance exam scores, $\mathbf{E}_k$, a set of school indicators, ϕ_m, and a random error:

$$\hat{\eta}_{km} = \boldsymbol{\omega}_1 \mathbf{U}_k + \boldsymbol{\omega}_2 \mathbf{E}_k + \phi_m + \xi_{km} \tag{8}$$

The estimates of the coefficient vector $\boldsymbol{\omega}_1$ indicate the partial correlation between the characteristics of a teacher's pre-service education and their future contribution to student achievement. Thus they can be interpreted as signals of future productivity. Following Dickens and Katz (1986), equation (8) is estimated by weighted least squares, with the square root of the numbers of students per teacher/school spell as weights.

IV. Data

We make use of a unique panel data set of school administrative records from Florida[12] that allows us to overcome many of the challenges associated with measuring the impact of education and training on teacher productivity. The data cover all public school students throughout the state and include student-level achievement test data for both math and reading in each of grades 3-10 for the years 1999-2000 through 2004-2005.[13] The panel data on individual

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[12] A more detailed description of the data is provided in Sass (2006).

[13] The state of Florida currently administers two sets of reading and math tests to all 3rd through 10th graders in Florida. The "Sunshine State Standards" Florida Comprehensive Achievement Test (FCAT-SSS) is a criterion-based exam designed to test for the skills that students are expected to master at each grade level. The second test is the FCAT Norm-Referenced Test (FCAT-NRT), a version of the Stanford Achievement Test used throughout the country. Version 9 of the Stanford test (the Stanford-9) was used in Florida through the 2003/2004 school year. Version 10 of the Stanford test (the Stanford-10) has been used since the 2004/05 school year. To equate the two versions of the exams we convert Stanford-10 scores into Stanford-9 equivalent scores based on the conversion tables in Harcourt (2003). The scores on the Stanford-9 are scaled so that a one-point increase in the score at one place on the scale is equivalent to a one-point increase anywhere else on the scale. The Stanford-9 is a vertically

students allow us to control for unobserved student characteristics with student-specific fixed effects. Summary statistics are available in Table 2.

Unlike other statewide databases, we can precisely match students and their teachers to specific classrooms at all grade levels.[14] With consistent teacher identification over time, this allows us to control for time-invariant teacher characteristics via fixed effects. Another advantage of the data is that we can determine the specific classroom assignments of middle-school and high-school students, who typically rotate through classrooms during the day for different subjects. This enables us to better separate the effects of teachers from students and their peers. Having data from all K-12 grades allows us to estimate separate models for elementary, middle and high school which affords us the opportunity to see how the impacts of teacher education and training vary across the three school types. For example, one might expect that a teacher's content knowledge of mathematics might be more important in a high school trigonometry class than in a fourth grade class learning arithmetic.

Not only does our data directly link students and teachers to specific classrooms, it also provides information on the proportion of each student's time spent in each class. This is potentially important for correctly matching teachers and their students at the elementary school level. While primary school students typically receive all of their academic instruction from a single teacher in a single "self-contained" classroom, this is far from universal. In Florida, five percent of elementary school students enrolled in self-contained classrooms are also enrolled in a

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scaled exam, thus scale scores typically increase with the grade level. We use FCAT-NRT scale scores in all of the analysis. The use of vertically scaled scores to evaluate student achievement is important since a one-unit change has the same meaning for low- and high-achieving students.

[14]Currently, the Texas data do not provide a way to link teachers and students to specific classrooms. For North Carolina, one can only (imperfectly) match specific teachers and students to classrooms at the elementary school level. Matching is done by identifying the person who administers each student the annual standardized test, which at the elementary school level is typically the classroom teacher.

separate math course, four percent in a separate reading course and four percent in a separate language arts course. In addition, nearly 13 percent of elementary students enrolled in self-contained elementary classes are also enrolled in some type of exceptional student education course apart from their regular classroom, either special-education or gifted courses.[15]

We restrict our analysis of student achievement to students who receive instruction in the relevant subject area in only one classroom. Only elementary school students in "self-contained" classrooms are included. Elementary students spending less than one hour per day in the class are not considered as a member of the classroom peer group. At the middle and high-school levels, students who are enrolled in more than one course in the relevant subject area (mathematics and reading/language arts) are dropped, though all students enrolled in a course are included in the measurement of peer-group characteristics. To avoid atypical classroom settings and jointly taught classes we consider only courses in which 10-40 students are enrolled and there is only one "primary instructor" of record for the class. Finally, we eliminate charter schools from the analysis since they may have differing curricular emphases and student-peer and student-teacher interactions may differ in fundamental ways from traditional public schools.

Despite limiting the sample to students who have only one class per subject, our ability to match the content taught in each classroom with the content on the state test varies by grade and subject. In elementary schools, the matching of subjects is relatively easy because students typically have only one teacher and, as indicated above, we have dropped the small percentage of students who have more than one teacher. In middle and high school, however, more students have multiple classes for the same subject, especially in reading, so that more students are

[15] Since previous studies lack data on students' complete course enrollments, they either ignore the fact that students may receive instruction outside their primary classroom or deal with the issue in an ad-hoc fashion.

dropped; and some who are not dropped may have their reading scores influenced by classes such as social studies, that involve reading but where developing reading is not the primary purpose. Also, even if we were able to match the test content to a specific classroom, our ability to isolate the effect of classroom factors is further constrained in the case of reading because some students may read in their leisure time. Few students do math during leisure time so this is less of a problem in that subject. For all of these reasons, we have greater confidence in our results for mathematics than for reading.

The ability to link teachers to their university coursework is another unique feature of the Florida data. For relatively young teachers (those who attended a Florida public university or community college since 1995) our data include complete college transcript information, including entrance exam scores, courses taken and degrees received. Because Florida has a uniform course numbering system, we are able to create variables that describe each course according to its focus on teacher content knowledge, pedagogical knowledge, and classroom observation/practice in teaching.[16] We then aggregate these measures for each teacher to capture the relevant characteristics of each teacher's entire undergraduate training. We also know the major associated with each college degree and can thus distinguish future teachers who

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[16] Courses were coded using the course descriptions in the State of Florida State Course Numbering System. The following categories are used: *Education theory/foundations* includes courses that cover general education theory or general issues in education. *Pedagogical-instructional* includes general instructional methods and theories to instruction. *Pedagogical-management* includes classroom management issues in general or for different groups of students. *Pedagogical-content* includes combinations of subject and pedagogy. *Other development* includes issues such as ethics, professionalism or administration. *Classroom observation* includes observation in the classroom. *Classroom practice* includes courses that require field experience. *Subject content* includes subject content (e.g. math). Each course was assigned a total value of one which was, in some cases, distributed over several types of training. An example may help to illustrate: SCE 4361 Introduction to Middle School Science Teaching was coded as *pedagogical-content* (0.3) and *classroom observation* (0.7). This is the based on the course description: "Introduction to the roles and responsibilities of science teachers with an emphasis on middle school students. Extensive fieldwork required."

graduated with an education major from those who earned a degree in various non-education disciplines like mathematics and English literature.

V. Results

A. Effects of Experience and Professional Development Training

Initial estimates of the student achievement model, equation (6), without teacher fixed effects, are presented in Table 3.[17] Experience enhances teacher productivity at all grade levels in reading and in both elementary and middle-school math, though experience effects decline as we progress from elementary to middle and high school. The bulk of the experience effects occur in the first year, with subsequent experience yielding diminishing increases in teacher productivity.

Without teacher fixed effects we find contemporaneous professional development (PD) is associated with higher teacher productivity, but only in middle-school. Prior-year professional development coursework is positively correlated with current productivity only in middle-school math and in elementary school reading. PD that occurs two and three years in the past is associated with higher teacher productivity in high school math, with mixed results for other grade/subject combinations. Even where PD does seem to show positive effects, they appear modest in size relative to experience. Given the average number of hours of professional development coursework per year is approximately 50, the difference between having no professional development versus the average professional development is at most about

[17] Only estimates of the coefficients on the teacher training variables are reported. Time-varying student, class and school variables included in the model are delineated in the tables notes. While some "structural" student mobility (ie. inter-school moves not made by most classmates) are potentially endogenous, such movement is not common and exclusion of structural movers from the sample does not affect our results.

($0.002 \times 50 = 0.10$) scale score points or about one-fourth to one-ninth the difference between a rookie middle school teacher and one with a year of experience.

Results of estimating the achievement model with both teacher time-varying characteristics and teacher fixed effects (to control for time-invariant teacher characteristics) are displayed in Table 4. The positive effects of early-career experience (1-2 years) in elementary and middle school found in the model without teacher effects (Table 3) remain largely unchanged; however, the precision is substantially reduced for experience effects above 5 years in elementary math and middle school reading. These experience effects are quantitatively substantial, ranging from 0.9 to 2.4 scale score points. This translates to 0.04 to 0.10 of a standard deviation in achievement gains or 0.02 to 0.06 of a standard deviation in the achievement level. In high school, the estimated effects of teacher experience are reduced relative to those from the model excluding teacher fixed effects. More experienced high school teachers are either no better and in many cases are less productive than when they were rookie high school instructors.

The addition of teacher effects makes the PD effects noticeably less positive. With teacher effects in the model, there is still evidence of positive PD effects in middle and high-school math, but not in reading or in elementary math. Interestingly, the remaining positive effects do not occur in the period in which the PD occurs, but PD does appear to improve teaching in subsequent years. The possibility of a lagged PD effect has been observed elsewhere (Goldhaber and Anthony (2007), Harris and Sass (2008)). One possible explanation is that PD reduces the amount of time teachers have to devote to their students when the PD is taking place. In addition, if substitute teachers are hired so that the PD can take place during school hours, and if the substitutes are less effective or unable to maintain the continuity of instruction in the teacher's absence, then this too may reduce measured teacher value-added. Finally, because some portion of the school year has typically passed when PD occurs, and lesson plans for later in the year may already be established, teachers may have little opportunity to immediately incorporate what they learn. They can of course make changes in subsequent time periods and this appears to be reflected in the lagged effects in Tables 3 and 4.

Tables 5-7 present results from a number of alternative specifications and samples that provide evidence on the robustness of our initial findings. Tables 5A-5C report evidence on the estimated impact of PD where the persistence of lagged schooling inputs (λ) is allowed to vary from 1.0 to 0.2. The positive effects of lagged PD on contemporaneous student achievement in middle and high school math are relatively robust to changes in the assumed level of persistence. Only in the case of very low persistence (0.2) does the effect of lagged PD for middle school math teachers become statistically insignificant.

