Who Becomes a School Leader? An Investigation of Teachers' Careers and Value-Added

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Current draft: October 3, 2022†

Abstract

This paper investigates whether the most effective teachers progress up the management ladder to school leadership positions. Using data on 4th through 8th grade teachers at elementary and middle schools in North Carolina, I estimate a linear probability model to document the relationship between a teacher's effectiveness in teaching (as measured by value-added to math and reading standardized test scores) and their likelihood of becoming an assistant principal in the next academic year. I find that one standard deviation higher value-added math (reading) teachers are on average 33.8% (7.8%) more likely to become an assistant principal in the next academic year after controlling for differences in demographics and teaching experience. These results are robust to the use of alternative estimation strategies, including logistic regression, survival analysis, and competing risk analysis. Finally, math value-added is a stronger predictor of becoming assistant principal in the next academic year for male teachers and for non-white teachers. I am able to uncover the first statistically significant evidence of positive selection into school leadership. These results suggest caution in studying the observable relationship between teacher and principal value-added in future studies given the existence of a great deal of selection based on teacher value-added.

Keywords: Value-added, principals, assistant principals, teachers, management

JEL codes: I20, J24, J45, M51

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†I would like to thank Kara Bonneau and the North Carolina Education Research Data Center for access to data. I would also like to thank Kelly Bedard, Heather Royer, Dick Startz, Peter Kuhn, Cathy Weinberger, Sarah Robinson, Richard Uhrig, Luisa Wallossek, Antoine Dib, and the UCSB Applied Micro Economics Lunch for their careful advice and feedback on versions of this paper. All errors are my own.

1 Introduction

A growing body of empirical research documents the important role of public school principals in improving student achievement, including raising student test scores and improving school attendance (Branch, Hanushek and Rivkin, 2008, 2012; Coelli and Green, 2012; Dhuey and Smith, 2014, 2018; Li, 2015; Bartanen, 2020). While we know principals can impact students, we know very little about who becomes principal and what makes someone an effective principal. One thing we do know is that most principals were once teachers themselves. According to the 2011-2012 Schools and Staffing Survey from the National Center for Education Statistics, 98.3% of public school principals in the U.S. had teaching experience before becoming principal.

Understanding which teachers become principals is important for several reasons. High principal turnover can negatively impact student achievement, and schools serving large shares of disadvantaged students often struggle the most with finding and retaining qualified school leaders (Loeb, Kalogrides and Horng, 2010; Béteille, Kalogrides and Loeb, 2012). Additionally, principal turnover is costly; conservatively, the cost to develop, hire, and onboard a new principal is estimated to be $75,000 (Jensen, 2014). Though superintendents and schools boards have institutional knowledge about who makes a good school leader, systematically examining this topic from an empirical lens can help to expand our knowledge on the current state of the school leadership pipeline and to understand areas for improvement and targeted policy.

The focus of this paper is the role of assistant principal (AP), which is an increasingly important stepping stone from teaching to becoming a principal.[1] Most APs are no longer providing classroom instruction, so they are responsible for aiding the principal in school management responsibilities, such as observing teachers, scheduling testing, and student discipline (Goldring, Rubin and Herrmann, 2021). Understanding who becomes an AP is critical to understanding who eventually becomes principal and consequently the impact

[1]The share of principals who were once APs ranges from 50-90% across several states (Austin et al., 2019). The recent national average has increased from 50% to over 75% in the last 30 years (Goldring, Rubin and Herrmann, 2021).

principals have on their schools. This paper investigates the career transition from teacher to AP to understand the first step up the school leadership ladder.[2]

I investigate whether more effective teachers, as measured by having higher value-added (VA) to student achievement, are more likely to be promoted to AP compared to their less effective colleagues. Teacher VA modeling is used to quantify how much an individual teacher contributes to their students' achievement while controlling for other important factors impacting students' human capital accumulation up to that point. The most commonly used outcome in teacher VA modeling is student standardized test scores, which I employ in this paper, though non-cognitive outcomes such as attendance and suspensions are also used in the literature. Having a teacher with higher VA has been linked to improved long run outcomes for students, such as increased high school graduation, college attendance, and lifetime earnings (Chetty, Friedman and Rockoff, 2014b; Jackson, 2018). Thus, teacher VA has been shown to be a useful and meaningful proxy for teacher effectiveness.

Using administrative data on 4th through 8th grade teachers in elementary and middle schools in North Carolina, I quantify the relationship between teacher VA and a teacher's likelihood of becoming an AP in the next academic year. In my main analysis, I employ a linear probability model and find that teachers who have one standard deviation (SD) higher math (reading) VA are 0.114 (0.025) percentage points likelier to become AP in the next academic year, conditional on teacher experience and demographic factors, such as age, gender, and race/ethnicity. Relative to the outcome mean of 0.337% for teachers with average math VA and 0.323% for teachers with average reading VA, these results correspond to math (reading) teachers being 33.8% (7.8%) likelier to become AP in the next academic year. I also investigate non-linearity in these results. Teachers in the top quintile of math VA are 153.2% likelier to become AP in the next academic year compared to those in the bottom quintile, whose likelihood is about 0.2%. Given that there are approximately 40,000 elementary and middle school teachers in NC, across one year, 16 people in the bottom quintile would become AP and 40 people in the top quintile would become AP.

[2]In this paper, I define school leaders as APs and principals.

These main results are robust to alternative estimating strategies, including logistic regression, survival analysis, and competing risk analysis, which are important to consider due to the small outcome mean and teacher attrition. Additionally, I investigate heterogeneity in the main results by teacher gender and race/ethnicity. I find that math VA is a stronger predictors of becoming an AP for male teachers compared to female teachers and for non-white teachers compared to white teachers. A 1 SD higher math VA male teacher is 106.8% likelier to become an AP next year relative to the outcome mean, while the same value for women is only 23.2%. Similarly, a 1 SD higher VA non-white teacher is 75.2% likelier to become an AP next year relative to the outcome mean, while a 1 SD higher VA white teacher is only 24.4% likelier to become AP next year.

This paper makes several important contributions. First, this paper extends the teacher retention literature by looking at transitions to other positions in the education system. This is the first paper to investigate the relationship between VA and transitions to school leadership positions, while prior work has devoted attention to the relationship between teacher VA and teacher transitions to other schools, districts, or out of the state's public school system (Hanushek et al., 2005; Krieg, 2006; West and Chingos, 2009; Goldhaber, Gross and Player, 2011; Feng and Sass, 2017). A goal of these retention papers is to understand whether the best teachers are staying in teaching. This paper broadens our understanding of where the good teachers go by highlighting that the top teachers are leaving the classroom to work in school leadership. It is important to investigate loss to school leadership because, depending on the relationship between teacher effectiveness and principal effectiveness, there may be a net benefit to students due to this specific type of attrition.

Second, this paper contributes to the management and personnel economics literature, especially the topic of the "Peter principle" (Peter, Hull et al., 1969). This principle states that because current performance is used for deciding promotions and different skills are often needed at the next level, employees are promoted to the point of incompetence. This paper addresses the first half of the principle; I find that current job performance is indeed predictive of promotion to the role of AP. Further investigation is required to understand whether the second condition of the principle holds in the setting of public K-8 education, which I discuss further in Section 5.

