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WORKING PAPER 101 • JULY 2013

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Acknowledgements

This research was supported by the Bill & Melinda Gates Foundation as part of the evaluation of the Intensive Partnership Sites Initiative. The authors thank the North Carolina Education Research Data Center and the Florida Department of Education's K-20 Education Data Warehouse (through the National Center for the Analysis of Longitudinal Data in Education Research, supported by Grant R305A060018 to the American Institutes for Research from the Institute of Education Sciences, U.S. Department of Education) for providing access to the data used in this paper. The authors gratefully acknowledge comments and feedback from Mike Garet and Jane Hannaway. Special thanks to Kilchan Choi who provided key advice on HLM modeling.

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CALDER Working Paper No. 101

July 2013

Abstract

This study explores whether teacher performance trajectory over time differs by school poverty settings. Focusing on elementary school mathematics teachers in North Carolina and Florida, we find no systematic relationship between school student poverty rates and teacher performance trajectories. In both high (>=60% FRL) and lower-poverty (<60% FRL) schools, teacher performance improves the fastest in the first five years and then flattens out in years five to ten. Teacher performance growth resumes between year ten and 15 in North Carolina but remains flat in Florida. In both school poverty settings, there is significant variation in teacher performance trajectories. Among novice and early-career teachers, the fastest-growing teachers (75th percentile) improve by 0.04 standard deviations more in student gain scores annually than slower teachers (25th percentile). In both school settings, novice teachers who started with low effectiveness also grew at a slower rate in the next 5 years than novice teachers with higher initial effectiveness. Our findings suggest that the lack of productivity "return" to experience in high-poverty schools reported in the literature is unlikely to be the result of differential teacher learning in high and lower-poverty schools.

1. Introduction

Evaluating the productivity of school teachers has taken a focal point in recent policy efforts to improve the nation's public school system. Motivated in part by the U.S. Department of Education's recent Race to the Top Initiative, thirty-six states have updated their teacher evaluation policies since 2009 to take a more active role in managing workforce quality (National Council on Teacher Quality, 2012).[1] In light of this growing public interest, unanswered questions about the contexts in which teachers develop their human capital have come to the fore.

One of these unanswered questions, in particular, is whether teachers' experience productivity profiles systematically differ across school settings. This issue is significant because the interaction between teachers' productivity growth and the school setting where teachers are initially gaining their experience has the potential to either inadvertently reinforce or compensate for pre-existing inequalities when high stakes are attached to performance. Sass, et al.'s (2012) examination of the distributions of teacher quality in high- and low-poverty schools in North Carolina and Florida motivate the investigation presented here. These authors present cross-sectional evidence showing no association between experience and value-added productivity in high-poverty schools in both states, but were unable to address whether this finding was due to the composition of the teacher workforce in those schools (due to non-random selection into and out of the schools) or whether it was due to systemic differences in the development of teachers' productivity in high-poverty environments.

We investigate this surprising finding further by asking the following research question: Do teachers in high-poverty schools exhibit different productivity trajectories over various stages in their careers than those in low-poverty schools? To address this question, we utilize longitudinal

[1] The Great Teachers and Leaders component was the most heavily weighted of the six primary selection criteria on which applicants to the Race to the Top competition were judged, accounting for 27 percent of the overall score. For more information, see U.S. Department of Education (2009).

administrative data from North Carolina and Florida spanning 11 and 8 years, respectively. We apply a random slope model to estimate the mean and variance in teacher trajectories across these school types to test for significant differences.

In summary of our results, we find no systematic relationship between school student poverty rates and teacher performance trajectories. In both high (>=60% FRL) and lower-poverty (<60% FRL) schools, teacher performance improves the fastest in the first five years and then flattens out in years five to ten. Teacher performance growth resumes between year ten and 15 in North Carolina but appears to remain flat in Florida. In both school poverty settings we examine, there is significant variation in teachers' individual performance trajectories. Among novice and early-career teachers, the fastest-growing teachers (75th percentile) improve by about 0.04 standard deviations more in student gain scores annually than slower teachers (25th percentile), which is roughly equivalent to half a year of growth during an average teacher's first 3-5 years of teaching. In both school settings, novice teachers who started with low effectiveness also grew at a slower rate in the next 5 years than novice teachers with higher initial effectiveness. Our findings suggest that the lack of a "return" to experience in high-poverty schools reported in Sass, et al. (2012) is unlikely to be the result of differential teacher learning in high and lower-poverty schools; rather this appears to be more likely the result of non-random selection among experienced teachers into the workforce of high-poverty schools.

This paper is organized into six sections. In the following section, we describe some of the research background to situate our study here. Sections 3 and 4 present the data and methods we use. We present our results in Section 5 and Section 6 concludes.

2. Research Background

Research in recent years about the influence of teacher productivity on student learning has produced three key findings, which have emerged as a consensus. First, the variability of teacher productivity across the workforce is large, with the differential effect of having an effective teacher versus an ineffective teacher greater than the effect sizes associated with other educational interventions, such as class size reduction.[2] Second, differences in past teacher productivity are associated with not only short-term cognitive gains but also long-term outcomes including college enrollment, future wages, and other non-cognitive outcomes (Chetty, et al. 2011). And third, teacher characteristics most commonly observed in administrative educational data (e.g., teachers' credentials and experience) are only weakly associated with differences in teacher value-added productivity (Aaronson et al., 2007; Koedel and Betts, 2007).

Consequently, research in recent years has moved towards investigating how workforce management policies may be crafted to identify and retain the best teachers while removing ineffective teachers from the classroom.[3] Yet, proposed approaches to manage workforce quality generally take teacher productivity as a given and do not address the context in which it develops over time. This is a consequential omission, given the prior evidence demonstrating the difficulties disadvantaged schools have in retaining their best teachers (Boyd, et al., 2009; Hanushek et al., 2004; Scafidi, et al., 2008). If the development of teacher productivity systematically differed in disadvantaged schools compared to

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[2] For recent reviews of the findings in this literature, see Hanushek and Rivkin (2010) or Staiger and Rockoff (2010).
[3] Gordon, et al. (2006) suggest lowering barriers to entry into the teaching profession, but just being more selective at the point of tenure may improve productivity overall. Goldhaber and Hansen (2010) present evidence suggesting that pre-tenure teacher value-added estimates are significantly predictive of post-tenure performance. And Staiger and Rockoff (2010) present the argument that the most effective policy to manage workforce productivity would be to selectively retain teachers based on their first year of performance in the classroom.

non-disadvantaged schools, then the adoption of policies making high stakes decisions about teachers' careers based on performance have particular implications for disadvantaged schools. On one hand, if teachers, on average, increase their productivity more quickly when staffed in disadvantaged schools than they are expected in other schools, then the adoption of such policies could indirectly attract teachers to such schools and thereby reduce inequalities. Conversely, if teachers do not improve their practice as quickly in disadvantaged schools then workforce high-stakes policies may inadvertently reinforce inequalities by deterring teachers from such schools even more.