Table 6 reports estimates of the achievement model where student fixed effects are replaced by a set of observed student characteristics. These experience effects are very similar to those reported in Table 4, where student fixed effects are used. Once-lagged PD becomes statistically significant in the elementary school math equation and thrice-lagged PD is no longer a significant determinant of high school math achievement.

A concern when evaluating the determinants of gains in student achievement is the possibility that test scores at the upper end of the achievement distribution may be attenuated if the test questions are not sufficiently difficult. Such "ceiling effects" would tend to bias downward the gains for the most able students. Given we are estimating models with teacher fixed effects, and thus making within-teacher comparisons, ceiling effects would only bias our estimates of the impact of training on teacher productivity if a teacher's acquisition of training was correlated with the proportion of high achieving students in a teacher's classroom. For example, if a teacher who anticipated being assigned to an advanced class sought to prepare for the course by obtaining additional training, ceiling effects could bias downward the estimated impact of training on teacher productivity. However, if teachers who acquire lots of training consistently teach more advanced classes, any ceiling effects would be absorbed by the teacher fixed effect. Nonetheless, to determine if any such bias exists we re-estimate the achievement model, including an indicator for students who scored above the 95th national percentile in the prior year. Results are displayed in Table 7. Consistent with the presence of ceiling effects, the indicator for prior-year high achievers is negative and highly significant in all cases. However, as expected, accounting for possible ceiling effects does not significantly alter our findings with respect to teacher training. The only notable difference is that the estimated negative effects of experience on the productivity of high school teachers become less precise.

In Table 8 we report estimates of the achievement model that includes student and teacher/school effects, but where all grade levels are estimated simultaneously rather than in separate elementary, middle and high school equations. This obviously constrains the coefficients to be equal across school types. However, it does have the advantage of increasing the number of observations per student and thus perhaps improving the identification of student and teacher effects. Pooling all grades we find that contemporaneous PD has a positive and significant effect on student math achievement. Consistent with earlier results, the positive contemporaneous effect is smaller in magnitude than the once-lagged hours of PD. The estimated impacts of twice and three-lagged PD for math teachers are much smaller than for once-lagged PD and only marginally significant for the thrice-lagged PD. As in the separate elementary/middle/high models, we find no positive and statistically significant effects of PD for reading achievement.

Student and teacher/school fixed effects provide powerful protection against selection bias resulting from the non-random assignment of teachers to PD and students to teachers based on unobserved time-invariant characteristics. However, there still exists the possibility that time-varying factors could be correlated with either student-teacher assignments or teacher choices about training and with student achievement, thereby producing biased estimates of the effects of teacher training. For example, suppose that students who have a "bad year" in which they obtain a low test score are systematically assigned to teachers with a particular set of characteristics (eg. highly experienced teachers) in the following year. If the bad year was indeed a transitory phenomenon and the students bounce back in the next year, this would tend to bias upward the estimated effect of teacher experience. Similarly, teachers whose students perform poorly in one year could be encouraged to acquire in-service training the next year as a remedial measure. If poor student performance was due to a random event outside the teacher's control, the students in her next-year class would have performed better even in the absence of additional PD.

To determine if student-teacher assignments are based on transitory student performance that is correlated with observed teacher characteristics, we construct a measure of transitory changes in student test score gains and then correlate that measure with the characteristics of the teacher they are assigned to in the subsequent year. To determine whether prior-year test score gains are atypical, it is necessary to compare them to a student's test score gains in previous years. We therefore compute the difference in a student's test score gain in year t-1 and the average of their test score gains in years t-2 and t-3. Given that testing begins in grade 3, thrice-lagged achievement gains can only be computed for grades 7 and beyond. Partial correlations between this measure of prior-year transitory achievement gains and observable teacher characteristics, broken down by subject and grade, are displayed in Table 9. The correlations are no greater than 0.02 in absolute value, suggesting there is not significant teacher/student sorting based on transitory student achievement gains.

In order to investigate the relationship between student performance and teacher professional development, we estimate a random-effects Tobit model of contemporaneous PD acquisition. The model can be interpreted as an estimate of a reduced-form equation, where PD acquisition is determined both by the teacher's supply of hours to PD coursework and the demand for PD acquisition coming from school administrators and re-certification requirements. To account for possibility that PD is driven by the desire to remediate past performance, we include the average gain scores of the teacher's students in the prior year. If the remediation explanation is correct then the average lagged gain score should carry a negative coefficient. Alternatively, PD acquisition might be driven by exogenous factors such as certification requirements. Florida, like most states, requires teachers to participate in a certain number of PD hours in order to maintain full certification. Teachers have a strong incentive to maintain certification because state and federal requirements make it difficult for schools to employ uncertified teachers. We also control for the possibility that PD acquisition is driven by the desire to meet re-certification requirements by including indicators of the number of years until the teacher's current certification expires and whether they currently hold a temporary certificate (which is non-renewable). We control for a teacher's stock of human capital, and hence their desire to obtain additional training through PD coursework, by including measures of experience, possession of a post-baccalaureate degree, participation in the process to become certified by the National Board for Professional Teaching Standards (NBPTS), and whether they have obtained

NBPTS certification.[18] The teacher-specific random effect accounts for unmeasured teacher characteristics that could influence teacher acquisition of professional development. Year indicators control for inter-temporal variation in funding for professional development.

Estimates of the professional development acquisition model are presented in Table 10. The results tend to favor the re-certification hypothesis. At both the elementary and middle school levels, PD acquisition is correlated with the timing of re-certification. For these grades, PD acquisition drops the year a teacher's license expires, suggesting teachers acquire the mandatory PD credits prior to the school year that their license expires and then cut back on their PD acquisition since the next renewal is five years in the future.[19] Similarly, PD acquisition by elementary and middle school teachers is negatively correlated with possession of a (non-renewable) temporary teaching certificate, though the effect is only statistically significant for middle school math teachers. The results provide less support for the remediation hypothesis. While the negative signs on the coefficients associated with lagged achievement gains suggest that teachers whose students gain less in one period spend more time in PD in the subsequent period, only the coefficient associated with high school math is statistically significant. PD coursework is highest for rookie teachers and the number of PD hours steadily increases with experience.

In Table 11 we identify the effects of different types of PD and find that the positive effects of total PD on the productivity of middle high school math teachers, discussed above, are

[18]For a detailed analysis of certification by the National Board for Professional Teaching Standards as its relationship to teacher effectiveness, see Harris and Sass (2008).

[19] For new teachers, their experience level is correlated with the time to re-certification. Likewise, experience may be correlated with NBPTS certification since a teacher must have taught for three years prior to application. To account for possible multicollinearity between experience, NBPTS certification and time to re-certification we re-estimated the PD acquisition model excluding the experience and NBPTS measures. The estimates for the re-certification parameters were very similar to those from the model including experience and NBPTS variables.

attributable mainly to content-oriented training. The lagged coefficients for this PD type remain consistently positive and statistically significant for middle school math. They are also positive for high school math, but only twice lagged PD is statistically significant for high school math teachers. The lagged effect of other in-service hours on middle school math is never significant and is only positive and significant for thrice lagged PD in the case of high school math teachers. On the reading side we continue to find no positive correlations between PD and teacher productivity, no matter what the nature of the in-service coursework.

Our generally weak and inconsistent findings for the effect of PD on teacher productivity across grades and subjects are in line with those of the only other study that considers the effects of PD in the U.S. (Jacob and Lefgren, 2004). They found no significant effects for professional development training in the aggregate. The results in the present study are somewhat more positive (especially in middle school math), perhaps because Jacob and Lefgren estimate only the short-term effects of PD and are not able to distinguish between different types of professional development.

We consider the impact of advanced degrees in Table 12. Since our model includes teacher fixed effects, post-baccalaureate degrees earned prior to the period of analysis wash out when we demean the data. Thus our approach measures the impact of *changes* in the possession of an advanced degree (for a given teacher) during the period of study.[20] Our results indicate that obtaining an advanced degree during one's teaching career is positively correlated with teacher

[20] The estimated coefficient on the advanced-degree variable measures the average productivity differential between the time before and the time after receipt of the degree. Before the degree is received some knowledge may have already been acquired through coursework already completed, thus biasing the estimated effect toward zero. However, work toward an advanced degree may take away from time available for class preparation and other teaching-related activities, which would tend to lower productivity before receipt of the degree and upwardly bias the estimated impact of the degree.

productivity only in the case of middle school math. For elementary teachers there is no correlation between receipt of an advanced degree and performance. For middle school reading teachers and both math and reading high school teachers there is actually a significant negative association between attainment of an advanced degree and measured productivity. This may be because graduate degrees include a combination of pedagogy and content and our other evidence suggests that only the latter has a positive influence on teacher productivity.

Other explanations for the graduate degree results arise from issues of methodology. Most previous studies suffer from selection bias, as noted earlier, and our solution is to study the effects of graduate degree attainment within teachers using teacher fixed effects. However, this approach imposes the implicit assumption that the receipt of the graduate degree reflects a sudden infusion of new preparation. In reality, the receipt of the degree is the culmination of several years of graduate courses whose influence may already be reflected in the teacher effects, especially for those teachers who take graduate courses over many years before receiving a graduate degree. Another possibility is that teachers load up on courses in the academic year preceding the receipt of the degree and therefore have less time to devote to their students. We found evidence above of such a contemporaneous decline in productivity when we considered the effects of other forms of professional development.