Third, this paper is the first to thoroughly document positive selection into school leadership. If we are interested in understanding the second component of the Peter principle (whether teachers are promoted to incompetency in school leadership), it is first important to understand who becomes a school leader so we can put bounds on understanding the observed relationship we see between teacher VA and principal VA. Several recent papers have attempted to correlate teacher and principal VA to understand whether the best teachers make the best principals (Goldhaber, Holden and Chen, 2019; Liebowitz and Porter, 2020; Grissom, Woo and Bartanen, 2020). They find a modest positive relationship between teacher and principal VA. Two of these papers very briefly address the issue of selection into school leadership but find statistically insignificant positive results (Goldhaber, Holden and Chen, 2019; Liebowitz and Porter, 2020). Using a greater number of years of data and in a study designed to specifically investigate selection, I am able to uncover the first statistically significant evidence of positive selection into school leadership, which suggests caution in studying the relationship between teacher and principal VA in future studies, especially in North Carolina.

The rest of the paper proceeds as follows. Section 2 provides a brief background on the role of AP in NC and describes the administrative education data from North Carolina. Section 3 discusses the VA model and the regression model which quantifies the relationship between teacher VA and becoming an AP. Section 4 presents the main results and an analysis of heterogeneity by teacher gender and race/ethnicity. Additionally, it investigates robustness to alternative estimators and variations in VA calculation, regression specification, and sample. Finally, Section 5 discusses the policy relevance of these results and concludes.

2 Background and data

2.1 Becoming an assistant principals in NC

This project focuses on APs in NC. The overarching rules and guidelines for APs and principals in NC are governed by North Carolina General Statutes, Chapter 115C Article 19. The typical process for becoming a school leader in NC starts with a vacancy being posted through a state-wide system. Applicants are initially screened and interviewed by district administrators, teachers, staff, and parents at the school, who then recommend final candidates to the superintendent. Then, the superintendent recommends an individual to the local board of education (Miller, 2013). Both APs and principals are required to have the same certification, which involves passing an exam from the State Board of Education and meeting proper education and training requirements. The education requirement is satisfied by having a master's degree in public school administration or comparable education and training. The State Board of Education can also give out one-year provisional assistant principal certifications under special circumstances, such as a shortage of qualified principals. An assistant principal's duties are delegated by the principal from the principal's duties.

2.2 Data

The data for this project comes from the North Carolina Education Research Data Center, which partners with the North Carolina Department of Public Instruction to manage data on the state's public schools, teachers, and students. This administrative data contains information at the individual-level, such as individual students' test scores and individual teachers' employment records. It is recorded at the academic-year-level, which ranges from fall of one calendar year to spring of the following calendar year. I will subsequently identify academic years by the spring semester (e.g., 2018-2019 is henceforth 2019).

2.2.1 Teacher data

To construct a record of teachers' careers over time, I create an individual-level teacher panel using yearly teacher pay data. This data contains employment information for certified employees in NC public schools, which includes positions such as teachers, counselors, and principals.[3] It is available for the 1995 to 2019 academic years. The dataset contains budget codes for an employee's position. There are unique budget codes for teachers, assistant principals, principals, superintendents, psychologists, teaching support, and more. When individuals are employed in more than one position in a given year, I denote their position for that year based on the position code with the highest percent of employment. Using the unique employee ID, I track individuals across years to construct their employment histories. Then, I merge this data with additional information on teacher's demographic characteristics, education, and licensure. Importantly, years of experience in the NC public school system is reported starting in 2012. In Figure 1, I use the 2012-2019 years of data to plot the years of experience an individual has the first time they become AP. I include only APs at elementary, middle, or combined elementary and middle schools. It is clear from this figure that one's likelihood of becoming an AP varies with experience. The most frequent time to become AP is in one's 9th year. It is quite rare for very inexperienced or very experienced individuals to become AP. This indicates that controlling for experience will be extremely important for understanding the relationship between VA and becoming AP.

Most individuals who become AP were once teachers—94% of the 2,614 individuals who are hired to be an AP in the 2012-2019 data are observed as teachers at least once before becoming AP. Those who are not observed as teachers in NC likely had teaching experience in another state or in private schools. Additionally, the most frequent position in the year before becoming AP is teacher. 63% of these individuals are teachers in the year before becoming AP.[4] Since most APs were once teachers, effectiveness as a teacher is likely a

[3]Positions that do not require certification, such as teaching assistants, are not included in this dataset.
[4]The next most common position is instructional facilitators at 19%.

factor involved in one's career advancement and a relevant predictor to examine.

2.2.2 Student data

To calculate teacher VA to student achievement, I use the student-level end-of-grade test score data spanning from 2007 to 2019. In North Carolina, 3rd through 8th grade students are tested in reading and mathematics at the end of each year. To account for differences in the test across grade and year, I normalize students' test scores by subject, grade, and year to have a mean of zero and standard deviation of one. The VA model I will use relies on controlling for a student's one-year lagged test score in a given subject. Therefore, 3rd grade test scores and data for the year 2007 are only used for obtaining students' prior year test scores. A key variable in the dataset is the identifier for a student's reading and/or math teacher. For the data years 2008 to 2019, I use course membership data to link students to the exact instructor of their reading or math course.[5] To ensure accuracy in my value-added model, I drop a small number of students who repeat a grade, attend more than one school in a given year, are in a classroom with fewer than 10 students, or lack demographic information.

In Table 1, I present summary statistics on my final sample of 4th through 8th grade students in North Carolina at the student-by-academic-year level for years 2008-2019. Of these students, 5.1% have limited English proficiency and 50.6% are economically disadvantaged. Just over half of students are White, about one quarter are Black, and about 15% are Hispanic. Though math and reading test scores are normalized by grade and year to have a mean of 0 and standard deviation of 1, this table only includes students who are successfully matched to their teacher and to demographic data.[6] The average test scores for math (reading) students are slightly below (above) average in terms of student achievement

[5]For the data years 1998-2007, the data only allows for identification of the teacher listed as administering the math or reading exam to identify the student's math and/or reading teacher, respectively. Prior literature using the NC data suggests that this match is most reliable for only grades 4 through 6. Thus, I do not include data years that rely on an imprecise match so as to minimize incorrect attribution of student achievement to teacher.

[6]72% (66%) of students with math (reading) scores are successfully matched to their teacher and to demographic data.

compared to the overall sample of math (reading) students.

2.2.3 Sample restrictions for main analysis

I begin with 449,085 teacher-by-year observations for teachers at elementary, middle, or combined elementary and middle schools in the years 2012-2018.[7] After dropping the 6% of individuals with missing demographic data, I am left with 421,636 observations. The final and key restriction I make is that individuals must be linked to teaching 4th-8th grade students math or reading in the years 2008-2019 so I can calculate VA for them. This restriction reduces my final sample to 161,580 teacher-by-year observations.

Table 2 reports the summary statistics for the 421,636 teacher-by-year observations with demographic information and compares the differences between those for whom I can and cannot calculate VA. Of the 161,580 teacher-by-year observations with VA, 84,688 have both math and reading VA, while 76,892 have only math or only reading VA. Correspondingly, there are 260,056 teacher-by-year observations for whom I cannot link to VA. Teachers in the "No VA" column are those who across the years 2008-2019 never taught math or reading in grades 4-8. For example, a kindergarten teacher, a PE teacher, and a middle school social studies teacher will not have student standardized test scores for the grade and/or subject they teach.