Prior studies on the returns to teachers' experience have not directly addressed this issue. To begin, literature shows teachers grow the most in the first few years of their careers (Rockoff, 2004), and more recent evidence suggests that returns to experience, on average, may continue to be significantly positive throughout their careers (Papay and Kraft, 2011; Wiswall, 2010). Kraft and Papay's (2012) recent analysis using North Carolina data suggests the school context may be an important factor in developing teachers' productivity, though the explanatory variables of interest in these authors' analysis are those extracted from a Working Conditions Survey that capture the level of administrative and colleague support rather than different schools as determined by the socioeconomic composition of the student body. Similarly, studies on changes in teacher productivity over time have investigated how productivity levels vary across different school settings, but have not investigated systematically different trajectories (i.e., changes in levels over time) by settings.[4] Hence, this topic represents an important gap in the research base.

[4] For instance, Jackson (2010) presents evidence that roughly a quarter of teacher value-added productivity is school-specific. Jackson and Bruegmann (2009) quantify the importance of teachers' colleagues effectiveness in developing their own productivity. In an analysis focused on explaining changes in teacher performance over time, Goldhaber and Hansen (forthcoming) present evidence that teacher performance is dynamic, though the large majority of these changes over time within teachers cannot be explained by various variables included in their models such as experience, credentials, being new to a school, having a new principal, the average effectiveness of peer teachers, or absences among peer teachers. And Xu, Ozek and Corritore (2012) present evidence that suggests teacher productivity is portable across different school settings, or in other words, that settings do not determine teacher quality.

Recent findings from Sass, et al. (2012), in particular, show a surprising empirical puzzle, which motivates our inquiry here. Using two states' data, the authors find the distributions of teacher performance in low-poverty schools are, surprisingly, virtually identical to those in high-poverty schools. The notable exception between the distributions, however, is the presence of a thick lower tail in the teacher performance distribution in high-poverty schools, which therefore pulls down its average relative to the distribution in low-poverty schools. They investigate this phenomenon further and, based on cross-sectional results, find no significant relationship between teacher performance and experience in high-poverty schools, which diverged from that in low-poverty schools. The authors conclude this empirical result is likely due to one of two possible sources: either the development of human capital takes on a significantly different trajectory for teachers in high-poverty schools or low-quality experienced teachers are systematically sorted into high-poverty schools (via a "dance of the lemons" mechanism, Miller and Chait, 2008).

These two competing hypotheses invite inquiry into whether trajectories of teachers' performance (i.e., the slopes in their productivity over time) may systematically differ in high-poverty schools, as has already been shown to be the case with the average level of teacher performance in such schools. These different slopes could feasibly arise from the outset of a teacher's career—teachers in high-poverty schools may have lower returns to experience in the initial years to begin with and never catch up to their counterparts in low-poverty schools. Alternatively, different slopes may come into play after teachers have obtained several years of experience where teachers in high-poverty schools may be more likely to plateau in their performance or even decline (i.e., "burnout"), whereas teacher performance in low-poverty schools may be more likely to be continually improve over time.

3. Data and Samples

This study draws on longitudinal student and teacher data from North Carolina (1998-99 through 2008-09) and Florida (2002-03 through 2009-10). In both states, we focus on 4th and 5th grade mathematics teachers. The relatively long study periods (11 and 8 years) increase our chance of observing the same teacher repeatedly over a longer period of time and allow us to estimate their growth more reliably. Additionally, using large-scale data from two distinct public education systems would greatly strengthen the findings in this study if consistent patterns were to emerge despite all the differences in student testing, curriculum, practices and policy contexts in general. Analytic samples were drawn from the populations in two steps: First, we extracted student-teacher-level samples to estimate teacher annual performance using value-added models. Next, we constructed teacher-year samples to investigate teacher performance growth over time.

Samples Used to Estimate Teacher Performance

In both states, End-of-grade (EOG) mathematics tests are administered annually to elementary school students starting from the 3rd grade. This allows us to estimate value-added for teachers in grades 4 and 5, using previous year's student test scores to control for student prior performance.

We restricted our North Carolina samples to teachers and students in "self-contained" classrooms, mainly because North Carolina did not have direct instructor-student links prior to 2006-07. For those earlier years, therefore, we need to verify whether test proctors are actual instructors. Specifically, information on students and teachers is contained in two separate files in North Carolina. The instructional classes file is a *classroom level* file that includes aggregate student characteristics and instructor IDs. The test score file is a *student level* file that includes test proctor IDs as well as student test scores and student characteristics. As a result, instructors are not linked directly to individual students; only proctors are. We can verify if proctors are indeed instructional teachers by comparing student characteristics (percent male, percent white, and class size) in the instructional classrooms and those in the test classrooms. To do this we 1) aggregated individuals in the test score file into test classrooms and 2) linked the test and instructional classes (now both are classroom-level files) by LEA (district), school ID and teacher ID. If the two sets of student characteristics were sufficiently similar (defined as the mean squared difference of the three classroom characteristics), we would confirm a test proctor to be the actual instructor.

The Florida data, on the other hand, contain student-teacher links throughout the study period and therefore we did not need to restrict our samples to those in self-contained classrooms. However, to attribute student learning gains to teachers more accurately, we restricted our samples to teachers and students in "core" mathematics courses, which are defined as those that more than 50 percent of students in a given grade took at a given school. We further excluded students "exposed" to more than one teacher in a given subject during a school year.

After these steps, we were able to identify about 42,000 unique elementary school mathematics teachers in North Carolina, among which 32,000 teachers could be verified as classroom instructors. In Florida, we identified about 36,000 unique elementary school mathematics teachers. In order to reduce potential sample heterogeneity, we further restricted our samples by 1) removing charter school teachers 2) removing students and teachers who changed schools during a school year (about 2-4 percent of observations), 3) keeping classrooms (in the analytic sample) with 10 to 40 students, and 4) removing classrooms with more than 50 percent special education students. The final samples used to estimate teacher value-added include around 21,000 and 30,000 elementary school mathematics teachers in North Carolina and Florida, respectively (table 1).

Samples Used to Estimate Teacher Growth

To explore how teacher performance improves with experience and how the rate of improvement may vary by school student poverty rates, we divided teachers with valid value-added estimates into three groups according to their experience levels. Research consistently finds disproportionate representation of inexperienced teachers in high-poverty schools, and that the returns to experience are the most evident during the earlier years. Therefore, a direct comparison of the average growth rates among *all* teachers in high and lower-poverty schools would be misleading. By stratifying teachers according to their experience levels and examining subgroups of teachers at comparable career stages, we can remove this potential confounding factor.

The “novice teacher” group includes teachers with 0 or 1 year of experience who can be followed for up to five years in our data. We are particularly interested in those who have taught continuously in a high-poverty school setting (with >=60 percent students eligible for free/reduced-priced lunch) or in a lower-poverty school setting (with <60 percent student eligible for free/reduced-priced lunch) during this five-year period. The “early career teacher” group includes teachers with 5 or 6 years of experience who can be followed for up to five years after that. Similarly, we focus on those who have stayed in the same school poverty setting during this period. Finally, the “mid-career teacher” group includes teachers with 10 or 11 years of experience who can be followed for up to five years. We again focus on those who have not switched school poverty settings. These three groups roughly correspond to various key stages in a teacher’s career that have been documented to have distinct performance trajectories. The sample sizes of each group are reported in the bottom panel of table 1.