B. Pre-Service Training Effects

The results in Tables 4-8, 11 and 12 are based on models that include teacher-school fixed effects. In this section we use these effects as the dependent variable in order to analyze the effects of pre-service training, as shown in equation (8). Table 13 displays the results for the effects of teachers with various undergraduate majors, including different types of education degrees as well as majors in math and English. Note that the sample size drops significantly because our data only contain information on a teacher's college major if she entered a public university in Florida in 1995 or later. Nonetheless, our remaining sample size is still larger than many previous studies on the subject. We find that general education majors are less productive than non-math/non-education majors in middle school math. In contrast, English/Language Arts Education majors are more productive than non-education/non-English majors in boosting student achievement in middle school reading. Surprisingly, math education and math majors are less productive than non-education/non-math majors when teaching high school math. These mixed results are consistent with findings from the only other recent studies to include data on college majors, Aaronson, et al. (2007) and Betts, et al. (2003).[21]

In Table 14 we present estimates that control for the pre-college ability of teachers by including the SAT-equivalent entrance exam scores of future teachers. This allows us to distinguish between the human capital effects of particular majors and the self-selection of individuals into college majors. Unfortunately, this further reduces our sample size as there are a substantial number of missing observations on the college entrance exam.[22] When controlling for pre-college ability all of the college major effects become insignificant, save for a large negative correlation between math majors and productivity in teaching high school math. As indicated by the extremely large coefficient, this result ought to be interpreted with caution as it

[21] Among the pre-2001 studies, Goldhaber and Brewer (1997) and Rowan et al. (1997) both find math majors are relatively more productive at teaching high-school math. However, a later study, Goldhaber and Brewer (2000) finds no relationship between major and high school math teaching performance. Murnane (1975) finds no effect of major on teacher productivity in the elementary grades. Similarly Boyd et al. (2006) find little difference in the effectiveness of teachers who enter teaching through "alternate routes" and those who become teachers through the traditional route of completing a degree in a college of education.

[22] To maximize the amount of college entrance exam information available we include data from the state university system, the community college system and a database on applicants for a state merit-based scholarship known as "bright futures." ACT scores as well as community college placement exam scores were converted to SAT-equivalent scores using concordance tables.

is based on very few observations. We also find that teacher entrance exam scores are not associated with teacher productivity.[23]

Table 15 displays the estimated effects of pre-service training but, in this case, we focus on the specific content of education courses. Again, few of the coefficients indicate positive and significant correlations between taking particular kinds of courses and later productivity as a teacher. The one notable exception is the number of subject content credits, which has a strongly significant correlation with teacher productivity in high school math. In contrast, mathematics and statistics coursework outside the college of education does not appear to increase teacher productivity and in fact is negatively correlated with teacher value-added in some instances. When pre-college ability is taken into account by including SAT-equivalent entrance exam scores (Table 16), none of the measures of coursework are significantly correlated with later performance as a teacher.

Overall, while our results are inconsistent across grades and subjects, it appears that colleges of education might improve the performance of their graduates, and schools might improve the productivity of existing teachers, by placing somewhat greater emphasis on content knowledge, including that which is pedagogically oriented. This conclusion is suggested by both the apparently positive effects of content-oriented courses in teacher preparation programs and the effects of content-oriented in-service professional development in middle and high school math.

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[23] The only previous study to include entrance exam scores, Ferguson and Ladd (1996), utilizes school-level average composite scores on the American College Test (ACT), rather than the scores of individual teachers.

VI. Summary and Conclusions

Our study contributes to the rapidly expanding literature on teacher training in a number of ways. First, ours is the first large-scale study to simultaneously control for unobserved student, teacher and school heterogeneity through the use of multiple levels of fixed effects. We argue this significantly attenuates selection bias that may have plagued much of the previous literature on teacher training. Second, while most recent research has focused on teacher experience and attainment of advanced degrees, ours is the first analysis to concurrently estimate the impacts of experience, post-baccalaureate degrees, in-service professional development and pre-service undergraduate education on the productivity of teachers. Further, we are able to measure the various forms of training at a finer level than in most prior studies, including distinguishing specific types of coursework at the undergraduate level and differentiating between different kinds of professional development training received while teaching. Finally, ours is the first study to distinguish between the quality of undergraduate training and the innate ability of future teachers by including individual-specific college entrance exam scores.

While our findings corroborate some of the evidence presented in prior research, we also uncover some important new insights. Like other recent work, we find generally positive, but mixed, evidence on the effects of experience and little or no evidence of the efficacy of advanced degrees for teachers. We find that the first few years of experience substantially increase the productivity of elementary and middle school teachers but have little impact on the effectiveness of teachers at the high school level. Only in the case of middle school math do we find that obtaining an advanced degree enhances the ability of a teacher to promote student achievement. For all other grade/subject combinations the correlation between advanced degrees and student achievement is negative or insignificant.

Like the only previous study of in-service professional development in the U.S. (Jacob and Lefgren (2004)), we find no positive effects of in-service professional development on the productivity of elementary school teachers. However, at the middle and high school levels we find evidence that prior professional development training has positive effects on the productivity of math teachers. These positive effects are primarily due to increased exposure to content-focused training; other types of in-service coursework, such as pedagogical training, are not found to enhance teacher productivity.

While some recent studies have attempted to correlate teacher productivity with broad measures of undergraduate institutional quality, there is scant evidence on the impact of specific aspects of undergraduate training on future teacher productivity. The few existing studies yield mixed results on the relationship between college major and teacher effectiveness. Except for English/Language Arts education majors who teach middle school reading, we find no evidence that education majors are more productive as teachers than are students who major in non-education disciplines. When pre-college ability is taken into account by college entrance exam scores, even the English Education major differential becomes insignificant. We do, however, find that within College-of-Education coursework, increases in the number of subject content credits completed are positively correlated with the performance of high school math teachers.

Although much work remains to fully understand the ways in which training affects the ability of teachers to promote student learning, our analysis does offer some tentative suggestions for shaping future policy. First, our finding (at that of others) that experience greatly enhances the productivity of elementary and middle school teachers early in their careers indicates that policies designed to promote retention of young teachers can yield significant benefits over and above avoiding the cost of hiring new teachers. Second, our finding (consistent with prior research), that advanced degrees are uncorrelated with the productivity of elementary school teachers suggests that current salary schedules, which are based in part on educational attainment, may not be an efficient way to compensate teachers. Third, our evidence that only content-oriented professional development coursework taken by middle and high-school math teachers appears effective suggests that relatively more resources ought to be put into content-focused training for teachers in the upper grades and that changes are warranted in PD at the elementary level and in pedagogical in-service training generally. A similar conclusion arises for university-based education, given our finding that content-oriented undergraduate courses signal future teacher productivity in secondary grades. Finally, given we find no evidence that education majors are significantly more productive as teachers than non-education majors, it seems worthwhile to at least experiment with so-called “alternative certification” programs that facilitate the entry of non-education majors into teaching.

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Table 1
Results of Recent Studies of the Effects of Teacher Training on Student Achievement in the U.S., By Teacher Training Type

	Type of Training			
Method/Studies	**Undergraduate Studies**	**Graduate Degrees**	**In-Service Training**	**Experience**
Gain Score with Student Covariates				
Aaronson, et al. (2007)	Major (MH 0)			(MH 0)
Hill et al. (2005)				(ME 0)
Kane, et al. (2006)	GPA (ME/MM 0, RE/RM 0) College Selectivity (ME/MM 0, RE/RM 0)			(ME/MM ++, RE/RM ++)
Panel Data with Student Fixed Effects				
Betts et al. (2003)	Major (All Mix)	MA (ME +, RE 0, MM 0, RM 0, MH 0, RH ++)		(ME 0, RE 0, MM +, RM 0, MH 0, RH 0)
Boyd, et al. (2006)				(ME/MM ++, RE/RM ++)
Clotfelter, et al. (2007a)	Univ. Prestige (ME +, RE 0)	MA (ME 0, RE--)		(ME ++, RE ++)
Clotfelter, et al. (2007b)	Univ. Prestige (CH ++)	MA (CH 0)		(CH ++)
Hanushek, et al. (2005)		MA (ME 0, MM 0)		(ME +, MM +)
Jepsen (2005)		>BA (ME 0, RE 0)		(ME +, RE +)
Rivkin, et al. (2005)		MA (MM 0, RM 0)		(MM +, RM 0)
Rockoff (2004)		MA (ME 0, RE -)		(ME 0, RE ++)
Random Assignment and "Natural Experiments"				
Clotfelter, et al. (2006)	Univ. Prestige (ME 0, RE 0)	MA (ME --, RE --)		(ME ++, RE ++)
Dee (2004)		MA (ME +, RE 0)		(ME 0, RE ++)
Ding and Lehrer (2005)		MA (ME 0, RE 0)		(ME 0, RE +)
Jacob and Lefgren (2004)			(ME 0, RE 0)	
Nye, et al. (2004)		MA (ME +, RE 0)		(ME +, RE +)

Each cell starts by listing the specific variable under consideration, except for the last two columns where in-service training and experience are defined the same way across studies. Effects on student achievement are given in parentheses. The first letter indicates the subject area: M = math, R = reading, C=combined. The second letter indicates the grade level: E = elementary, M = middle school, and H = high school. This is followed by information regarding the effects of the specified variable on student achievement scores in the previously specified subject and grade in the preferred specifications: ++ = positive and significant in nearly all preferred specifications; + = often positive and significant; 0 = insignificant; - = often negative and significant; -- = negative and significant in nearly all preferred specifications; and Mix = mix of positive/significant and negative/significant.

Table 2
Summary Statistics for Florida Public School Students and Teachers, 1999/2000-2004/2005

	Math			Reading		
	Elementary (Grades 3-5)	Middle (Grades 6-8)	High School (Grades 9-10)	Elementary (Grades 3-5)	Middle (Grades 6-8)	High School (Grades9-10)
In-Service (Student-Level)Variables						
Achievement Gain	18.838	14.069	10.155	16.663	16.257	-0.594
Std. Dev. of Achiev. Gain	25.677	23.167	26.246	26.599	25.383	25.893
Achievement Level	649.451	677.513	719.763	655.061	697.048	707.490
Std. Dev. of Achiev. Level	37.405	37.373	38.967	38.712	38.811	34.560
Number of Schools Attended	1.033	1.037	1.019	1.033	1.027	1.018
"Structural" Mover	0.008	0.244	0.294	0.008	0.179	0.345
"Non-Structural" Mover	0.105	0.147	0.140	0.105	0.124	0.154
Fraction Female Peers	0.499	0.496	0.515	0.499	0.514	0.523
Fraction Black Peers	0.221	0.227	0.187	0.221	0.195	0.175
Fraction Mover Peers	0.143	0.417	0.416	0.143	0.329	0.513
Fraction "Strc.-Mover" Peers	0.009	0.246	0.262	0.009	0.182	0.334
Average Age of Peers (Mo.)	121.450	150.965	179.195	121.454	152.946	181.489
Average Class Size	25.325	26.576	27.761	25.324	26.726	27.689
Teacher Experience	11.092	9.733	11.378	11.095	9.871	10.612
Total In-service Hours	51.770	45.971	37.275	51.763	50.390	42.571
Content In-service Hours	20.131	15.120	13.200	20.127	17.825	15.422
Other In-service Hours	31.639	30.850	24.075	31.636	32.565	27.149
Advanced Degree	0.315	0.311	0.385	0.315	0.333	0.380
Principal Experience	11.646	11.894	12.377	11.652	12.025	12.431
New Principal at School	0.137	0.155	0.170	0.137	0.158	0.165
New School	0.001	0.001	0.001	0.001	0.003	0.001
Pre-Service (Teacher/School Spell-Level) Variables						
Education Major	0.964	0.752	0.625	0.964	0.582	0.456
Math Ed. Major	0.000	0.133	0.380			
English Ed. Major				0.001	0.270	0.305
Math Major	0.000	0.017	0.105			
English Major				0.004	0.262	0.425
SAT Total Score	970.033	989.019	1038.217	970.641	1004.781	1018.732
No. of Obs. (In-service)	506,990	1,006,871	665,126	508,605	691,227	411,284
No. of Obs. (Pre-service)	1,373	928	429	1,373	753	485