In general, these two samples are quite similar, but there are several differences between the teachers with VA and those without. Those with VA are more likely to be at middle schools and less likely to be at elementary schools than those without VA. This is likely because there are more untested grades at elementary schools, while all grades are tested in middle schools. Additionally, those with VA are more likely to become AP and have a principal license compared to those without VA.[8] 0.34% of teacher-year-observations with VA will become AP in the next year, while only 0.25% of those without VA will do so. A two-sided t-test of this difference is statistically significant (p-value of 0.000). 3.71%

[7] I do not include data from the year 2019 because my outcome of interest is becoming AP in the next year, which is not observed in the last data year.

[8] A teaching license is required as a pre-requisite for a principal license, so individuals with principal licenses also have teaching licenses.

of teacher-year-observations with VA have a principal license while only 2.53% of those without VA have one (p-value of 0.000). So, while the investigation of VA and becoming AP unfortunately does not facilitate the inclusion of all teachers, it does target those relatively more likely and more qualified to become AP.[9]

3 Methods

To understand the relationship between a teacher's effectiveness and the likelihood of becoming an AP, I first need to obtain a measure of teacher quality. I estimate teacher's VA to student test scores separately for math and reading. Teacher VA in a subject is conceptualized through the following student-level estimating equation:

$$A_{ijct} = X_{ijct}\beta + \nu_{ijct}, \text{ where } \nu_{ijct} = \mu_j + \theta_{jct} + \varepsilon_{ijct} \tag{1}$$

The dependent variable A_{ijct} is the end-of-grade standardized test score for student i taught by teacher j in classroom c in year t. The vector X_{ijct} contains controls for student and classroom characteristics, such as prior year standardized test scores, demographics, and classroom- and school-year-level means of those variables, to account for individual and peer factors influencing student achievement. The residual ν_{ijct} is the sum of three components: the teacher's time-invariant VA (μ_j), classroom-level shocks (θ_{jct}), and idiosyncratic student shocks (ε_{ijct}). For teacher VA to be interpreted as a causal estimate of teachers' impacts on student achievement, any non-random sorting of students into classrooms must be fully controlled for by observable characteristics in the estimating equation. A large literature has focused on the choice of controls, estimation method, and richness of data needed to reduce bias in the estimation of teacher VA in non-experimental settings (see Koedel and Rockoff (2015) for a review.) Following best practices, I interpret teacher VA as a causal estimate of a teacher's impact on student achievement.

[9] In Appendix Table A1, I compare teachers in the math VA sample to those in the reading VA sample and find few substantial differences, though the reading sample has more women than the math sample.

To estimate VA for teachers using the 2008-2019 student standardized test score data, I follow the two-step method often attributed to Kane and Staiger (2008). The two steps are as follows:

1. First, estimate equation 1 using ordinary least squares and generate the residual, ν_{ijct}, for each student.

2. Average the student-level residuals within a classroom.

Next, I use these classroom average residuals to recover a single VA estimate per teacher. Since some teachers lead more than one classroom per year (e.g., an 8th grade math teacher who teaches multiple math classes in an academic year), I first take a precision-weighted average of the average classroom residuals for a given teacher-year, as in Chetty, Friedman and Rockoff (2014a).[10] Since I then have one value for each teacher-year, I take a precision-weighted average of the teacher-year values for each teacher. At this point, I have one VA estimate for each teacher, but it is estimated with error. The final step is to construct an empirical Bayes estimate by multiplying this value by a Bayesian shrinkage factor that shrinks the estimate toward the common Bayesian prior of the average teacher VA (which is 0 by construction). The use of the Bayesian shrinkage factor provides a conservative estimate of the standard deviation of VA and is especially important when using VA as an explanatory variable since it reduces the estimation-error variance.

To understand whether more effective teachers are more likely to become school leaders, I match my estimate of teacher j's VA, $\hat{\mu}_j$, to their employment data across the years 2012-2018. I then estimate the following linear probability model (LPM) using ordinary least squares:

$$\mathbb{1}\{\text{Become AP next year}\}_{jt} = \gamma_1 \hat{\mu}_j + \gamma_2 X_{jt} + \epsilon_{jt} \tag{2}$$

where $\mathbb{1}\{\text{Become AP next year}\}_{jt}$ is a binary indicator if teacher j becomes an AP in the

[10] A precision-weighted average is a weighted average that uses weights based on the inverse of variance. Based on the formula for the precision weights, larger classrooms receive more weight and smaller classrooms receive less weight.

NC public school system in year $t+1$. The variable $\hat{\mu}_j$ is teacher VA as estimated above, and X_{jt} is a vector of other factors that influence one's likelihood of becoming AP, such as age, gender, ethnicity, experience, training, and education. The outcome is a binary variable, so the estimate of $\hat{\gamma}_1$ indicates the average percentage point change in the likelihood of becoming AP next year when a teacher has 1 unit higher VA. The independent variable, $\hat{\mu}_j$, is constructed and thus may contain measurement error. However, classical measurement error in an explanatory variable biases the results toward zero, so the coefficient on $\hat{\mu}_j$ may be an underestimate of the true relationship.

This regression model estimates the relationship between VA and one's likelihood of promotion, holding important determinants of promotion constant. However, causality is extremely difficult to uncover in this relationship since VA is not randomly assigned. Instead, the purpose of estimating this equation is to quantify the relationship between teacher VA and promotion to school leadership rather than show a causal relationship between the two, though one may still exist. We still care about the relationship, even if it isn't causal, because it offers important insights into the current state of the school leadership pipeline. The most important threat to identification of the relationship is omitted variable bias. To tend to this concern, in Section 4.5 I explore how the coefficient on VA changes with the inclusion of various observable factors and find no qualitative difference in the results across specification. Though an imperfect check on omitted variable bias, this exercise suggests stability in the relationship, which mitigates concern regarding omitted variable bias.

3.1 Alternative estimators

While the LPM has several benefits, such as ease of interpretability and estimation, it also has limitations. I discuss these limitations and the alternative estimators I use to address whether my main results are robust to the choice of estimator. These three alternatives are logistic regression, survival analysis, and competing risk analysis.

First, I consider the use of a logistic regression. A standard logistic regression estimates the relationship between linear independent variables and the log odds ratio of a binary outcome occurring. Since the outcome in the main analysis is a binary variable with a very small mean, a LPM may not provide a good fit and the logistic regression may be more suitable. I estimate a logistic regression of the following form using maximum likelihood:

$$\frac{p}{1-p} = e^{\gamma_1 \hat{\mu}_j + \gamma_2 X_{jt}} \tag{3}$$

where p is the probability of becoming AP next year and $\frac{p}{1-p}$ is the corresponding odds ratio. As in the LPM, $\hat{\mu}_j$ and X_{jt} are used as explanatory variables. The estimated coefficient, $\hat{\gamma}_1$ indicates the change in the log odds ratio when a teacher has a VA of 1 compared to a VA of 0. Since the odds ratio is not directly comparable to the outcome in the main analysis, I also calculate the marginal effect of a 1 unit increase in VA, which can be directly compared to the percent impact of VA in the main results using the coefficient on VA divided by the outcome mean.