4. Methodology

Evaluating Teacher Performance

We first estimate teacher annual performance using "value-added" scores. In a value-added framework, education is viewed as a cumulative process. It is assumed that time-lagged student achievement sufficiently captures all historical inputs and heritable endowments in the education process (Todd & Wolpin, 2003), thus separating the current teacher's contribution to student learning from the effects of teachers and other education inputs in earlier years. To account for other contributing factors to student learning in the current period and to mitigate non-random sorting among teachers, students and schools, value-added models typically also control for a number of observable student characteristics in addition to lagged student test scores. We estimate teacher value-added using the following teacher fixed-effects model[5]:

$$A_{it} - A_{it-1} = T_{it}\beta_{it} + X_{it}\gamma + \varepsilon_{it}$$

A_{it} - A_{it-1} is student test score gain between year *t-1* and year *t*. T_{it} is a vector of indicators measuring student *i*'s teacher assignment in year *t*. β_{it} represents the effect of individual teachers (i.e. teacher value-added). X_{it} includes 1) whether or not a student repeated a grade in year *t*, 2) his free/reduced price lunch eligibility, 3) sex, 4) race/ethnicity, 5) whether or not he is classified as gifted, 6) special education status by type of disability (speech/language disability, learning disability, cognitive/mental disability, physical disability, emotional disability and other types of disability), 7) school mobility and 8) grade level. We differentiate two types of school mobility: structural school change and non-structural school change. Structural school change is defined as when at least 30% of student *i*'s classmates from the previous school moved to the same receiving school in the current year. Otherwise a student school change is defined as non-structural.

[5] We have also explored using the level-score as the dependent variable and control for the lagged score and its quadratic term on the right hand side of the equation. Resulting value-added estimates are very highly correlated with estimates from the gain score model at 0.96.

Student test scores are normalized by year and grade so that they have a mean of 0 and standard deviation of 1. One concern with the gains model is that score gains are often higher for students who start at a lower initial performance level. This correlation could be the result of regression to the mean; it could also result from the properties of state-designed standardized tests, which may have more differentiation power at the lower end of the student ability distribution than at the higher end. The effectiveness estimate of teachers in high-performing classrooms and schools, as reflected on state standardized tests, could be penalized as a result. Following a strategy suggested by Hanushek, et al (2005), we divide students into deciles according to their lagged test scores and then standardize score gains within each lagged score decile.

Estimating Teacher Performance Trajectories

Next, we use the estimated teacher value-added scores as the outcome in estimating individual teachers' performance trajectories as they gain experience. As pointed out in the introduction, early work on the productivity return to experience among teachers uses cross-sectional data that do not truly track the same teachers over time. Those experience-productivity profiles therefore reflect differences between teachers with varying experience levels rather than within-teacher productivity growth. We estimate individual-specific performance trajectories using a hierarchical linear model with a random intercept and random slopes:

Level-1 Model:

$$b_{tj} = \beta_{tj} + \varepsilon_{tj}$$

Level-2 Model:

$$\beta_{tj} = \pi_{0j} + \pi_{1j} * (Experience_{tj}) + \pi_{2j} * (Experience^2_{tj}) + Z_{tj}\pi_{qj} + e_{tj}$$

Level-3 Model:

$$\pi_{0j} = \beta_{00} + r_{0j}$$

$$\pi_{1j} = \pi_{10} + r_{1j}$$

$$\pi_{2j} = \pi_{20} + r_{2j}$$

$$\pi_{qi} = \pi_{q0}$$

Level 1 is a measurement model where the estimated value-added (b_{tj})[6] for teacher *j* in year *t* is a function of her true value-added score (β_{tj}) and the estimation error (ε_{tj}). To make the 3-level model identifiable, the estimation error is replaced with the estimated standard error associated with each value-added estimate b_{tj} (This is sometimes called a "V-Known" model). At level 2, teacher *j*'s true performance in year *t* is modeled as a function of experience and other time-varying covariates Z_{tj}. For novice teachers, the intercept, π_{0j}, estimates the value-added for teacher *j* when she had one year of experience. It randomly varies across teachers in the level-3 model, with a grand mean of β_{00} and variance of $VAR(r_{0j}) \equiv \tau_{00}$. The slope π_{1j} estimates teacher-specific performance trajectories, or returns to experience. It represents the instantaneous rate of growth in experience year 1. Like the intercept, π_{1j} is also allowed to randomly vary across teachers at level 3, with a mean return to experience of π_{10} and variance of $VAR(r_{1j}) \equiv \tau_{11}$. The coefficient π_{2j}, similarly a random variable, captures any nonlinearities in teachers' performance trajectories.

We estimate this 3-level model for three subgroups of teachers separately: novice teachers, early career teachers, and mid-career teachers. For each group of teachers, we track their value-added scores for up to five years. For early career teachers and mid-career teachers, they start out in our samples with 6 and 11 years of experience respectively. We re-center the experience variable accordingly such that π_{0j} always corresponds to teacher value-added in those starting years. Similarly, π_{1j}

[6] The estimated value-added scores are all centered on within-year averages. Therefore, these scores measure a teacher's performance relative to all other teachers' in a particular year. The estimated performance trajectory measures how a teacher's *relative* performance changes with experience. Our assumption is that the overall distribution of teacher performance remains roughly the same from year to year.

represents the instantaneous rate of growth in experience year 6 and 11 respectively. We could alternatively have kept all teachers in one sample and estimate non-linear returns to experience by entering years of experience as a series of dummy variables. However, few teachers have data points spanning all the years of our study period, and therefore individual teachers' growth rates at one career stage or another for most teachers would have to be extrapolated. It is unclear how such extrapolation may affect performance trajectory estimates. By dividing teachers into subgroups of similar career stages, we increase the chance of teachers in each subgroup having complete data and reduce the need of extrapolation.

Because our value-added model did not control for any school effects or classroom characteristics, changes in teacher effectiveness over time may reflect changes in the overall school quality. Teachers may also be assigned to different types of students and classrooms as they gain seniority. If seniority-related teacher-student sorting patterns differed systematically between high and lower-poverty schools, estimated differences in teacher performance trajectories between school types would be confounded. To mitigate these concerns, our HLM model includes additional level-2 control variables Z_{tj}. These include: the average value-added of a teacher's peers in the same school[7], the classroom average pretest scores, and the standard deviation of pretest scores within classrooms.