Table 3
Iterated OLS Estimates of the Effects of Teacher Experience and In-Service Training on Student Math and Reading Achievement in Florida, 1999/2000-2004/2005

	Math			Reading		
	Elementary (Grades 4-5)	Middle (Grades 6-8)	High School (Grades 9-10)	Elementary (Grades 4-5)	Middle (Grades 6-8)	High School (Grades9-10)
1-2 Years of Experience	1.5424***	0.8747***	-0.2236	2.3272***	0.4021*	0.3731*
	(4.10)	(6.81)	(0.95)	(7.00)	(1.82)	(1.78)
3-4 Years of Experience	1.6308***	1.6964***	-0.1540	2.4186***	0.2756	0.0931
	(4.41)	(9.89)	(0.68)	(6.70)	(1.00)	(0.37)
5-9 Years of Experience	1.8827***	1.7876***	0.3086	2.7279***	0.5840***	0.1205
	(5.51)	(13.38)	(1.45)	(9.02)	(2.57)	(0.48)
10-14 Years of Experience	2.2564***	2.2309***	0.0385	2.8320***	0.7081***	0.4416*
	(6.44)	(13.93)	(0.17)	(8.80)	(2.92)	(1.67)
15-24 Years of Experience	2.2649***	2.1716***	0.0660	2.8361***	1.1522***	0.0222
	(6.42)	(13.86)	(0.35)	(12.47)	(5.00)	(0.09)
25+ Years of Experience	1.6457***	2.1761***	-0.4827**	3.4779***	1.1049***	0.6389**
	(4.00)	(13.86)	(2.21)	(11.08)	(4.84)	(2.30)
Total In-service Hours$_t$	-0.0023	0.0022***	-0.0003	-0.0010	0.0023**	-0.0022
	(1.64)	(3.33)	(0.23)	(0.85)	(2.29)	(1.43)
Total In-service Hours$_{t-1}$	0.0020	0.0034***	-0.0013	0.0028*	-0.0019*	0.0009
	(1.54)	(4.97)	(1.00)	(1.83)	(1.83)	(0.47)
Total In-service Hours$_{t-2}$	-0.0018*	-0.0009	0.0024*	-0.0016	0.0009	-0.0022
	(1.86)	(0.97)	(1.84)	(1.40)	(1.00)	(1.49)
Total In-service Hours$_{t-3}$	0.0029**	0.0009	0.0035**	0.0017*	-0.0008	-0.0015
	(2.51)	(1.11)	(2.40)	(1.65)	(0.68)	(1.09)
Student Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Teacher Fixed Effects	No	No	No	No	No	No
School Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Students	249,906	435,573	298,470	250,694	306,305	204,218
Number of Observations	507,010	1,007,646	665,504	508,625	691,861	411.454

Models include the following time varying student/class/school characteristics: number of schools attended by the student in the current year, "structural" move by student, "non-structural move" by student, indicator of a student repeating a grade, class size, fraction of classroom peers who are female, fraction of classroom peers who are black, average age (in months) of classroom peers, fraction of classroom peers who changed schools, fraction of classroom peers who made a "structural move," indicator for a new school, indicator for a new principal at a school, principal's years of administrative experience and principal's experience squared. All models also include grade-by-year and repeater-by-grade dummies. Absolute values of bootstrapped t-statistics, based on 50 repetitions, appear in parentheses. * indicates statistical significance at the .10 level and ** indicates significance at the .05 level and *** indicates significance at the .01 level in a two-tailed test.

Table 4
Iterated OLS Estimates of the Effects of Teacher Experience and In-Service Training on Student Math and Reading Achievement in Florida, 1999/2000-2004/2005

	Math			Reading		
	Elementary (Grades 4-5)	Middle (Grades 6-8)	High School (Grades 9-10)	Elementary (Grades 4-5)	Middle (Grades 6-8)	High School (Grades9-10)
1-2 Years of Experience	1.3963**	1.6058***	0.4734	2.4049***	0.8758**	-0.5381
	(2.25)	(6.80)	(1.39)	(4.85)	(2.10)	(1.23)
3-4 Years of Experience	2.0236***	2.2389***	0.1009	2.9006***	0.4309	-1.5640**
	(3.03)	(6.41)	(0.21)	(4.19)	(0.83)	(2.23)
5-9 Years of Experience	1.3522	2.1853***	-0.1611	2.7655***	0.9414	-2.2109***
	(1.58)	(6.36)	(0.35)	(4.28)	(1.56)	(2.69)
10-14 Years of Experience	1.6290	2.1331***	-0.9470*	2.3675***	1.4036*	-2.8850***
	(1.49)	(4.18)	(1.68)	(2.93)	(1.94)	(2.96)
15-24 Years of Experience	1.1776	2.8384***	-2.0257***	3.2846***	2.5293***	-3.5074***
	(0.90)	(4.67)	(2.60)	(2.87)	(2.80)	(2.80)
25+ Years of Experience	0.1381	3.5177***	-3.3615***	2.5739*	2.1933*	-3.7343**
	(0.09)	(4.56)	(3.30)	(1.76)	(1.86)	(2.18)
Total In-service Hours$_t$	-0.0030	0.003	0.0020	-0.0040*	0.0001	-0.0007
	(1.47)	(0.29)	(1.11)	(1.92)	(0.08)	(0.67)
Total In-service Hours$_{t-1}$	0.0013	0.0034**	0.0011	0.0000	-0.0034**	0.0026
	(0.53)	(2.33)	(0.55)	(0.01)	(2.05)	(0.94)
Total In-service Hours$_{t-2}$	-0.0040**	0.0003	0.0047*	-0.0039	0.0002	-0.0009
	(2.26)	(0.19)	(1.90)	(1.59)	(0.13)	(0.35)
Total In-service Hours$_{t-3}$	-0.0021	-0.0003	0.0048**	-0.0015	-0.0015	-0.0025
	(1.18)	(0.24)	(2.33)	(0.91)	(0.99)	(0.88)
Student Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Teacher Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
School Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Students	249,906	435,573	298,470	250,694	306,305	204,218
Number of Observations	507,010	1,007,646	665,504	508,625	691,861	411,454

Models include the following time varying student/class/school characteristics: number of schools attended by the student in the current year, "structural" move by student, "non-structural move" by student, indicator of a student repeating a grade, class size, fraction of classroom peers who are female, fraction of classroom peers who are black, average age (in months) of classroom peers, fraction of classroom peers who changed schools, fraction of classroom peers who made a "structural move," indicator for a new school, indicator for a new principal at a school, principal's years of administrative experience. All models also include grade-by-year and repeater-by-grade dummies. Absolute values of bootstrapped t-statistics, based on 50 repetitions, appear in parentheses. * indicates statistical significance at the .10 level and ** indicates significance at the .05 level and *** indicates significance at the .01 level in a two-tailed test.

Table 5A - Elementary
Impact of Varying Persistence Assumptions on the Estimated Effects of Teacher In-Service Training on Elementary Student Math and Reading Achievement in Florida, 1999/2000-2004/2005

	Math					Reading				
	λ=1.0	λ=0.8	λ=0.6	λ=0.4	λ=0.2	λ=1.0	λ=0.8	λ=0.6	λ=0.4	λ=0.2
Total In-service Hours$_t$	-0.0030	-0.0023	-0.0016	-0.0009	-0.0003	-0.0040*	-0.0035*	-0.0029*	-0.0024	-0.0018
	(1.47)	(1.27)	(0.99)	(0.66)	(0.19)	(1.92)	(1.82)	(1.70)	(1.53)	(1.27)
Total In-service Hours$_{t-1}$	0.0013	0.0013	0.0013	0.0014	0.0014	0.0000	-0.0000	-0.0000	-0.0001	-0.0002
	(0.53)	(0.61)	(0.69)	(0.80)	(0.91)	(0.01)	(0.01)	(0.04)	(0.07)	(0.11)
Total In-service Hours$_{t-2}$	-0.0040**	-0.0031*	-0.0022	-0.0013	-0.0004	-0.0039	-0.0030	-0.0022	-0.0013	-0.0004
	(2.26)	(1.88)	(1.42)	(0.88)	(0.27)	(1.59)	(1.37)	(1.10)	(0.73)	(0.26)
Total In-service Hours$_{t-3}$	-0.0021	-0.0013	0.0005	0.0003	0.0011	-0.0015	-0.0010	-0.0004	0.0001	0.0006
	(1.18)	(0.81)	(0.37)	(0.23)	(0.89)	(0.91)	(0.66)	(0.33)	(0.11)	(0.61)
Student Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Teacher Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Students	249,906	249,906	249,906	249,906	249,906	250,694	250,694	250,694	250,694	250,694
Number of Observations	507,010	507,010	507,010	507,010	507,010	508,625	508,625	508,625	508,625	508,625

Models include the following time varying student/class/school characteristics: number of schools attended by the student in the current year, "structural" move by student, "non-structural move" by student, indicator of a student repeating a grade, class size, fraction of classroom peers who are female, fraction of classroom peers who are black, average age (in months) of classroom peers, fraction of classroom peers who changed schools, fraction of classroom peers who made a "structural move," indicator for a new school, indicator for a new principal at a school, principal's years of administrative experience. All models also include grade-by-year and repeater-by-grade dummies. Absolute values of bootstrapped t-statistics, based on 50 repetitions, appear in parentheses. * indicates statistical significance at the .10 level and ** indicates significance at the .05 level and *** indicates significance at the .01 level in a two-tailed test.