Second, I turn to survival analysis to investigate whether the main results are biased due to attrition. Even if both the LPM and logistic regression provide similar results, they might both provide biased estimates of the relationship between VA and becoming AP if attrition is significant. Survival analysis is a natural method choice when dealing with attrition due to its accommodation of censoring.[11] Survival analysis is a type of time to event analysis, where the event is called the "failure". In this context, the failure is becoming an AP for the first time in the next academic year. I investigate whether one's hazard of becoming AP next year is related to their VA.

Using the Cox Proportional Hazard Model (CPHM) (Cox, 1972), the hazard function $h_j(t)$ for teacher j takes the form

$$h_j(t) = h_0(t) e^{\gamma_1 \hat{\mu}_j + \gamma_2 X_j} \tag{4}$$

where $h_0(t)$ is an arbitrary baseline hazard representing the probability of failure conditional

[11] For example, a teacher may leave the data after a few years because they leave the profession or move to another state, so we never see them become AP. Additionally, the data is censored for all individuals after 2019, since that is the last year of data.

on surviving to time period t. The estimated coefficient $\hat{\gamma}_1$ indicates the change in the hazard rate when a teacher has a VA of 1 compared to a VA of 0. If the coefficient is greater than 1, then higher VA increases one's likelihood of becoming AP. If for example the coefficient is 1.5, then teachers with a VA of 1 are 50% likelier to become AP next year compared to teachers with a VA of 0. This value of 50% can be compared to the percent impact of VA from the main results. I estimate the CPHM using maximum likelihood.

Third, I estimate a variant of the hazard function that accommodates competing risk. The CPHM assumes censoring is uninformative, or orthogonal to the independent variable of interest. The more prevalent a competing risk is, the greater the divergence between the estimates from a CPHM and a competing risk model. Evidence from Goldhaber, Gross and Player (2011) suggests early career attrition does indeed vary by VA, so the results from the CPHM may be biased. I use a competing risk model, which is an extension of the hazard function with multiple risks to failure. The risks I consider are 1. becoming AP next year and 2. leaving the data in a given year. The competing risk model takes the form

$$h_j c(t) = h_{0c}(t) e^{\gamma_1 \hat{\mu}_{jc} + \gamma_2 X_{jc}} \text{where } c = 1, 2 \tag{5}$$

with competing risks c. The subhazard model for $c = 1$ is estimated using maximum likelihood per the methods in Fine and Gray (1999). The estimated coefficient $\hat{\gamma}_1$ will indicate the change in the subhazard rate of becoming AP next year for a teacher with a VA 1 of compared to a teacher with a VA of 0. Similar to the CPHM, a coefficient greater than 1 indicates an increased risk of failure and can be compared to the main results in the same way.

4 Results

4.1 Teacher value-added

To estimate teacher VA for 4th-8th grade teachers, I first estimate equation 1 using ordinary least squares. The outcome variable is standardized test scores from end-of-grade state-wide testing, normalized by subject, grade, and year. The vector of control variables, X_{it}, contains a cubic polynomial of the one year lagged standardized test score in the subject, indicators for sex, age, race and ethnicity, grade, economic disadvantage, and limited English proficiency, academic year fixed effects, school fixed effects, and class- and school-by-year means of the demographic controls. Importantly, the regression includes teacher fixed effects so that the estimate of β is unbiased, but these are not subtracted out in the creation of the residual. The estimation sample includes only 4th through 8th graders so that all observations have a lagged test score. I include all students in the model, even if their teacher can't be linked to the 2012-2018 employment data, to reduce bias in estimating β.

Following the method detailed in section 3, I estimate one value per teacher and merge this information into the 2012-2018 employment panel to investigate the relationship between VA and becoming AP. Summary statistics for VA are found in Table 3, separated by subject. This table first reports VA for all 2008-2019 teachers and then VA for the subset of teachers that I can link to the 2012-2018 employment data. Consistent with prior literature, math VA has a larger standard deviation than reading VA. These values indicate that a 1 SD higher VA teacher raises student test scores by about 16% of a standard deviation for math teachers and 10.5% of a standard deviation for reading teachers. These values fall well within typical ranges, so I proceed with the subsequent analyses. For brevity, I henceforth use the term "math teacher" to describe all teachers in the math VA analysis and "reading teacher" to describe all teachers in the reading VA analysis, even though some of these teachers may also teach other subjects, such as a 5th grade teacher who teaches all subjects.

4.2 Value-Added and becoming assistant principal

Next, I estimate equation 2 with a binary indicator for becoming AP in the next academic year as the outcome and $\hat{\mu}_j$ (estimated VA) as the independent variable of interest. For ease of interpretation, VA is normalized to have a mean of zero and standard deviation of one. I also provide the outcome mean for teachers in the sample and report the results as percents relative to this value. The control variables include indicator variables for race/ethnicity, gender, education, national board certification, licensing level, school type, and academic year, as well as a second order polynomial of age and indicators for teaching experience in 5 year intervals.[12] In all regressions, robust standard errors are clustered at the teacher-level.

Table 4 reports the results for equation 2 for math in column (1) and for reading in column (3). Turning to the results in column (1), I find that a 1 SD higher VA math teacher is 0.114 percentage points (pp) likelier to become AP next year. In percent terms, this corresponds to a 33.8% difference relative to the average likelihood of becoming AP next year, 0.345%. This result is highly significant. Column (3) reports the corresponding results using reading VA. A 1 SD higher reading teacher is 0.025 pp or 7.8% likelier to become AP next year. However, this result is only marginally significant. These results indicate that both math and reading teachers with higher VA are more likely to become AP, holding other important factors constant. Being a higher math VA teacher, however, is a much stronger predictor than being a higher reading VA teacher.

Equation 2 imposes linearity in the relationship between VA and one's likelihood of becoming AP next year. To relax this assumption, I use VA quintiles as my independent variables of interest. In Table 4, I use math VA quintiles in column (2) and reading VA quintiles in column (4). These results are also reported in Figure 2. The first quintile is used as the reference group, so to get results in percent terms relative to the bottom quintile, I provide the outcome mean for the first quintile. For math teachers, there is a monotonic and somewhat linear relationship between VA quintile and becoming AP. From quintile two to quintile five, the percent increase in one's likelihood of becoming AP, relative to the

[12]School type is elementary, middle, or combined elementary and middle school.

bottom quintile, is 55.5, 80.7, 85.2, and 153.2%, respectively. The left panel of Figure 2 highlights this relationship. For reading teachers in column (4), none of the quintiles can be distinguished from the lowest quintile, as seen in the right panel of Figure 2. Thus, the results for math and reading VA do not suggest a highly non-linear relationship between VA and becoming AP, so I proceed with using the linearly specified VA in subsequent analyses.

4.3 Heterogeneity

Next, I investigate the heterogeneity of the main results based on teacher characteristics. This analysis is important for several reasons. First, elementary and middle school teachers in NC are predominately female (84%) and white (87%), though both men and non-white teachers are more represented in school leadership than in the general teacher population.[13] Second, if we care about improving student outcomes, it is important to understand the promotion propensity for different groups because minority teachers and school leaders can positively impact minority student achievement (Dee, 2005; Gershenson et al., 2018; Bartanen and Grissom, 2021).

I return to the LPM with VA included as a linear independent variable and interact VA with indicators for gender or race/ethnicity.[14] Due to the predominance of female and white teachers in the sample, I am not able to precisely estimate the coefficients in a regression with the triple interaction of VA, gender, and race/ethnicity; I instead investigate heterogeneity separately by gender and race/ethnicity.