Compare Teacher Performance Trajectories

With the estimated performance trajectory for each individual teacher, we first explore how teacher growth varies between high- and lower-poverty school settings and within each type of school poverty settings. Variation in teacher performance trajectories could be associated with a number of factors in addition to school poverty. Kraft and Papay (2012) and Loeb, et al. (2012), for instance, identified perceived school working conditions and overall school effectiveness as factors related to

[7] Past research has shown that a teacher's colleagues play a significant role in her productivity (Jackson and Bruegmann, 2009; Jackson 2012). Moreover, peer quality may be indicative of a school's ability in attracting, developing and retaining good teachers.

teacher growth. With the data available to us, we are limited to exploring three possible correlates of teacher growth and their interaction with school poverty: teachers' initial value-added, the number of school changes a teacher made during the study period, and the effectiveness gap between a teacher and her peers in the starting years of each career stage. We hypothesize that teachers who started highly effective may have less room to grow (and therefore flatter performance trajectory), that frequent switches from one school to another may slow a teacher's growth as she constantly needs to relearn her working environment, and that having colleagues more effective than oneself may help one develop faster. More importantly to our current context, these factors may differ systematically along the school poverty dimension. Therefore we compare teacher performance trajectories between high- and lower-poverty schools after controlling for these factors in a regression analysis which uses the estimated individual teacher trajectories as the dependent variable and takes into account estimation error associated with the dependent variable using FGLS.

5. Findings

At the start of each career stage, teachers who went on to teach consistently in high-poverty schools in the next five years appear to be statistically different from those who would teach in lower-poverty schools (Table 2). In both states, elementary school mathematics teachers always in high-poverty schools are more likely to start with temporary or provisional licenses than teachers in lower-poverty schools. The difference is more apparent among novice teachers than teachers with 5-6 or 10-11 years of experience. A higher percentage of novice teachers in lower-poverty schools start their teaching careers with graduate degrees than novice teachers in high-poverty schools. In North Carolina where data are available, novice teachers in lower-poverty schools are more likely than novice teachers in high-poverty schools to be certified through traditional state accredited education programs. Nearly half of novice teachers in high-poverty schools are certified through none-traditional routes to teaching, such as lateral entries, completion of licensing requirements through a regional alternative licensing center, and permit to teaching under the state's Alternative Entry regulations.

Novice teachers who would later persist in high-poverty schools tend to start with significantly lower value-added than those who were in lower-poverty schools. The teacher effectiveness gap is about 0.02 standard deviations of student gain scores in both states. At the start of the early- and mid-career stages, by comparison, teachers in high- and lower-poverty school settings are equally effective on average. PRAXIS test scores, which are available in the North Carolina data set and an alternative indicator of teacher effectiveness, are significantly lower among teachers in high-poverty schools than those in lower-poverty schools across all career stages. The average gaps are sizeable and range from 0.20 to 0.37 standard deviations.

These baseline differences between teachers in high and lower-poverty schools are important to keep in mind when we examine variation in teacher performance trajectories. This is not only because the rate of improvement may be related to where a teacher started, but also because growth may be more imperative for teachers who started at a lower level than for teachers who were already highly effective.

Tables 3, 4 and 5 report the estimated random and fixed effects corresponding to novice, early career and mid-career teacher samples respectively. In each table, the top panel reports variance components in an unconditional HLM model with no covariates. For teachers at all career stages in North Carolina, slightly over 50 percent of the total (net of variance due to estimation error) variation in teacher value-added is between teachers. The remaining variation is attributed to within-teacher changes over time. About one-third of the year-to-year within-teacher value-added fluctuations, however, can be explained by teacher experience as well as annual changes in classroom characteristics and teacher peer performance. For all teacher groups, one standard deviation difference in teacher value-added is estimated to be associated with 0.24 (square root of the between-teacher variance component) standard deviations in student mathematics score gains.

The size of the variance components among elementary school mathematics teachers in Florida is very comparable to that in North Carolina. About 50 to 60 percent of the total (net of variance due to estimation error) variation in yearly teacher value-added is between teachers. The remaining variation, of which around one-fourth can be explained by experience gains and other time-varying classroom and school factors, is year-to-year changes within teachers. One standard deviation difference in teachers' value-added is associated with 0.27 standard deviations in student mathematics score gains at all career stages.

The mean annual performance growth rate among novice teachers is 0.07 standard deviations in student mathematics score gains both states (Table 3). Teacher performance growth, however, starts to slow down even during the first five years of teaching as captured by the negative and statistically significant coefficients on the quadratic form of experience. Among early-career teachers, the mean performance trajectory is flat and statistically insignificant (Table 4). However, among mid-career teachers with at least 10 or 11 years of experience, teacher performance starts to improve again in North Carolina (although at a much slower rate of 0.015 standard deviations in student score gains) but remains flat in Florida (Table 5). On average, teacher performance does not appear to decline as teachers become more experienced. In other words, there is no evidence of teacher “burn out”.

The distinct teacher performance trajectories at various career stages are consistent with findings reported in the literature on teacher experience and performance. However, average growth rates mask significant variation in teacher performance improvement across individuals, especially at novice level. In both states, the variation in teacher growth rate is statistically significant (Table 3). Among novice teachers in North Carolina, for example, slower-growth teachers (those whose growth rate is at the 25th percentile) improve their performance by 0.05 standard deviations in student score gains annually, a considerable rate of growth. However, the faster-growth teachers (those with growth rate at the 75th percentile) improve their performance by over 0.09 standard deviations, almost 80 percent faster than their slower-improving peers (Table 6). In other words, faster-growing teachers gain more than half a year equivalent of average teacher performance growth annually than slower-growth teachers (On average one year of additional experience is associated with 0.07 standard deviations among novice teachers). Similarly, among novice elementary mathematics teachers in Florida, teachers at the top quartile improve their performance by 0.09 standard deviations, compared with 0.04 standard deviations among teachers at the bottom quartile.

Compared with novice teachers, the variation in performance trajectory among early career teachers with at least five or six years of experience is smaller in both states. It remains significant in North Carolina and but becomes statistically insignificant in Florida (Table 4). At this career stage, it appears that the median teacher has stopped improving, while those near the bottom quarter start to see their performance decline (at an annual rate of -0.02 standard deviations or worse). On the other hand, the performance of some other teachers continues to improve in North Carolina, even though at a slower rate than the growth rate during the first five years of teaching.

Throughout the performance trajectory distribution among mid-career teachers, few teachers appear to experience substantial amount of performance decline. At the bottom quartile of the performance trajectory, teacher performance trajectories largely remain flat in both states. At the top quartile, by comparison, teachers grow at a moderate rate of 0.03 standard deviations in student score gains annually in North Carolina and 0.02 standard deviations in Florida. This is consistent with recent literature that teachers with 10 or more years of experience can continue to improve their performance.