Table 5B - Middle
Impact of Varying Persistence Assumptions on the Estimated Effects of
Teacher In-Service Training on Middle School Student Math and Reading Achievement in Florida, 1999/2000-2004/2005

	Math					Reading				
	λ=1.0	λ=0.8	λ=0.6	λ=0.4	λ=0.2	λ=1.0	λ=0.8	λ=0.6	λ=0.4	λ=0.2
Total In-service Hours$_{t}$	0.0003	0.0002	0.0001	-0.0001	-0.00 2	0.0001	0.0003	0.0005	0.0007	0.0009
	(0.29)	(0.19)	(0.06)	(0.09)	(0.27)	(0.08)	(0.22)	(0.40)	(0.62)	(0.89)
Total In-service Hours$_{t-1}$	0.0034**	0.0029**	0.0024**	0.0019*	0.0014	-0.0034**	-0.0030**	-0.0027***	-0.0023**	-0.0020*
	(2.33)	(2.22)	(2.07)	(1.85)	(1.54)	(2.05)	(2.06)	(2.05)	(2.00)	(1.89)
Total In-service Hours$_{t-2}$	0.0003	0.003	0.0004	0.0004	0.0004	0.0002	0.0001	-0.0001	-0.0002	-0.0003
	(0.19)	(0.22)	(0.26)	(0.29)	(0.34)	(0.13)	(0.05)	(0.05)	(0.16)	(0.29)
Total In-service Hours$_{t-3}$	-0.0033	0.0000	0.0004	0.0008	0.0012	-0.0015	-0.0014	-0.0013	-0.0013	-0.0012
	(0.24)	(0.05)	(0.40)	(0.82)	(1.34)	(0.99)	(1.04)	(1.10)	(1.15)	(1.20)
Student Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Teacher Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Students	435,573	435,573	435,573	435,573	435,573	306,305	306,305	306,305	306,305	306,305
Number of Observations	1,007,646	1,026,528	1,007,646	1,007,646	1,007,646	691,861	691,861	691,861	691,861	691,861

Models include the following time varying student/class/school characteristics: number of schools attended by the student in the current year, “structural” move by student, “non-structural move” by student, indicator of a student repeating a grade, class size, fraction of classroom peers who are female, fraction of classroom peers who are black, average age (in months) of classroom peers, fraction of classroom peers who changed schools, fraction of classroom peers who made a “structural move,” indicator for a new school, indicator for a new principal at a school, principal’s years of administrative experience. All models also include grade-by-year and repeater-by-grade dummies. Absolute values of bootstrapped t-statistics, based on 50 repetitions, appear in parentheses. * indicates statistical significance at the .10 level and ** indicates significance at the .05 level and *** indicates significance at the .01 level in a two-tailed test.

Table 5C - High
Impact of Varying Persistence Assumptions on the Estimated Effects of
Teacher In-Service Training on Middle School Student Math and Reading Achievement in Florida, 1999/2000-2004/2005

	Math					Reading				
	λ=1.0	λ=0.8	λ=0.6	λ=0.4	λ=0.2	λ=1.0	λ=0.8	λ=0.6	λ=0.4	λ=0.2
Total In-service Hours$_t$	0.0020	0.0018	0.0015	0.0013	0.0011	-0.0017	-0.0016	-0.0014	-0.0013	-0.0012
	(1.11)	(1.10)	(1.06)	(1.00)	(0.89)	(0.67)	(0.69)	(0.70)	(0.70)	(0.71)
Total In-service Hours$_{t-1}$	0.0011	0.0015	0.0019	0.0023	0.0027*	0.0026	0.0024	0.0021	0.0018	0.0014
	(0.55)	(0.82)	(1.13)	(1.49)	(1.87)	(0.94)	(0.96)	(0.93)	(0.88)	(0.79)
Total In-service Hours$_{t-2}$	0.0047*	0.0048**	0.0050**	0.0052***	0.0054***	-0.0009	-0.0005	-0.0002	0.0001	0.0004
	(1.90)	(2.15)	(2.44)	(2.78)	(3.16)	(0.35)	(0.25)	(0.11)	(0.06)	(0.26)
Total In-service Hours$_{t-3}$	0.0048**	0.0052***	0.0056***	0.0059***	0.0062***	-0.0025	-0.0023	-0.0021	-0.0019	-0.0017
	(2.33)	(2.77)	(3.29)	(3.90)	(4.59)	(0.88)	(0.97)	(1.02)	(1.07)	(1.11)
Student Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Teacher Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
School Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of Students	298,470	298,470	298,470	298,470	298,470	204,218	204,218	204,218	204,218	204,218
Number of Observations	665,504	665,504	665,504	665,504	665,504	411,454	411,454	411,454	411,454	411,454

Models include the following time varying student/class/school characteristics: number of schools attended by the student in the current year, “structural” move by student, “non-structural move” by student, indicator of a student repeating a grade, class size, fraction of classroom peers who are female, fraction of classroom peers who are black, average age (in months) of classroom peers, fraction of classroom peers who changed schools, fraction of classroom peers who made a “structural move,” indicator for a new school, indicator for a new principal at a school, principal’s years of administrative experience. All models also include grade-by-year and repeater-by-grade dummies. Absolute values of bootstrapped t-statistics, based on 50 repetitions, appear in parentheses. * indicates statistical significance at the .10 level and ** indicates significance at the .05 level and *** indicates significance at the .01 level in a two-tailed test.

Table 6
OLS Estimates of the Effects of Teacher Experience and In-Service Training on Student Math and Reading Achievement in Florida, 1999/2000-2004/2005

	Math			Reading		
	Elementary (Grades 4-5)	Middle (Grades 6-8)	High School (Grades 9-10)	Elementary (Grades 4-5)	Middle (Grades 6-8)	High School (Grades9-10)
1-2 Years of Experience	0.7893***	1.2285***	0.2035	1.1595***	0.5280**	-0.4335
	(2.57)	(7.59)	(0.91)	(3.72)	(2.45)	(1.58)
3-4 Years of Experience	1.0656***	1.7886***	-0.0105	1.2551***	0.2615	-1.1316***
	(2.77)	(8.45)	(0.04)	(3.21)	(0.90)	(3.05)
5-9 Years of Experience	0.5368	2.1200***	-0.6863**	1.1045**	0.5602*	-1.6864***
	(1.23)	(8.58)	(2.14)	(2.49)	(1.67)	(3.70)
10-14 Years of Experience	0.6263	2.1360***	-1.3017***	1.0514*	0.8450*	-1.5182**
	(1.13)	(6.56)	(3.20)	(1.87)	(1.93)	(2.47)
15-24 Years of Experience	0.7136	2.7603***	-2.6968***	1.5430**	1.5828 ***	-1.8980***
	(1.09)	(6.75)	(5.49)	(2.31)	(2.99)	(2.62)
25+ Years of Experience	-0.3718	3.4026***	-4.2178***	0.3712	1.4507**	-1.6004*
	(0.46)	(6.70)	(7.07)	(0.45)	(2.19)	(1.80)
Total In-service Hours$_{t}$	-0.0001	-0.0001	-0.0002	0.0000	0.0005	-0.0041***
	(0.11)	(0.11)	(0.17)	(0.03)	(0.55)	(2.71)
Total In-service Hours$_{t-1}$	0.0028**	0.0024***	-0.0013	0.0006	-0.0023**	-0.0004
	(2.37)	(2.90)	(1.02)	(0.47)	(2.42)	(0.27)
Total In-service Hours$_{t-2}$	-0.0014	0.0008	0.0020*	-0.0018	-0.0010	-0.0018
	(1.23)	(0.93)	(1.67)	(1.56)	(1.06)	(1.27)
Total In-service Hours$_{t-3}$	0.0003	0.0004	0.0004	-0.0001	-0.0015	-0.0010
	(0.32)	(0.48)	(0.36)	(0.13)	(1.60)	(0.67)
Student Fixed Effects	No	No	No	No	No	No
Teacher Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
School Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Students	249,900	435,555	298,258	250,688	306,286	204,029
Number of Observations	506,998	1,007,609	665,074	508,613	691,820	411,074

Models include the following time varying student/class/school characteristics: number of schools attended by the student in the current year, “structural” move by student, “non-structural move” by student, indicator of a student repeating a grade, class size, fraction of classroom peers who are female, fraction of classroom peers who are black, average age (in months) of classroom peers, fraction of classroom peers who changed schools, fraction of classroom peers who made a “structural move,” indicator for a new school, indicator for a new principal at a school, principal’s years of administrative experience. Included student time-invariant (or quasi-time-invariant) covariates are: racial/ethnic and gender indicators, free-lunch status, gifted status, limited-English proficiency status, and a set of indicators for mental, physical, emotional and other disabilities. All models also include grade-by-year and repeater-by-grade dummies. Absolute values of bootstrapped t-statistics, based on 50 repetitions, appear in parentheses. * indicates statistical significance at the .10 level and ** indicates significance at the .05 level and *** indicates significance at the .01 level in a two-tailed test.

Table 7
Iterated OLS Estimates of the Effects of Teacher Experience and In-Service Training on Student Math and Reading Achievement in Florida, 1999/2000-2004/2005

	Math			Reading		
	Elementary (Grades 4-5)	Middle (Grades 6-8)	High School (Grades 9-10)	Elementary (Grades 4-5)	Middle (Grades 6-8)	High School (Grades9-10)
Scored Above 95th Percentile$_{t-1}$	-55.6503***	-45.8573***	-40.6019***	-56.4644***	-49.7315***	-47.6495***
	(212.83)	(238.98)	(276.34)	(176.84)	(217.46)	(152.90)
1-2 Years of Experience	1.3169**	1.4484***	0.4085	2.3121***	0.7156*	-0.2579
	(2.19)	(6.15)	(1.29)	(4.69)	(1.82)	(0.71)
3-4 Years of Experience	2.2110***	2.0106***	0.1137	2.9125***	0.1366	-1.0592*
	(3.35)	(5.80)	(0.26)	(4.29)	(0.27)	(1.79)
5-9 Years of Experience	1.3689*	1.9550***	0.1634	2.5333***	0.5692	-1.4604*
	(1.72)	(5.84)	(0.39)	(3.91)	(1.00)	(1.91)
10-14 Years of Experience	1.2729	2.0959***	-0.7187	2.7446***	0.8954	-2.2112**
	(1.36)	(4.17)	(1.48)	(3.12)	(1.39)	(2.18)
15-24 Years of Experience	0.8918	2.5378***	-1.5988**	3.3643***	2.1868***	-2.5514*
	(0.81)	(4.45)	(2.32)	(3.07)	(2.62)	(1.92)
25+ Years of Experience	-0.1945	3.2025***	-2.1352**	2.7178*	1.8404*	-2.6147
	(0.14)	(4.23)	(2.29)	(1.87)	(1.72)	(1.63)
Total In-service Hours$_t$	-0.0028	-0.0005	0.0007	-0.0039*	-0.0002	-0.0015
	(1.52)	(0.46)	(0.42)	(1.86)	(0.10)	(0.62)
Total In-service Hours$_{t-1}$	0.0004	0.0026*	0.0018	-0.0002	-0.0031**	0.0041
	(0.16)	(1.77)	(0.93)	(0.11)	(2.19)	(1.59)
Total In-service Hours$_{t-2}$	-0.0039**	0.0000	0.0040*	-0.0034	-0.0007	-0.0000
	(2.32)	(0.03)	(1.78)	(1.53)	(0.47)	(0.01)
Total In-service Hours$_{t-3}$	-0.0015	0.0002	0.0049***	-0.0015	-0.0004	-0.0017
	(0.85)	(0.12)	(2.62)	(0.92)	(0.28)	(0.71)
Student Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Teacher Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
School Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Students	249,906	435,573	298,470	250,694	306,305	204,218
Number of Observations	507,010	1,007,646	665,504	508,625	691,861	411,454