I first interact VA with an indicator for being a female teacher. These results are reported in Table 5. Using math teachers in column (1), I find that there is a difference in the relationship between VA and becoming principal based on teachers' gender. For male teachers, being a 1 SD higher VA math teacher equates to being 0.359 pp likelier to become an AP next year; for female teachers, the same value is 0.078 pp. The difference between these two values is captured in the coefficient on the interaction Female$\times$VA, which is statistically

[13] 70% of APs are female and 66% are white.

[14] The heterogeneity results are robust to fully interacting the characteristic of interest with all controls.

significant at the 1% level. Relative to the outcome mean of 0.337%, these values equate to 106.8% for men and 23.2% for women. For reading teachers in column (3), the same pattern appears. While men with a 1 SD higher reading VA are 0.118 pp (36.5%) likelier to become AP next year, female teachers with a 1 SD higher reading VA are only 0.015 pp (4.8%) likelier to become AP next year. However, the percentage point difference is not statistically significant at conventional levels. These results show that VA is a stronger predictor of becoming AP for men compared to women, though the relationship is only statistically significant for math teachers.

In columns (2) and (4), I interact VA with an indicator for being white, using non-white teachers as the reference category. I pool together all non-white teachers into the same category for precision since NC teachers are predominately white.[15] For white math teachers, being a 1 SD higher VA teacher corresponds to being 0.082 pp (24.4%) likelier to become AP next year. For non-white math teachers, this value is 0.253 pp or 75.2% relative to the outcome mean. The percentage point difference between white and non-white teachers is significant at the 1% level. For reading teachers, the results go in the same direction, though they are very small and insignificant. A 1 SD higher reading VA white teacher is 0.023 pp (7.0%) likelier to become AP next year, but the same value is 0.032 pp (9.9%) for non-white reading teachers. These results suggest that for math teachers, VA is a stronger predictor of becoming AP for non-white teachers compared to white teachers, but for reading teachers, there is not enough precision to detect strong racial differences in the relationship between VA and becoming AP.

In general, the results for gender and race/ethnicity go in the same direction when considering which groups are in the minority of teachers. Though the results are only statistically significant for math teachers, they suggest that VA is a stronger predictor of promotion for people in the gender minority group (male teachers) and the racial/ethnic minority group (non-white teachers). This aligns with discrimination theory, which would suggest that mem-

[15] In Appendix Table A2, I instead use separate indicators for teachers who are Black, Hispanic, and other race/ethnicity. For math VA, the race/ethnicity differences are driven by Black teachers, who make up the highest share of non-white teachers.

bers of minority groups have to work harder to prove themselves "worthy" of promotion. As indicated by the coefficient on Female in columns (1) and (3) and Non-White in columns (2) and (4), male teachers have a higher likelihood of becoming AP compared to female teachers and non-white teachers have a higher likelihood of becoming AP compared to white teachers. Thus, the gap in the likelihood of becoming AP between male and female teachers (the gender gap) and white and non-white teachers (the race gap) is larger for more effective teachers than average teachers.

4.4 Alternative estimators

Importantly, I have thus far estimated LPMs for understanding the relationship between VA and becoming AP. However, there are several other regression models that may also suit this analysis, which I mention in Section 3: the logistic regression, survival analysis, and competing risk analysis. In Table 6, I report results using these methods. The logistic regressions contain the same controls as mentioned previously. Since the survival analysis and competing risk analysis are estimated as functions of experience, I remove experience as a control variable.

In column (1), I find that for math teachers, being a 1 SD higher VA teacher increases the odds ratio for becoming AP next year by 36.1%. I also compute the marginal effect in percent terms for comparability to the LPM results. Using a logistic regression, 1 SD higher VA math teachers are on average 29.0% likelier to become AP next year relative to the average teacher. In column (2), I employ the survival analysis and estimate how VA impacts one's risk of becoming AP next year. Based on the survival analysis, a 1 SD higher VA teachers' risk of becoming AP next year is 28.4% higher. In column (3), I further account for the competing risk of leaving the NC data. These results imply a 1 SD higher VA math teacher's risk of becoming AP next year is 36.3% higher. These values are similar to the value of 33.8% that I find using the LPM.

Similarly for reading teachers, I report the results for logit, survival analysis, and competing risk analysis in columns (3) through (5). The marginal effect from the logit model implies that 1 SD higher reading teachers are 6.7% likelier to become AP next year relative to the average teacher. For the survival analysis and competing risk analysis, a 1 SD higher reading VA teacher's risk of becoming AP next year is 3.6% and 9.4% higher. Similar to the result of 7.8% that I find using the LPM, these results are small and at most marginally significant. In summary, I find that the results using alternative estimators for both math and reading teachers are all in line with LPM results I report in columns (1) and (3) of Table 4.

4.5 Robustness

Finally, I consider a variety of robustness checks on the main specification. These checks include investigating the robustness of the LPM to the method of estimating VA, choice of controls, and choice of sample.

Table 7 explores different ways of estimating VA. First, I calculate VA in the same way as the main specification without the school fixed effect. The choice to use a school fixed effect in the VA estimating equation has benefits and drawbacks. While it can reduce bias in the estimate of VA, it also restricts the identification to be based on within-school differences and thus relies on interconnected networks of teachers working at multiple schools ("switchers") for comparison. With few years of data, this can cause issues, but given that I have 12 years of data, my estimation likely doesn't suffer from this problem. The results in column (1) for math teachers and column (4) for reading teachers highlight that the main results still hold without using school fixed effects in the VA calculation, though the magnitude of the coefficient is larger for reading teachers.

Second, I revert back to the main specification using the school fixed effect but remove controls for classroom and school-by-academic-year means of student characteristics. Use of these controls can over-attribute the teacher's impact on students to the coefficients on those variables. The results in column (2) for math teachers and in column (5) for reading teachers show that the main results still hold when removing these controls in the VA calculation.

Third, I employ the drift-adjusted VA model from Chetty, Friedman and Rockoff (2014a) that accounts for changes in a teacher's VA over time. While the estimating equation for this method matches the one used in the main specification, the Chetty, Friedman and Rockoff (2014a) method uses a jackknife (leave one year out) estimator to find a teacher-by-year measure of VA rather than a precision weighted average and Bayesian shrinkage factor. Using this jackknife method, teachers who are only observed teaching tested students in one year across 2008-2019 are dropped, hence the smaller sample size shown in columns (3) and (6). However, VA with this method can closer approximate one's effectiveness in each year, rather than the constant component of their effectiveness over time. Regardless, the results in columns (3) and (6) are very similar to the main results.

Next, I investigate the choice of controls used in the estimation of equation 2. Columns (1) and (4) of Table 8 report the results for math and reading, respectively, with VA as the only independent variable. Columns (2) and (5) report the main results, which include controls for demographic factors, education, licensing, etc. Columns (3) and (6) also include school fixed effects to control for time-invariant school factors that might impact a teacher's employment in NC, such as a school being close to a border with another state. For math teachers, the results are very robust to the inclusion of additional covariates. For reading teachers, the point estimate attenuates slightly and becomes noisier with the inclusion of additional covariates. This suggests that for reading teachers, the unadjusted relationship between VA and becoming AP may overstate the true relationship, which is mediated by other factors, such as education, training, gender, etc.