Considerable variation in teacher performance trajectories, however, does not appear to be related with school student poverty rates. Table 6 shows generally no significant difference in teacher growth between teachers in high and lower-poverty schools throughout the distribution of performance trajectories. However, as demonstrated earlier, teachers in high-poverty schools start at a lower performance level than teachers in lower-poverty schools. Since growth rates are likely to be inversely correlated with starting performance levels we compare teacher growth trajectories in high and lower-poverty schools using multiple regressions that control for teacher's starting performance level and interact it with school poverty status. Additionally, some teachers in our samples may have switched between schools with similar student poverty rates during the five-year study period. Such school switches may affect a teacher's performance trajectory because of potential disruptions to development every time she changes schools. If teachers in one type of schools tended to be more mobile than other teachers, comparisons of average teacher performance trajectories between school settings could be biased. As a result, our regressions also control for the number of school switches a teacher made. Finally, as reported in tables 3-5, a significant amount of year-to-year fluctuation in a teacher's value-added is explained by the average quality of her colleagues, consistent with findings documented in Jackson and Bruegmann (2009). However, it is unclear whether the association between a teacher's own value-added and her colleagues' is because having higher quality colleagues makes an average teacher improve faster or is because teachers tend to work with other teachers with similar performance levels (or schools tend to attract and select teachers of comparable qualities). Feng and Sass (2010) find that a teacher is more likely to leave a school or exit teaching when the gap between her performance and that of her peers is large, possibly supporting the theory of teacher sorting among themselves. To directly explore whether the relative quality of a teacher's peers is associated with how fast she improves, we added in our regression a variable that measures the average difference between a teacher's value-added and the value-added of her colleagues, calculated at the start of each career stage, and its interaction term with school poverty status.

The results of these regressions are reported in tables 7-9. Overall we find that teacher performance trajectories do not differ significantly by school poverty settings. Novice teachers in North Carolina's high-poverty schools and mid-career teachers in Florida's high-poverty schools appear to grow slightly slower than their counterparts in lower-poverty schools. In both cases the statistically significant differences are substantively small. Contrary to our hypothesis, teacher performance trajectories are not always negatively related with starting performance levels. In both states, it is the higher-performing novice teachers who improved the fastest (Table 7). In the first five years of teaching, it appears that the initial gap in teaching effectiveness could be further widened. This pattern holds in both high- and lower-poverty school settings, and it seems to be consistent with findings reported in Atteberry, Loeb and Wyckoff (2013) that the initially lowest-performing teachers on average fail to "catch up" with other teachers and remain consistently the lowest-performing even after five years.

The relationship between teachers' initial performance levels and performance growth rates starts to diverge between North Carolina and Florida among early- and mid-career teachers. Whereas better teachers continue to improve at faster rates than teachers with lower starting performance level in Florida, the opposite is true among North Carolina teachers (Tables 8 and 9). Similar contradiction is found in the direction of the coefficients on the initial performance gap between oneself and peers. In Florida, positive coefficients indicate that a teacher improves faster when she is more efficient than her peers in the same school; by contrast, North Carolina teachers appear to improve faster when they have colleagues better than themselves. We do not have explanations for these contradictions. Though not the focus of this study, they warrant further investigation.

We next divide teachers by their starting performance level and explore whether high-performing (top quarter based on starting year value-added) and low-performing (bottom quarter) teachers have distinct growth trajectories in schools with different student poverty rates. Similarly, we generally find no systematic difference in teacher performance growth between school poverty settings, regardless of teachers starting performance level. Our findings are best summarized in Figures 1 and 2, where the y-axis represents the predicted teacher value-added (based on parameters estimated for the HLM model and the regressions) and the x-axis represents years of experience. The solid lines represent teachers in lower-poverty schools and dashed lines represent teachers in high-poverty schools. The bolded, black lines depict the average predicted value-added by years of experience among all teachers in each school-poverty setting. The unbolded, colored lines represent the predicted value-added for subgroups of teachers by their starting performance level (in quarters). The growth trajectories for teachers in both school-poverty settings almost always parallel each other.

It becomes clear that school poverty settings are not correlated with variations in teacher performance trajectories in any systematic way. However, we define high- and lower-poverty schools at the 60 percent FRPL cutoff, and some schools on both sides of the cutoff may be very similar in terms of school poverty settings. To check the sensitivity of our findings, we redefine lower-poverty schools as those enrolling less than 40 percent FRPL-eligible students, and keep high-poverty schools defined as those with 60 percent or more FRPL-eligible students. Our findings remain very similar (Table 10). That is, there is generally no systematic difference in teacher performance trajectories between school poverty settings. Categorizing schools into even more distinct poverty categories (>=70 percent FRPL vs <30 percent FRPL), we still could not find systematic differences in teacher growth.

6. Summary and Discussion

This study is a descriptive analysis on whether teachers in high-poverty schools and lower-poverty schools follow different performance growth paths. It is directly motivated by Sass, et al.'s (2012) study, which finds differential "returns" to experience between teachers in high and lower-poverty schools. Specifically, they find no evidence of increased productivity among teachers in high-poverty schools with greater levels of experience, whereas the productivity profile among teachers in lower-poverty schools suggests large growth over the first five years and then the rate of growth flattens out in later years.

Because that study is based on cross-sectional data, it is unclear what may be underlying the observed experience-productivity profiles. The authors suggested at least two possible explanations. The first is that teachers learn at different rates in high and lower-poverty school settings. Teachers in more disadvantaged schools, for instance, may need to provide more support to their students or devote more time to classroom discipline. This diverts their energy away from perfecting their instruction, compared to teachers in lower-poverty schools. The second possible explanation is teacher-school sorting. If less-productive, experienced teachers were more likely to move into high-poverty schools, cross-sectional data would also show a flat experience-productivity profile for high-poverty school teachers. Determining which of these two hypotheses appear to be driving the phenomenon has important policy implications. If it could be explained by teacher learning, policymakers may instead promote teacher professional development in high-poverty schools; if the explanation was sorting, our teacher labor policy should probably focus more on the equitable distribution of high- and low-performing teachers.

Our results show that nearly half of the total variation in teachers' yearly value-added estimates (net of variance due to estimation error) is within teachers. About one-fourth to one-third of these within-teacher year-to-year changes can be explained by teachers' increasing experience level as well as other time-varying classroom and school-level characteristics. We find teacher-specific performance trajectories to be the steepest among novice teachers. It becomes flat among early-career teachers, but performance improvement resumes among mid-career teachers, at least in the North Carolina data.

The average experience-productivity profiles at all career stages mask significant variations across teachers. The fastest improving teachers gain more than half a year equivalent of performance growth annually than the slowest improving teachers. Such variations, however, are not systematically correlated with school poverty status. Our findings, hence, are inconsistent with the "teacher learning" theory proposed to explain the lack of "return" to experience among teachers in high-poverty schools.[8] These findings also contradict the related hypothesis of teacher burnout in high-poverty schools explaining this phenomenon. Rather, this evidence suggests teacher mobility and attrition patterns across schools may be a more plausible explanation for the inequitable distribution of particularly low-performing teachers in high-poverty schools.

[8] This does not mean that teacher performance trajectories are unrelated with other school-level factors. Kraft and Papay (2012), for instance, report that teachers improve faster in schools that are perceived as more supportive. Similarly, Loeb, et al. (2012) report that teachers who work in schools that were more effective at raising achievement in a prior period improve more rapidly in a subsequent period than do those in less effective schools.