Models include the following time varying student/class/school characteristics: number of schools attended by the student in the current year, "structural" move by student, "non-structural move" by student, indicator of a student repeating a grade, class size, fraction of classroom peers who are female, fraction of classroom peers who are black, average age (in months) of classroom peers, fraction of classroom peers who changed schools, fraction of classroom peers who made a "structural move," indicator for a new school, indicator for a new principal at a school, principal's years of administrative experience. All models also include grade-by-year and repeater-by-grade dummies. Absolute values of bootstrapped t-statistics, based on 50 repetitions, appear in parentheses. * indicates statistical significance at the .10 level and ** indicates significance at the .05 level and *** indicates significance at the .01 level in a two-tailed test.

Table 8
Iterated OLS Estimates of the Effects of Teacher Experience and In-Service Training on Student Math and Reading Achievement in Florida, 1999/2000-2004/2005

	Math	Reading
	Elementary/Middle/High (Grades 4-10)	Elementary/Middle/High (Grades 4-10)
1-2 Years of Experience	1.4517***	0.4353**
	(11.28)	(2.52)
3-4 Years of Experience	1.9463***	-0.0628
	(9.97)	(0.25)
5-9 Years of Experience	1.9935***	-0.0324
	(8.20)	(0.12)
10-14 Years of Experience	2.0871***	-0.0887
	(7.13)	(0.26)
15-24 Years of Experience	1.9591***	0.3785
	(5.45)	(0.92)
25+ Years of Experience	1.9915***	0.0835
	(4.38)	(0.16)
Total In-service Hours$_{t}$	0.0012**	0.0003
	(2.27)	(0.34)
Total In-service Hours$_{t-1}$	0.0030***	-0.0002
	(3.98)	(0.28)
Total In-service Hours$_{t-2}$	0.005	-0.0008
	(0.64)	(1.20)
Total In-service Hours$_{t-3}$	0.0012*	-0.0006
	(1.71)	(0.65)
Student Fixed Effects	Yes	Yes
Teacher Fixed Effects	Yes	Yes
School Fixed Effects	Yes	Yes
Number of Students	1,002,566	799,373
Number of Observations	2,885,594	2,118,098

Models include the following time varying student/class/school characteristics: number of schools attended by the student in the current year, “structural” move by student, “non-structural move” by student, indicator of a student repeating a grade, class size, fraction of classroom peers who are female, fraction of classroom peers who are black, average age (in months) of classroom peers, fraction of classroom peers who changed schools, fraction of classroom peers who made a “structural move,” indicator for a new school, indicator for a new principal at a school, principal’s years of administrative experience. All models also include grade-by-year and repeater-by-grade dummies. Absolute values of bootstrapped t-statistics, based on 50 repetitions, appear in parentheses. * indicates statistical significance at the .10 level and ** indicates significance at the .05 level and *** indicates significance at the .01 level in a two-tailed test.

Table 9
Partial Correlation of Observed Teacher Attributes with
Lagged Transitory Changes in Student Achievement Gains by Grade Level in Florida, 2004/05

	Math				Reading			
	Grade 7	Grade 8	Grade 9	Grade 10	Grade 7	Grade 8	Grade 9	Grade 10
1-2 Years of Experience	0.0111	0.0037	-0.0051	0.0051	-0.0011	-0.0072	-0.0007	-0.0057
3-4 Years of Experience	0.0009	0.0112	-0.0075	0.0056	0.0053	-0.0053	-0.0035	-0.0047
5-9 Years of Experience	0.0047	0.0095	-0.0107	0.0010	0.0068	-0.0078	0.0022	-0.0078
10-14 Years of Experience	0.0096	0.0136	-0.0215	0.0018	0.0067	-0.0017	0.0049	-0.0055
15-24 Years of Experience	0.0072	0.0183	-0.0278	0.0034	0.0098	-0.0069	0.0028	-0.0112
25+ Years of Experience	0.0092	0.0161	-0.0227	0.0071	0.0023	-0.0004	0.0012	-0.0093
Total In-Service Hours$_t$	0.0018	0.0002	0.0052	0.0019	0.0103	0.0032	0.0130	0.0056
Total In-Service Hours$_{t-1}$	0.0035	0.0038	0.0006	-0.0034	0.0049	0.0024	0.0000	-0.0152
Total In-Service Hours$_{t-2}$	-0.0080	-0.0055	0.0018	-0.0062	-0.0037	-0.0044	0.0205	0.0024
Total In-Service Hours$_{t-3}$	0.0030	0.0018	-0.0044	0.0095	0.0055	0.0002	-0.0048	0.0060
Advanced Degree	-0.0084	0.0074	-0.0181	0.0066	-0.0000	0.0124	0.0010	0.0091

Note: The lagged transitory achievement gain is defined as $\Delta A_{t-1} - ((\Delta A_{t-2}+\Delta A_{t-3})/2)$.

Table 10
Random Effects Tobit Estimates of In-Service Hours in Florida, 1999/2000-2004/2005
(Coefficients are Marginal Effects)

	Math			Reading		
	Elementary (Grades 4-5)	Middle (Grades 6-8)	High School (Grades 9-10)	Elementary (Grades 4-5)	Middle (Grades 6-8)	High School (Grades9-10)
Average Achievement Gain	-0.0023	0.0483	-0.0569**	-0.0254	-0.0124	-0.0305
	(0.10)	(1.22)	(2.18)	(1.13)	(0.25)	(0.83)
Certification Expires At End of Current Year	-1.634*	-2.1063**	0.2061	-1.6225**	-3.5935**	-0.8231
	(1.85)	(1.99)	(0.23)	(1.84)	(2.43)	(0.59)
Certification Expires At End of Year t+1	-0.3333	1.9187*	0.1466	-0.352	-0.0761	-2.0942
	(0.37)	(1.76)	(0.16)	(0.39)	(0.05)	(1.50)
Certification Expires At End of Year t+2	-1.0336	-1.2843	1.0972	-1.0065	-1.2134	-1.1754
	(1.16)	(1.23)	(1.24)	(1.13)	(0.83)	(0.87)
Certification Expires At End of Year t+3	-0.2437	0.4207	0.4935	-0.2346	0.4924	-1.3046
	(0.28)	(0.42)	(0.58)	(0.27)	(0.35)	(1.01)
Holds Temporary Teaching Certificate	-7.5962	-14.3426**	3.1733	-6.8739	-8.6691	-5.1773
	(0.72)	(2.48)	(0.49)	(0.63)	(0.94)	(0.36)
1-2 Years of Experience	-9.248*	-27.6558**	-7.8794	-9.2259*	-11.3267	-21.0855*
	(1.84)	(2.54)	(1.02)	(1.84)	(0.39)	(1.85)
3-4 Years of Experience	-9.5214*	-28.9307***	-8.3857	-9.556*	-15.889	-22.4405**
	(1.90)	(2.69)	(1.09)	(1.91)	(0.57)	(2.03)
5-9 Years of Experience	-14.5029***	-40.0271***	-10.818	-14.4482***	-21.0025	-26.1955**
	(2.95)	(2.72)	(1.41)	(2.94)	(0.76)	(2.34)
10-14 Years of Experience	-18.2584***	-34.7893***	-13.0101*	-18.2571***	-26.3517	-32.0388**
	(3.87)	(3.55)	(1.77)	(3.88)	(1.05)	(2.24)
15-24 Years of Experience	-22.6162***	-36.5056***	-12.271	-22.6203***	-28.9664	-30.9421***
	(4.87)	(3.53)	(1.59)	(4.88)	(1.12)	(2.78)
25+ Years of Experience	-25.3392***	-38.3287***	-15.5402**	-25.3495***	-32.0488	-32.1531***
	(5.84)	(4.46)	(2.18)	(5.85)	(1.42)	(3.40)
Advanced Degree	-2.4884***	2.6733***	2.1973***	-2.4585***	1.3817	0.7925
	(3.31)	(2.96)	(2.95)	(3.27)	(1.11)	(0.71)
Year Prior to Obtaining NBPTS Certification	26.6744***	13.2364***	22.0368***	26.2265***	13.7946***	21.9019***
	(8.22)	(2.88)	(6.76)	(8.15)	(2.79)	(4.60)
NBPTS Certified	10.0482***	13.793***	10.4732***	9.9348***	12.789***	5.6549**
	(5.16)	(4.22)	(5.51)	(5.11)	(4.20)	(2.08)
Teacher Random Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Teachers	11,336	7,082	6,367	14,543	5,643	4,873
Number of Observations	20,919	18,162	18,289	37,131	13,307	11,400

All models include a set of year indicators. Absolute values of t-statistics appear in parentheses. * indicates statistical significance at the .10 level, ** indicates significance at the .05 level and *** indicates significance at the .01 level in a two-tailed test.