Finally, I investigate robustness to choices in the sample restrictions and employment panel creation in Table 9. Columns (1) and (3) no longer restrict to just using teachers when estimating equation 2. This means the sample now includes employees in other positions, such as instructional facilitators and instructional support personnel.[16] This is an important restriction to check since about one third of APs were in a position other than teacher in the year before becoming AP. I find that the results are similar for both math and reading teachers when including additional employees. In columns (2) and (4), I define teachers and

[16]Most of people in these positions were once teachers, which allows for calculation of VA for those individuals.

APs by whether they were employed at all in one of those positions in a school year rather than by the highest percent of employment. The main results hold when this definition is altered.

I summarize these robustness checks in Figure 3. None of these choices qualitatively impact the main results.

5 Discussion and conclusion

More effective teachers are more likely to become school leaders. A 1 SD higher math (reading) VA teacher is 33.8% (7.8%) likelier to become an AP in the next academic year relative to the outcome mean, holding demographic factors and teaching experience constant. These results are estimated using a linear probability model, but the main findings are robust to the use of alternative estimation strategies, including logistic regression, survival analysis, and competing risk analysis, as well as variations in the calculation of VA and controls used in the LPM. Additionally, heterogeneity analyses point to variation in the strength of the relationship between VA and becoming AP by both gender and race/ethnicity of teachers, especially for math teachers. A 1 SD higher male math teacher is 106.8% likelier to become AP next year compared to the outcome mean, while for female math teachers, the same value is only 23.2%. Additionally, relative to the outcome mean, 1 SD higher VA non-white math teachers are more likely to become AP next year (75.2%) than 1 SD higher VA white math teachers (24.4%).

There are important policy implications from this study that depend on the welfare effects of the loss of the most effective teachers from their classroom to school leadership. If the best teachers make the best APs and principals, then the welfare effects may be positive because principals can impact more students than teachers can. However, if teacher VA is unrelated or negatively related to effectiveness in school leadership, then promoting the best teachers to principal will on average be detrimental because of the loss of effective teachers from the classroom. Thus, uncovering the relationship between teacher and principal effectiveness is extremely important for understanding the policy recommendations. However, this paper suggests that we cannot simply correlate teacher effectiveness and principal effectiveness since this observed relationship is a product of selection into school leadership. This suggests much room for education researchers to think about possible quasi-experimental settings where one could investigate the true relationship between teacher and principal effectiveness.

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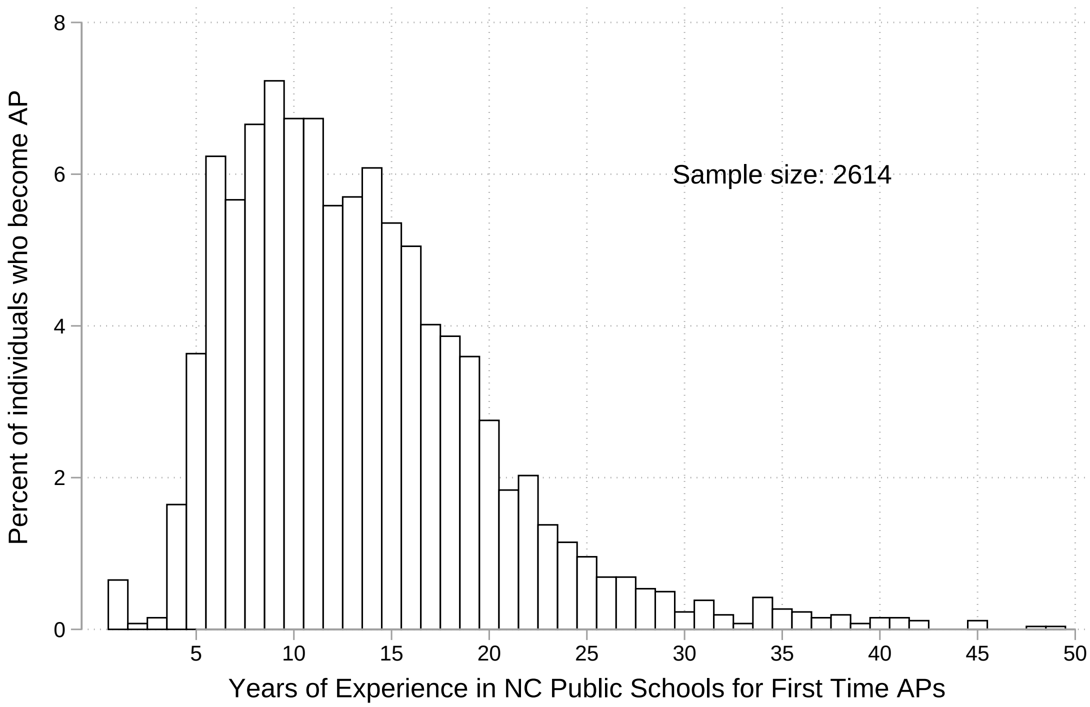
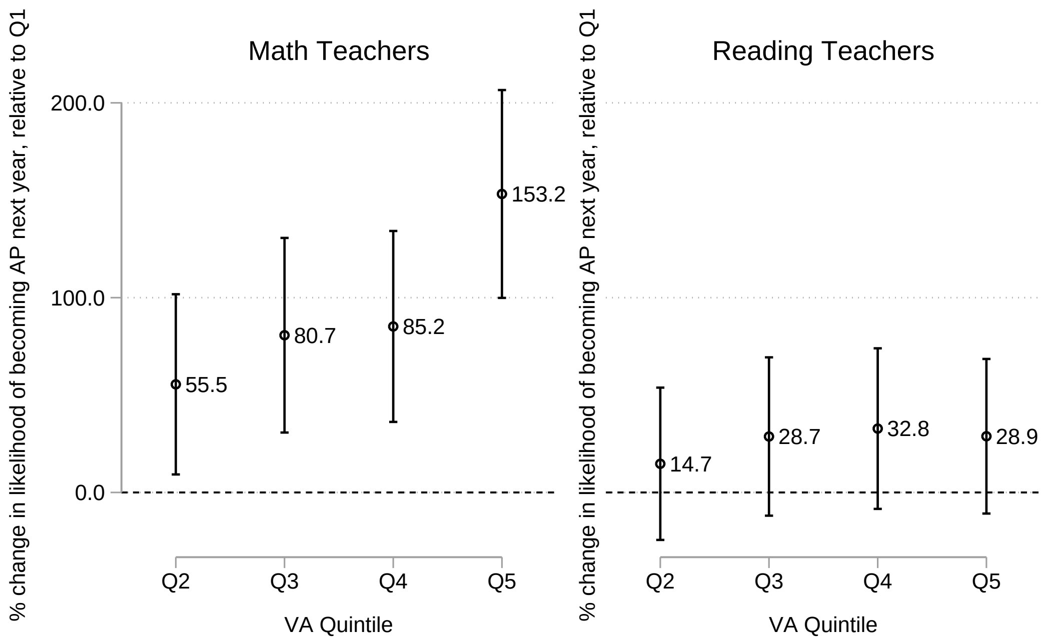
Figures and Tables