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Figures

Figure 1. Teacher Performance Trajectory in North Carolina: by Career Stage, Initial Value-Added, and School Poverty Status

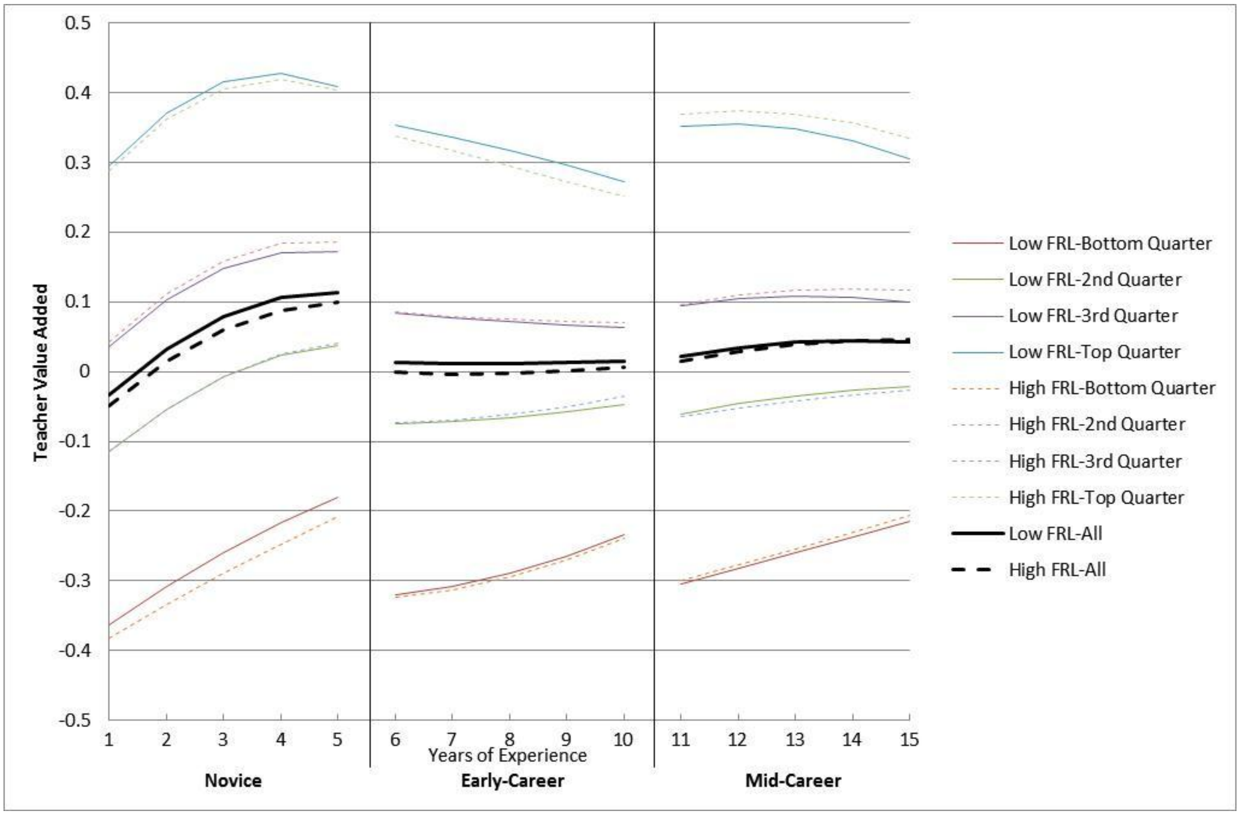
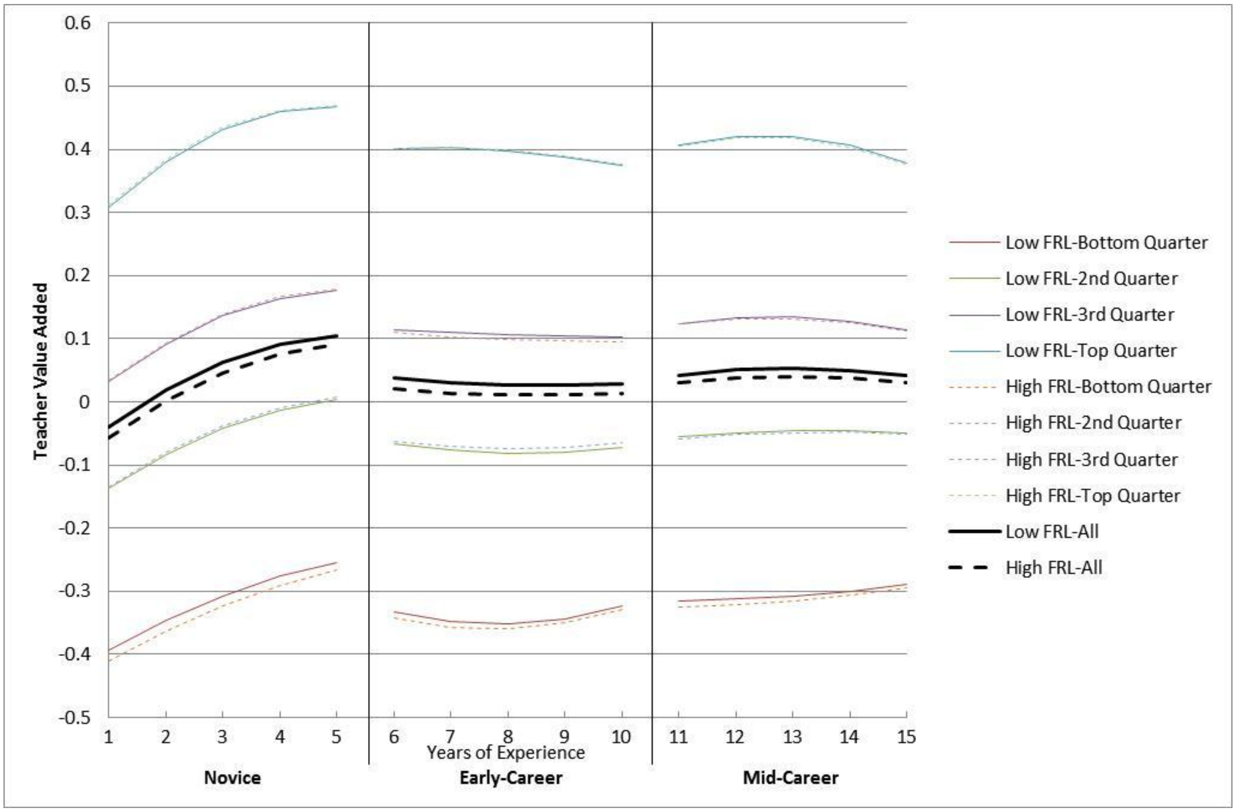


Figure 2. Teacher Performance Trajectory in Florida: by Career Stage, Initial Value-Added, and School Poverty Status



Tables

Table 1. Number of elementary school mathematics teachers in state and sub-samples, by sample restriction steps

	North Carolina	Florida
Samples used to estimate value-added		
Teachers of relevant classes	41,691	36,446
Teachers linked to students	32,205	36,446
Eliminate charter school classes	22,254	34,717
Keep classes with 10-40 students who has no missing values on student and teacher variables	21,119	29,989
Samples used to estimate teacher growth		
Novice teachers (Cohorts with 0-1 year of experience)	5,883	12,849
Stayed in the same school poverty setting[1]	4,109	12,013
Early-career teachers (Cohorts with 5-6 years of experience)	4,117	8,000
Stayed in the same school poverty setting[1]	2,969	7,183
Mid-career teachers (Cohorts with 10-11 years of experience)	2,775	4,010
Stayed in the same school poverty setting[1]	2,072	3,666

[1]Schools with 60 percent or more students eligible for free/reduced price lunch are defined as high-poverty schools. Otherwise they are defined as lower-poverty schools.