Table 11
Iterated OLS Estimates of the Effects of Teacher Experience and In-Service Training on Student Math and Reading Achievement in Florida, 1999/2000-2004/2005

	Math			Reading		
	Elementary (Grades 4-5)	Middle (Grades 6-8)	High School (Grades 9-10)	Elementary (Grades 4-5)	Middle (Grades 6-8)	High School (Grades9-10)
1-2 Years of Experience	1.3890**	1.6106***	0.4345	2.4386***	0.8420**	-0.5744
	(2.26)	(6.79)	(1.26)	(4.89)	(2.02)	(1.35)
3-4 Years of Experience	2.0140***	2.2361***	0.0753	2.9569***	0.4027	-1.5975**
	(3.03)	(6.37)	(0.16)	(4.28)	(0.77)	(2.32)
5-9 Years of Experience	1.3512	2.1888***	-0.1932	2.8796***	0.8838	-2.3024***
	(1.58)	(6.34)	(0.41)	(4.49)	(1.47)	(2.86)
10-14 Years of Experience	1.6422	2.1339***	-0.9852*	2.7907***	1.3674*	-3.0041***
	(1.49)	(4.19)	(1.74)	(3.07)	(1.91)	(3.18)
15-24 Years of Experience	1.1925	2.8396***	-2.0566***	3.4418***	2.5178***	-3.5930***
	(0.91)	(4.69)	(2.63)	(3.00)	(2.80)	(2.98)
25+ Years of Experience	0.1632	3.5017***	-3.3865***	2.7012*	2.1887*	-3.7833**
	(0.11)	(4.56)	(3.31)	(1.82)	(1.87)	(2.26)
Content In-service Hours$_t$	-0.0026	-0.0009	0.0054	-0.0085***	0.0045**	0.0036
	(0.73)	(0.49)	(1.53)	(2.93)	(2.00)	(0.89)
Content In-service Hours$_{t-1}$	0.0025	0.0056***	0.0045	-0.0035	-0.0003	0.0069
	(0.63)	(2.66)	(1.35)	(0.97)	(0.10)	(1.62)
Content In-service Hours$_{t-2}$	-0.0079**	0.0051*	0.0078*	-0.0108**	0.0001	-0.0125**
	(2.33)	(1.72)	(1.93)	(2.51)	(0.02)	(2.29)
Content In-service Hours$_{t-3}$	-0.0016	0.0040**	0.0004	0.0031	-0.0029	-0.0073
	(0.42)	(1.96)	(0.11)	(0.77)	(0.86)	(1.43)
Other In-service Hours$_t$	-0.0031	0.0007	0.0002	-0.0008	-0.0025	-0.0065**
	(1.26)	(0.55)	(0.11)	(0.27)	(1.16)	(2.08)
Other In-service Hours$_{t-1}$	0.0006	0.0023	-0.0007	0.0021	-0.0048***	-0.0004
	(0.23)	(1.41)	(0.33)	(0.71)	(2.64)	(0.12)
Other In-service Hours$_{t-2}$	-0.0023	-0.0017	0.0029	-0.0004	0.0000	0.0026
	(1.06)	(0.92)	(1.10)	(0.15)	(0.00)	(0.89)
Other In-service Hours$_{t-3}$	-0.0023	-0.0023	0.0067**	-0.0029	-0.0015	-0.0009
	(1.03)	(1.41)	(2.45)	(1.15)	(0.79)	(0.29)
Student Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Teacher Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
School Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Students	249,906	435,573	298,470	250,694	306,305	204,218

Number of Observations	507,010	1,007,646	665,504	508,625	691,861	411,454

Models include the following time varying student/class/school characteristics: number of schools attended by the student in the current year, “structural” move by student, “non-structural move” by student, indicator of a student repeating a grade, class size, fraction of classroom peers who are female, fraction of classroom peers who are black, average age (in months) of classroom peers, fraction of classroom peers who changed schools, fraction of classroom peers who made a “structural move,” indicator for a new school, indicator for a new principal at a school, principal’s years of administrative experience. All models also include grade-by-year and repeater-by-grade dummies. Absolute values of bootstrapped t-statistics, based on 50 repetitions, appear in parentheses. * indicates statistical significance at the .10 level and ** indicates significance at the .05 level and *** indicates significance at the .01 level in a two-tailed test.

Table 12
Iterated OLS Estimates of the Effects of Teacher Experience, In-Service Training and Advanced Degrees on Student Math and Reading Achievement in Florida, 1999/2000-2004/2005

	Math			Reading		
	Elementary (Grades 3-5)	Middle (Grades 6-8)	High School (Grades 9-10)	Elementary (Grades 3-5)	Middle (Grades 6-8)	High School (Grades9-10)
1-2 Years of Experience	1.3976**	1.6347***	0.4414	2.4264***	0.8464**	-0.5735
	(2.54)	(6.88)	(1.31)	(3.68)	(2.37)	(1.16)
3-4 Years of Experience	2.0225***	2.2494***	0.0982	2.9449***	0.4290	-1.5813**
	(2.76)	(5.88)	(0.20)	(3.47)	(1.00)	(2.29)
5-9 Years of Experience	1.3614*	2.1991***	-0.1086	2.8678***	0.9176**	-2.2717***
	(1.73)	(5.19)	(0.19)	(3.52)	(2.01)	(2.66)
10-14 Years of Experience	1.6445	2.1528***	-0.8912	2.7716***	1.3847**	-2.9893***
	(1.53)	(3.51)	(1.15)	(2.89)	(2.09)	(3.05)
15-24 Years of Experience	1.1893	2.8927***	-1.9987**	3.4171***	2.5153***	-3.5809***
	(0.90)	(4.05)	(2.38)	(2.92)	(3.24)	(2.94)
25+ Years of Experience	0.1489	3.5787***	-3.3438***	2.6640*	2.1833**	-3.7212**
	(0.08)	(3.99)	(3.45)	(1.74)	(2.03)	(2.23)
Content In-service Hours$_t$	-0.0026	-0.0008	0.0053	-0.0085***	0.0045*	0.0037
	(0.73)	(0.43)	(1.42)	(2.71)	(1.75)	(1.08)
Content In-service Hours$_{t-1}$	0.0024	0.0057***	0.0045	-0.0035	-0.0003	0.0068
	(0.64)	(2.98)	(1.23)	(1.30)	(0.11)	(1.60)
Content In-service Hours$_{t-2}$	-0.0079*	0.0052*	0.0078**	-0.0108***	0.0000	-0.0123***
	(1.91)	(1.81)	(2.05)	(2.69)	(0.02)	(2.61)
Content In-service Hours$_{t-3}$	-0.0016	0.0040	0.0003	0.0032	-0.0029	-0.0073
	(0.48)	(1.57)	(0.10)	(0.92)	(1.00)	(1.14)
Other In-service Hours$_t$	-0.0032	0.0008	0.0001	-0.0008	-0.0024	-0.0065*
	(1.15)	(0.49)	(0.06)	(0.30)	(1.42)	(1.95)
Other In-service Hours$_{t-1}$	0.0005	0.0023	-0.0008	0.0021	-0.0049**	-0.0005
	(0.16)	(1.31)	(0.30)	(0.60)	(2.18)	(0.17)
Other In-service Hours$_{t-2}$	-0.0023	-0.0017	0.0030	-0.0005	0.0000	0.0026
	(0.99)	(1.12)	(1.19)	(0.15)	(0.02)	(0.81)
Other In-service Hours$_{t-3}$	-0.0023	-0.0023	0.0066***	-0.0029	-0.0015	-0.0009
	(0.98)	(1.31)	(3.32)	(1.06)	(0.88)	(0.30)
Advanced Degree	-0.2834	0.7246**	-1.5889***	-0.2595	-1.0324**	-1.1856*
	(0.47)	(2.19)	(4.02)	(0.51)	(2.31)	(1.70)
Student Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Teacher Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
School Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Number of Students	249,896	435,288	298,297	250,684	306,023	204,135
Number of Observations	506,990	1,006,871	665,126	508,605	691,227	411,284

Models include the following time varying student/class/school characteristics: number of schools attended by the student in the current year, "structural" move by student, "non-structural move" by student, indicator of a student repeating a grade, class size, fraction of classroom peers who are female, fraction of classroom peers who are black, average age (in months) of classroom peers, fraction of classroom peers who changed schools, fraction of classroom peers who made a "structural move," indicator for a new school, indicator for a new principal at a school, principal's years of administrative experience. All models also include grade-by-year and repeater-by-grade dummies. Absolute values of bootstrapped t-statistics, based on 50 repetitions, appear in parentheses. * indicates statistical significance at the .10 level and ** indicates significance at the .05 level and *** indicates significance at the .01 level in a two-tailed test.

Table 13
WLS Estimates of the Effects of College Major and College Entrance Exam Scores on a Teacher's "Value-Added" to Student Math and Reading Achievement in Florida, 1999/2000-2004/2005

	Math			Reading		
	Elementary (Grades 3-5)	Middle (Grades 6-8)	High School (Grades 9-10)	Elementary (Grades 3-5)	Middle (Grades 6-8)	High School (Grades9-10)
Education Major	2.1098 (1.34)	-1.3994* (1.84)	0.5490 (0.35)	2.3306 (1.44)	-0.8411 (0.68)	3.2958 (1.49)
Math Ed./English Ed. Major	-1.4270 (0.08)	-0.0871 (0.08)	-4.3279*** (2.91)	23.1849 (1.20)	2.3139* (1.88)	-1.2756 (0.66)
Math/English Major		0.0643 (0.04)	-4.4534*** (2.76)	-0.7445 (0.12)	0.9673 (0.81)	0.8260 (0.48)
School Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.408	0.201	0.345	0.391	0.227	0.362
Number of Observations	3,930	3,336	1,685	3,932	2,491	1,442

The dependent variable is the teacher-school spell fixed effect estimated from a model of student achievement using all Florida public school students in the relevant grades. Observations are weighted by the square root of the number of students per teacher/school spell. Absolute values of t-statistics appear in parentheses. * indicates statistical significance at the .10 level and ** indicates significance at the .05 level and *** indicates significance at the .01 level in a two-tailed test.