Figure 1: Experience when Becoming AP for the First Time



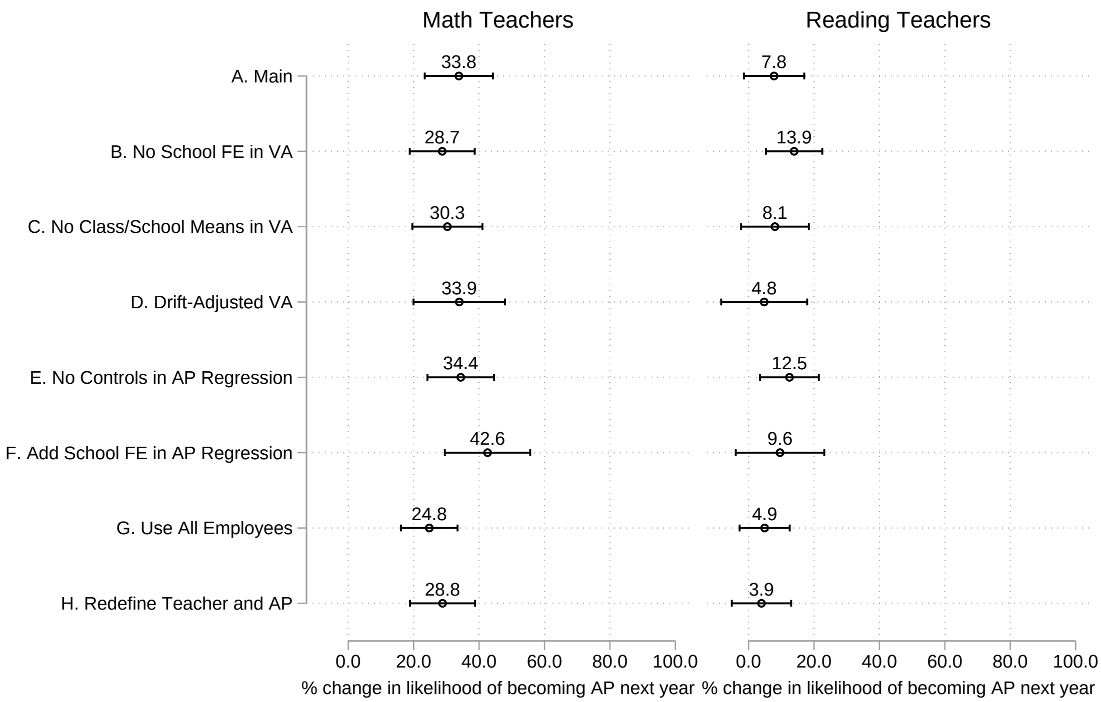
Note: This figure uses employment data from 2012-2019. Each of the 2,614 observations represents one employee who become AP for the first time in the data years 2012-2019.

Figure 2: 95% Confidence Intervals for VA Quintiles



Note: Point estimates and 95% confidence intervals are reported using columns (2) and (4) from Table 4.

Figure 3: 95% Confidence Intervals Summarizing Robustness Checks



Note: Point estimates and 95% confidence intervals are reported. Row A. reports the results from Table 4 column (1) for math and (3) for reading. Rows B. through D. report the results from Table 7 columns (1)-(3) for math and (4)-(6) for reading. Rows E. and F. report the results from Table 8 columns (1) and (3) for math and (4) and (6) for reading. Rows G. and H. report the results from Table 9 columns (1) and (2) for math and (3) and (4) for reading.

Table 1: Summary Statistics for 4th-8th Grade Students, 2008-2019

	Mean	SD
Normalized math score	-0.028	0.958
Normalized reading score	0.059	0.974
Female	0.497	0.500
Age	12.426	1.487
Limited English proficiency	0.051	0.221
Economic disadvantage	0.506	0.500
White	0.523	0.499
Black	0.248	0.432
Hispanic	0.149	0.356
Other race/ethnicity	0.081	0.272

Note: This table contains the sample of 5,305,100 students in 4th-8th grade in the years 2008-2019 who have end of year math and/or reading test scores and are successfully matched to their math and/or reading teachers as well as demographic data.

Table 2: Summary Statistics for Teachers 2012-2018

	Math or Reading VA	No VA	P-value
Female	0.8885	0.8655	0.000
	(0.315)	(0.341)	
White	0.8420	0.8331	0.001
	(0.365)	(0.373)	
Black	0.1295	0.1261	0.167
	(0.336)	(0.332)	
Hispanic	0.0112	0.0214	0.000
	(0.105)	(0.145)	
Other race/ethnicity	0.0173	0.0194	0.033
	(0.130)	(0.138)	
Age	40.6783	42.1779	0.000
	(10.741)	(11.456)	
Experience	12.4211	13.6586	0.000
	(8.219)	(9.161)	
Bachelors	0.6165	0.6399	0.000
	(0.486)	(0.480)	
Masters	0.3769	0.3528	0.000
	(0.485)	(0.478)	
Advanced deg	0.0040	0.0043	0.505
	(0.063)	(0.065)	
Doctorate	0.0026	0.0030	0.239
	(0.051)	(0.055)	
National board cert	0.1233	0.1141	0.000
	(0.329)	(0.318)	
Teaching license	0.9615	0.9732	0.000
	(0.192)	(0.161)	
Principal license	0.0371	0.0253	0.000
	(0.189)	(0.157)	
Superintendent license	0.0014	0.0014	0.862
	(0.037)	(0.038)	
Elem school	0.5866	0.7145	0.000
	(0.492)	(0.452)	
Elem and middle	0.0372	0.0343	0.033
	(0.189)	(0.182)	
Middle school	0.3762	0.2512	0.000
	(0.484)	(0.434)	
AP next year	0.0034	0.0025	0.000
	(0.058)	(0.050)	
Observations	161,580	260,056	
Teachers	35,779	65,035	

Note: This table contains the sample of teachers in the years 2012-2018 who worked at elementary, middle, or combined elementary and middle schools. Means are presented with standard deviations below in parentheses. P-value comes from a regression of the variable of interest on an indicator for having math or reading VA. Standard errors are clustered at the teacher level since there are multiple observations per teacher, and p-value comes from the statistical test of whether the coefficient on the indicator for having math or reading VA is different from zero.

Table 3: VA Summary Statistics

	Mean	SD	Min	Max	N
Math VA	-0.013	0.160	-0.837	0.827	33,812
Math VA - Analysis Sample	-0.011	0.162	-0.837	0.827	26,074
Reading VA	0.003	0.104	-0.565	0.620	35,379
Reading VA - Analysis Sample	0.002	0.106	-0.565	0.598	27,241

Note: Math (Reading) VA include all teachers from 2008-2019 who taught math (reading) to 4th-8th graders in at least one year. Math (Reading) VA - Analysis Sample includes only the subsample of math (reading) teachers who are in the employment data from 2012-2018, do not have missing demographic data, and teach in elementary, middle, or combined elementary and middle schools.