Table 2. Base year characteristics of elementary school mathematics teachers, by school setting and teacher cohorts

	North Carolina		Florida	
	Always in lower-poverty schools	Always in high-poverty schools	Always in lower-poverty schools	Always in high-poverty schools
Novice teachers				
Regular license (%)	96.14	89.11**	97.46	95.37**
Graduate degree (%)	11.71	8.36**	21.25	17.99**
Traditional route (%)	57.67	51.00**		
Praxis score (sd)	0.33	0.12**		
Value added scores (sd)	-0.03	-0.05*	-0.09	-0.11**
Observations	2,408	909	3,765	3,704
Early career teachers				
Regular license (%)	99.31	98.03**	99.96	99.84
Graduate degree (%)	22.27	17.30**	31.00	32.34
Traditional route (%)	60.37	63.15		
Praxis score (sd)	0.20	-0.10**		
Value added scores (sd)	0.01	0.00	0.044	0.044
Observations	1,877	659	2,545	1,945
Mid-career teachers				
Regular license (%)	99.58	98.82*	99.87	99.89
Graduate degree (%)	28.42	28.20	38.46	38.02
Traditional route (%)	67.18	72.45**		
Praxis score (sd)	0.11	-0.26**		
Value added scores (sd)	0.02	0.02	0.061	0.059
Observations	1,418	422	1,560	881

Note: Schools with 60 percent or more students eligible for free/reduced price lunch are defined as high-poverty schools. Otherwise they are defined as lower-poverty schools.
**Statistically significant at 0.05; *Statistically significant at 0.10

Table 3. Variance components and fixed effects estimates for novice elementary school mathematics teachers, by state and model

	North Carolina	Florida
Unconditional model		
Variance component		
Between teacher, τ_{00}	0.060**	0.071**
Within teacher, σ^2	0.059**	0.070
ICC (τ_{00}/ (τ_{00}+ σ^2)	0.50	0.50
Model with level-2 covariates		
Variance component		
Between teacher, τ_{00}	0.056**	0.059**
Random effects variance for return to experience, τ_{11}	0.011*	0.011**
Random effects variance for return to experience^2, τ_{22}	0.000	0.000*
Within teacher, σ^2	0.039**	0.049**
Fixed effect		
Mean initial value-added, β_{00}	-0.122**	-0.147**
	(0.010)	(0.014)
Mean return to experience, β_{11}	0.074**	0.066**
	(0.007)	(0.007)
Mean return to experience^2, β_{22}	-0.009**	-0.007**
	(0.001)	(0.001)
Classroom average pretest score, β_{33}	-0.119**	-0.023**
	(0.011)	(0.008)
Classroom s.d. of pretest scores, β_{44}	0.028**	0.049**
	(0.010)	(0.015)
Average peer teacher value-added, β_{66}	0.659**	0.812**
	(0.023)	(0.022)

Fixed effects presented with robust standard errors. The measurement model at level one takes into account estimated standard errors associated with teacher value-added estimates. **Statistically significant at 0.05; *Statistically significant at 0.10

Table 4. Variance components and fixed effects estimates for early career elementary school mathematics teachers, by state and model

	North Carolina	Florida
Unconditional model		
Variance component		
Between teacher, τ_{00}	0.058**	0.080**
Within teacher, σ^2	0.053**	0.055
ICC (τ_{00}/ (τ_{00}+ σ^2))	0.52	0.59
Model with level-2 covariates		
Variance component		
Between teacher, τ_{00}	0.077**	0.078**
Random effects variance for return to experience, τ_{11}	0.012**	0.004
Random effects variance for return to experience^2, τ_{22}	0.000**	0.000
Within teacher, σ^2	0.035**	0.041**
Fixed effect		
Mean initial value-added, β_{00}	-0.008	0.055**
	(0.012)	(0.019)
Mean return to experience, β_{11}	-0.003	-0.009
	(0.007)	(0.008)
Mean return to experience^2, β_{22}	0.001	0.002
	(0.001)	(0.002)
Classroom average pretest score, β_{33}	-0.103**	-0.018*
	(0.012)	(0.010)
Classroom s.d. of pretest scores, β_{44}	0.039**	-0.023
	(0.011)	(0.020)
Average peer teacher value-added, β_{66}	0.562**	0.732**
	(0.028)	(0.028)

Fixed effects presented with robust standard errors. The measurement model at level one takes into account estimated standard errors associated with teacher value-added estimates. **Statistically significant at 0.05; *Statistically significant at 0.10

Table 5. Variance components and fixed effects estimates for mid-career elementary school mathematics teachers, by state and model

	North Carolina	Florida
Unconditional model		
Variance component		
Between teacher, τ_{00}	0.061**	0.075**
Within teacher, σ^2	0.055**	0.055
ICC (τ_{00}/ (τ_{00}+ σ^2)	0.53	0.58
Model with level-2 covariates		
Variance component		
Between teacher, τ_{00}	0.073**	0.077**
Random effects variance for return to experience, τ_{11}	0.004	0.002
Random effects variance for return to experience^2, τ_{22}	0.000	0.000
Within teacher, σ^2	0.040**	0.042**
Fixed effect		
Mean initial value-added, β_{00}	0.009	0.042*
	(0.014)	(0.025)
Mean return to experience, β_{11}	0.015*	0.011
	(0.008)	(0.010)
Mean return to experience^2, β_{22}	-0.002	-0.003
	(0.002)	(0.002)
Classroom average pretest score, β_{33}	-0.142**	-0.041**
	(0.016)	(0.013)
Classroom s.d. of pretest scores, β_{44}	0.029**	0.011
	(0.012)	(0.027)
Average peer teacher value-added, β_{66}	0.546**	0.734**
	(0.032)	(0.030)

Fixed effects presented with robust standard errors. The measurement model at level one takes into account estimated standard errors associated with teacher value-added estimates. **Statistically significant at 0.05; *Statistically significant at 0.10

Table 6. Distribution of performance trajectories related to experience among elementary school mathematics teachers, by state, experience level and school poverty setting