Table 14
WLS Estimates of the Effects of College Major and College Entrance Exam Scores on a Teacher's "Value-Added" to Student Math and Reading Achievement in Florida, 1999/2000-2004/2005

	Math			Reading		
	Elementary (Grades 3-5)	Middle (Grades 6-8)	High School (Grades 9-10)	Elementary (Grades 3-5)	Middle (Grades 6-8)	High School (Grades9-10)
Education Major	-3.3386 (0.77)	-1.9950 (1.10)	-4.0358 (0.95)	-1.0190 (0.22)	-2.8450 (1.02)	3.8667 (0.86)
Math Ed./English Ed. Major		0.5352 (0.20)	0.6096 (0.14)	18.7300 (0.88)	1.9159 (0.72)	0.5215 (0.13)
Math/English Major		-0.2177 (0.03)	-12.6500** (2.35)	-9.8928 (0.66)	-0.9504 (0.34)	1.5600 (0.45)
SAT Total Score	-0.0027 (0.45)	-0.0043 (0.75)	-0.0024 (0.26)	0.0041 (0.65)	0.0041 (0.67)	-0.0006 (0.08)
School Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.619	0.422	0.613	0.585	0.470	0.552
Number of Observations	1,380	1,016	492	1,380	827	532

The dependent variable is the teacher-school spell fixed effect estimated from a model of student achievement using all Florida public school students in the relevant grades. Observations are weighted by the square root of the number of students per teacher/school spell. Absolute values of t-statistics appear in parentheses. * indicates statistical significance at the .10 level and ** indicates significance at the .05 level and *** indicates significance at the .01 level in a two-tailed test.

Table 15
WLS Estimates of the Effects of College Course Work and College Entrance Exam Scores on a Teacher's "Value-Added" to Student Math and Reading Achievement in Florida, 1999/2000-2004/2005

	Math			Reading		
	Elementary (Grades 3-5)	Middle (Grades 6-8)	High School (Grades 9-10)	Elementary (Grades 3-5)	Middle (Grades 6-8)	High School (Grades9-10)
Gen. Educ. Theory Credits	-0.2199 (0.41)	-0.0058 (0.01)	0.9512 (1.48)	0.6272 (1.14)	0.5694 (1.01)	-0.0105 (0.02)
Pedagogical - Instructional Credits	-1.2947*** (2.90)	-0.0266 (0.08)	0.6151 (1.14)	-1.0010** (2.16)	0.2289 (0.48)	-1.3663** (2.10)
Pedagogical - Management Credits	-4.1612 (0.67)	4.9624 (1.18)	7.5617 (0.97)	-1.1822 (0.19)	-2.0282 (0.45)	16.6030 (1.33)
Pedagogical - Content Credits	0.0446 (0.14)	-0.0757 (0.26)	0.1005 (0.16)	-0.4114 (1.01)	-1.3015** (2.47)	0.7488 (0.75)
Professional Development Credits	0.0807 (0.27)	-0.0208 (0.09)	-0.3859** (2.35)	0.0127 (0.04)	-0.1079 (0.32)	0.0050 (0.01)
Classroom Observation Credits	-0.3603 (0.10)			5.6006 (1.53)		6.7244 (0.39)
Classroom Practice Credits	0.1187 (0.26)	0.0707 (0.19)	-0.0188 (0.03)	0.1017 (0.22)	-0.1361 (0.26)	0.6477 (0.90)
Subject Content Credits	-0.5898 (0.45)	0.6000 (0.52)	3.6037** (2.31)	-0.2278 (0.18)	-1.8658 (1.10)	2.3298 (0.61)
Mathematics Credits	-0.1933** (2.16)	0.0091 (0.08)	0.1962 (1.18)			
Statistics Credits	-0.8585 (0.47)	0.1301 (0.13)	-0.9991 (1.05)			
English Literature Credits				-0.2696 (1.31)	0.0068 (0.04)	-0.0610 (0.29)
Math Education Credits	1.0998* (1.71)	-0.1471 (0.36)	-1.0367** (2.14)			
Language Arts Educ. Credits				0.9750 (1.53)	0.4892 (1.10)	-0.5298 (0.88)
School Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.305	0.120	0.225	0.283	0.171	0.292
Number of Observations	8,023	8,360	4,487	8,028	5,139	3,232

The dependent variable is the teacher-school spell fixed effect estimated from a model of student achievement using all Florida public school students in the relevant grades. Observations are weighted by the square root of the number of students per teacher/school spell. Absolute values of t-statistics appear in parentheses. * indicates statistical significance at the .10 level and ** indicates significance at the .05 level and *** indicates significance at the .01 level in a two-tailed test.

Table 16
WLS Estimates of the Effects of College Course Work and College Entrance Exam Scores on a Teacher's "Value-Added" to Student Math and Reading Achievement in Florida, 1999/2000-2004/2005

	Math			Reading		
	Elementary (Grades 3-5)	Middle (Grades 6-8)	High School (Grades 9-10)	Elementary (Grades 3-5)	Middle (Grades 6-8)	High School (Grades9-10)
Gen. Educ. Theory Credits	1.6723 (0.99)	-1.7268 (1.24)	4.5714 (1.47)	-0.7887 (0.46)	0.2302 (0.14)	-1.3676 (0.74)
Pedagogical - Instructional Credits	-0.5631 (0.44)	0.4940 (0.42)	-2.2467 (0.86)	-2.1628 (1.67)	2.1141 (1.45)	-0.3268 (0.20)
Pedagogical - Management Credits	-1.8622 (0.11)	6.7814 (0.59)		-14.9352 (0.89)	-3.7742 (0.33)	24.1089 (0.68)
Pedagogical - Content Credits	1.2395 (1.16)	0.7607 (0.92)	-2.7383 (1.04)	-0.8140 (0.63)	-1.5905 (1.10)	1.8109 (0.77)
Professional Development Credits	-1.6733 (1.64)	-0.1276 (0.13)	-2.6611 (1.13)	1.4927 (1.42)	0.2660 (0.20)	0.1175 (0.08)
Classroom Observation Credits	-1.4619 (0.24)			-0.1639 (0.03)		-0.1483 (0.01)
Classroom Practice Credits	-1.1074 (0.82)	-0.8230 (0.65)	4.1804 (1.54)	-0.9137 (0.66)	-2.2532 (1.53)	2.3914 (1.25)
Subject Content Credits	-0.8969 (0.25)	2.8835 (1.04)	0.5533 (0.10)	-2.3063 (0.63)	-6.5725 (1.43)	7.2439 (0.97)
Mathematics Credits	-0.2528 (1.36)	-0.1717 (0.76)	-0.9432 (1.56)			
Statistics Credits	1.5640 (0.49)	1.3459 (0.56)	-2.2807 (0.62)			
English Literature Credits				-0.0137 (0.04)	0.0442 (0.13)	0.5885 (1.20)
Math Education Credits	0.7590 (0.38)	-0.1529 (0.15)	-2.3996 (1.26)			
Language Arts Educ. Credits				0.4706 (0.22)	1.0212 (0.92)	-0.9369 (0.61)
SAT Total Score	-0.0011 (0.21)	-0.0024 (1.04)	-0.0104 (1.34)	0.0058 (1.09)	0.0020 (0.37)	-0.0042 (0.64)
School Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.571	0.382	0.574	0.553	0.460	0.524
Number of Observations	1,813	1,244	599	1,812	893	617

The dependent variable is the teacher-school spell fixed effect estimated from a model of student achievement using all Florida public school students in the relevant grades. Observations are weighted by the square root of the number of students per teacher/school spell. Absolute values of t-statistics appear in parentheses. * indicates statistical significance at the .10 level and ** indicates significance at the .05 level and *** indicates significance at the .01 level in a two-tailed test.

Table A1
Comparison of Iterated OLS and Standard Fixed-Effect Estimates of The Effects of Teacher Experience and In-Service Training on Student Math Achievement in 10 Randomly Selected Florida School Districts, 1999/2000-2004/2005

	Iterative FE			Standard FE		
	Elementary (Grades 4-5)	Middle (Grades 6-8)	High School (Grades 9-10)	Elementary (Grades 4-5)	Middle (Grades 6-8)	High School (Grades9-10)
1-2 Years of Experience	2.3468*	2.8551***	-0.04682	2.3355*	2.8560***	-0.0453
	(1.78)	(5.89)	(0.06)	(1.74)	(5.33)	(0.05)
3-4 Years of Experience	3.5903*	4.0519***	-1.5237	3.5577*	4.0510***	-1.5278
	(1.87)	(5.60)	(1.35)	(1.92)	(5.47)	(1.17)
5-9 Years of Experience	3.6217*	4.4444***	-1.5176	3.5859	4.4461***	-1.5195
	(1.75)	(4.72)	(0.92)	(1.59)	(4.83)	(0.92)
10-14 Years of Experience	2.1168	5.6155***	-1.8319	2.0522	5.6147***	-1.8334
	(0.80)	(4.37)	(0.86)	(0.72)	(4.73)	(0.89)
15-24 Years of Experience	-0.4805	7.6089***	-3.0132	-0.6063	7.6022***	-3.0103
	(0.16)	(4.29)	(1.23)	(0.18)	(5.07)	(1.17)
25+ Years of Experience	2.3142	8.8811***	-3.4903	2.1570	8.8772***	-3.5181
	(0.61)	(4.04)	(1.16)	(0.52)	(4.89)	(1.15)
Total In-service Hours$_t$	-0.0090	0.0030	0.0173***	-0.0089	0.0030	0.0173***
	(0.16)	(1.19)	(3.24)	(1.50)	(1.18)	(3.16)
Total In-service Hours$_{t-1}$	-0.0056	0.0058**	0.0182***	-0.0056	0.0058**	0.0182***
	(0.92)	(2.55)	(3.64)	(0.96)	(2.18)	(3.23)
Total In-service Hours$_{t-2}$	-0.0063	0.0024	0.0075	-0.0063	0.0024	0.0074
	(0.93)	(1.06)	(1.61)	(1.10)	(0.95)	(1.51)
Total In-service Hours$_{t-3}$	0.0007	-0.0019	0.0062	0.0007	-0.0018	0.0062
	(0.12)	(0.71)	(1.45)	(0.12)	(0.76)	(1.46)
Student Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Teacher Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
School Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of Students	37,096	106,709	45,920	37,096	106,709	45,920
Number of Observations	75,230	249,401	101,981	75,230	249,401	101,981

Models include the following time varying student/class/school characteristics: number of schools attended by the student in the current year, "structural" move by student, "non-structural move" by student, indicator of a student repeating a grade, class size, fraction of classroom peers who are female, fraction of classroom peers who are black, average age (in months) of classroom peers, fraction of classroom peers who changed schools, fraction of classroom peers who made a "structural move," indicator for a new school, indicator for a new principal at a school, principal's years of administrative experience. All models also include grade-by-year and repeater-by-grade dummies. Absolute values of t-statistics, appear in parentheses (t-statistics for iterative model are based on 50 bootstrap replications). * indicates statistical significance at the .10 level and ** indicates significance at the .05 level and *** indicates significance at the .01 level in a two-tailed test.

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