	North Carolina			Florida		
	25th percentile	50th percentile	75th percentile	25th percentile	50th percentile	75th percentile
Novice teachers	0.051	0.074	0.096	0.044	0.065	0.086
Lower-poverty schools	0.052	0.075	0.097	0.044	0.065	0.086
High-poverty schools	0.049*	0.073	0.093**	0.045	0.066	0.086
Early career teachers	-0.024	-0.004	0.017	-0.020	-0.009	0.003
Lower-poverty schools	-0.024	-0.004	0.018	-0.021	-0.009	0.003
High-poverty schools	-0.024	-0.004	0.016	-0.020	-0.009	0.003
Mid-career teachers	0.004	0.015	0.026	0.003	0.011	0.019
Lower-poverty schools	0.004	0.015	0.026	0.003	0.011	0.019
High-poverty schools	0.005	0.014	0.025	0.003	0.010**	0.018

Note: Schools with 60 percent or more students eligible for free/reduced price lunch are defined as high-poverty schools. Otherwise they are defined as lower-poverty schools.
**Significantly different from lower-poverty school estimates at the 0.05 level; *Statistically significant at 0.10

Table 7. Novice teachers

	North Carolina			Florida		
	All teachers	Low-performing teachers	High-performing teachers	All teachers	Low-performing teachers	High-performing teachers
High FRL school	-0.003*	0.003	-0.009	-0.001	-0.002	0.004
	(0.002)	(0.008)	(0.007)	(0.001)	(0.005)	(0.004)
Base year VA	0.047**	0.050**	0.069**	0.035**	0.031**	0.047**
	(0.005)	(0.015)	(0.014)	(0.004)	(0.011)	(0.012)
High FRL x Base year VA	0.003	0.007	0.016	-0.014**	-0.021	-0.015
	(0.009)	(0.024)	(0.026)	(0.006)	(0.014)	(0.015)
Number of school changes	-0.000	0.006*	-0.006	-0.004**	0.002	-0.010**
	(0.002)	(0.004)	(0.004)	(0.001)	(0.003)	(0.003)
VA gap from peer teachers	0.008	-0.013	0.010	0.021**	0.007	0.040**
	(0.005)	(0.012)	(0.010)	(0.005)	(0.009)	(0.009)
High FRL x VA gap	0.008	0.028	-0.005	-0.011*	0.020*	-0.007**
	(0.010)	(0.018)	(0.020)	(0.006)	(0.011)	(0.013)
Constant	0.077**	0.072**	0.071**	0.069**	0.064**	0.063**
	(0.001)	(0.005)	(0.004)	(0.001)	(0.003)	(0.003)
Observations	3308	814	825	6,941	1,729	1,776
R^2	0.136	0.055	0.093	0.161	0.285	0.108

Standard errors in parentheses. All regressions take into account estimation errors in the dependent variable.
* $p < 0.10$, ** $p < 0.05$

Table 8. Early career teachers

	North Carolina			Florida		
	All teachers	Low-performing teachers	High-performing teachers	All teachers	Low-performing teachers	High-performing teachers
High FRL school	-0.001	0.007	-0.012	-0.001	0.010**	-0.001
	(0.002)	(0.008)	(0.008)	(0.001)	(0.004)	(0.004)
Base year VA	-0.018**	-0.056**	-0.024*	0.017**	0.004	-0.020**
	(0.006)	(0.016)	(0.014)	(0.003)	(0.009)	(0.009)
High FRL x Base year VA	-0.001	0.041	0.038	0.009*	0.033**	0.014
	(0.010)	(0.028)	(0.027)	(0.005)	(0.013)	(0.013)
Number of school changes	-0.002	0.002	-0.003	0.002	0.001	-0.002
	(0.002)	(0.003)	(0.003)	(0.001)	(0.003)	(0.002)
VA gap from peer teachers	-0.028**	-0.005	-0.022**	0.023**	0.023**	0.031**
	(0.006)	(0.011)	(0.011)	(0.004)	(0.007)	(0.007)
High FRL x VA gap	-0.003	-0.022	-0.026	-0.012**	-0.013	-0.014
	(0.010)	(0.019)	(0.019)	(0.005)	(0.010)	(0.010)
Constant	-0.002**	-0.010**	-0.001	-0.010**	-0.014**	-0.014**
	(0.001)	(0.004)	(0.004)	(0.001)	(0.010)	(0.003)
Observations	2521	625	630	4,393	1,092	1,115
R^2	0.110	0.050	0.056	0.168	0.055	0.097

Standard errors in parentheses. All regressions take into account estimation errors in the dependent variable.
* $p < 0.10$, ** $p < 0.05$

Table 9. Mid-career teachers

	North Carolina			Florida		
	All teachers	Low-performing teachers	High-performing teachers	All teachers	Low-performing teachers	High-performing teachers
High FRL school	0.001	-0.003	0.005	-0.001*	-0.009**	-0.001
	(0.001)	(0.006)	(0.006)	(0.001)	(0.003)	(0.004)
Base year VA	-0.011**	0.000	-0.008	0.017**	0.015	0.029**
	(0.004)	(0.012)	(0.010)	(0.003)	(0.006)	(0.007)
High FRL x Base year VA	0.003	-0.017	-0.007	-0.004	-0.028**	-0.007
	(0.008)	(0.024)	(0.020)	(0.004)	(0.011)	(0.012)
Number of school changes	0.001	0.003	-0.000	0.0003	-0.002**	-0.004
	(0.001)	(0.002)	(0.003)	(0.0001)	(0.003)	(0.003)
VA gap from peer teachers	-0.012**	-0.020**	-0.009	0.010**	0.017**	-0.004
	(0.004)	(0.009)	(0.008)	(0.003)	(0.005)	(0.006)
High FRL x VA gap	-0.002	0.005	0.001	0.005	0.006	0.013
	(0.007)	(0.017)	(0.014)	(0.004)	(0.008)	(0.009)
Constant	0.015**	0.016**	0.013**	0.010**	0.012**	0.009**
	(0.001)	(0.003)	(0.003)	(0.0003)	(0.002)	(0.002)
Observations	1837	458	454	2350	602	587
R^2	0.071	0.033	0.022	0.220	0.078	0.073

Standard errors in parentheses. All regressions take into account estimation errors in the dependent variable.
* $p < 0.10$, ** $p < 0.05$

Table 10. Varying high- and low-poverty school definitions, by state and teacher experience level

	North Carolina		Florida	
Estimated differences in growth rate	>=60% vs. <40% FRL	>=70% vs <30% FRL	>=60% vs. <40% FRL	>=70% vs <30% FRL
Novice teachers	-0.006**	-0.007**	-0.001	-0.002*
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	2,013	1,118	5,225	3,618
Early-career teachers	-0.001	0.003	0.001	0.0003
	(0.002)	(0.002)	(0.001)	(0.001)
Observations	1,563	869	3,328	2,271
Mid-career teachers	0.002	-0.001	-0.002**	-0.001
	(0.001)	(0.002)	(0.001)	(0.001)
Observations	1,116	626	1,767	1,134

Standard errors in parentheses. Regression specifications remain the same as in tables 7 through 9.
* $p < 0.10$, ** $p < 0.05$