Table 4: VA and Likelihood of Becoming AP Next Year

	Math Teachers		Reading Teachers	
	(1)	(2)	(3)	(4)
VA	0.00114***		0.00025*	
	(0.00018)		(0.00015)	
VA Q2		0.00110**		0.00035
		(0.00047)		(0.00048)
VA Q3		0.00159***		0.00069
		(0.00050)		(0.00050)
VA Q4		0.00168***		0.00078
		(0.00049)		(0.00050)
VA Q5		0.00302***		0.00069
		(0.00054)		(0.00048)
Pct. Effect	33.8		7.8	
Pct. Effect - Q2		55.5		14.7
Pct. Effect - Q3		80.7		28.7
Pct. Effect - Q4		85.2		32.8
Pct. Effect - Q5		153.2		28.9
Outcome Mean	0.00337		0.00323	
Outcome Mean, Q1		0.00197		0.00239
N	120,653	120,653	125,615	125,615

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors are clustered at the teacher-level. In all columns, the outcome is a binary indicator for becoming AP in the next academic year. In columns (1) and (2), only math teachers and math VA are used. In columns (3) and (4), only reading teachers and reading VA are used. In columns (1) and (3), the independent variable of interest is math and reading VA, respectively, which is normalized to have a mean of zero and standard deviation of one. In columns (2) and (4), the independent variables of interest are math and reading VA quintile, respectively. The reference category is the first quintile. In all columns, there are also indicators for race/ethnicity, gender, education, national board certification, licensing level, school type, and academic year, as well as a second order polynomial of age and indicators for teaching experience in 5 year intervals.

Table 5: VA and Becoming AP - Heterogeneity by Gender and Race/Ethnicity

	Math Teachers		Reading Teachers	
	(1)	(2)	(3)	(4)
VA	0.00359***	0.00253***	0.00118*	0.00032
	(0.00078)	(0.00062)	(0.00071)	(0.00048)
Female	-0.00450***		-0.00344***	
	(0.00079)		(0.00083)	
Female X VA	-0.00281***		-0.00103	
	(0.00080)		(0.00073)	
White		-0.00192***		-0.00198***
		(0.00063)		(0.00063)
White X VA		-0.00171***		-0.00009
		(0.00064)		(0.00050)
Pct. Effect - Women	23.2		4.8	
Pct. Effect - Men	106.8		36.5	
Pct. Effect - White		24.4		7.0
Pct. Effect - Non-White		75.2		9.9
Outcome Mean	0.00337	0.00337	0.00323	0.00323
N	120,653	120,653	125,615	125,615

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Standard errors are clustered at the teacher-level. For brevity, the variables Black, Hispanic, and Other race/ethnicity are used in the regressions in columns (1) and (3) but the coefficient is not reported in this table. Similarly, the variable for Female is used in the regressions in columns (2) and (4) but the coefficient is not reported in this table. In all columns, the outcome is a binary indicator for becoming AP in the next academic year. In columns (1) and (2), only math teachers and math VA are used. In columns (3) and (4), only reading teachers and reading VA are used. Both math and reading VA are normalized to have a mean of zero and standard deviation of one. In all columns, there are also indicators for education, national board certification, licensing level, school type, and academic year, as well as a second order polynomial of age and indicators for teaching experience in 5 year intervals.

Table 6: VA and Becoming AP - Alternative Estimators

	Math Teachers			Reading Teachers		
	(1) Logistic	(2) Hazard	(3) Competing Hazard	(4) Logistic	(5) Hazard	(6) Competing Hazard
VA	1.361***	1.284***	1.363***	1.073	1.036	1.094*
	(0.068)	(0.061)	(0.069)	(0.054)	(0.050)	(0.056)
Marginal Effect (Pct.)	29.0			6.7		
N	120,653	120,653	120,653	125,615	125,615	125,615

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Standard errors are clustered at the teacher-level. In columns (1) and (4), I use a logistic regression with the outcome as the odds ratio of becoming AP next year. In columns (2) and (5), I estimate a hazard function with the outcome as becoming AP next year, conditional on surviving to the current year. In columns (3) and (6), I estimate a competing hazard model, focusing on the subhazard of becoming AP and accounting for the competing risk of leaving the data, where the outcome is becoming AP next year, conditional on surviving to the current year. In columns (1)-(3), only math teachers and math VA are used. In columns (4)-(6), only reading teachers and reading VA are used. In columns (1)-(3) and (4)-(6), the independent variable of interest is math and reading VA, respectively, which is normalized to have a mean of zero and standard deviation of one. In columns (2) and (4), the independent variables of interest are math and reading VA quintile, respectively. All models are estimated using maximum likelihood. All models additionally contain indicators for race/ethnicity, gender, education, national board certification, licensing level, school type, and academic year, as well as a second order polynomial of age. The logistic regressions also include indicators for teaching experience in 5 year intervals.

Table 7: VA and Becoming AP - Robustness to Choice of VA Method

	Math Teachers			Reading Teachers		
	(1) No School FE	(2) No Class and School Means	(3) Drift Adjusted	(4) No School FE	(5) No Class and School Means	(6) Drift Adjusted
VA	0.00097***	0.00102***	0.00110***	0.00045***	0.00026	0.00015
	(0.00017)	(0.00018)	(0.00023)	(0.00014)	(0.00017)	(0.00021)
Pct. Effect	28.7	30.3	33.9	13.9	8.1	4.8
Outcome Mean	0.00337	0.00337	0.00325	0.00323	0.00323	0.00309
N	120,651	120,638	65,548	125,609	125,603	67,247

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Standard errors are clustered at the teacher-level. In columns (1) and (4), VA is calculated without the use of school fixed effects. In columns (2) and (5), VA is calculated without the use of classroom and school-by-academic-year means of student characteristics. In columns (3) and (6), VA is calculated using the drift-adjusted method from Chetty, Friedman and Rockoff (2014a). In all columns, the outcome is a binary indicator for becoming AP in the next academic year. In columns (1)-(3), only math teachers and math VA are used. In columns (4)-(6), only reading teachers and reading VA are used. Both math and reading VA are normalized to have a mean of zero and standard deviation of one. In all columns, there are also indicators for race/ethnicity, gender, education, national board certification, licensing level, school type, and academic year, as well as a second order polynomial of age and indicators for teaching experience in 5 year intervals.

Table 8: VA and Becoming AP - Robustness to Choice of Controls in AP Regression

	Math Teachers			Reading Teachers		
	(1)	(2)	(3)	(4)	(5)	(6)
VA	0.00116***	0.00114***	0.00143***	0.00040***	0.00025*	0.00031
	(0.00017)	(0.00018)	(0.00022)	(0.00015)	(0.00015)	(0.00022)
Covariates		X	X		X	X
School FE			X			X
Pct. Effect	34.4	33.8	42.6	12.5	7.8	9.6
Outcome	0.00337	0.00337	0.00337	0.00323	0.00323	0.00323
N	120,653	120,653	120,653	125,615	125,615	125,615

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Standard errors are clustered at the teacher-level. In all columns, the outcome is a binary indicator for becoming AP in the next academic year. In columns (1)-(3), only math teachers and math VA are used. In columns (4)-(6), only reading teachers and reading VA are used. Both math and reading VA are normalized to have a mean of zero and standard deviation of one. In columns (1) and (4), there are no additional covariates. In columns (2) and (5), there are also indicators for race/ethnicity, gender, education, national board certification, licensing level, school type, and academic year, as well as a second order polynomial of age and indicators for teaching experience in 5 year intervals. In columns (3) and (6), there are additionally school fixed effects.

Table 9: VA and Becoming AP - Robustness to Data Choices

	Math Teachers		Reading Teachers	
	(1) Use All Employees	(2) Redefine Teacher and AP	(3) Use All Employees	(4) Redefine Teacher and AP
VA	0.00115***	0.00099***	0.00022	0.00013
	(0.00020)	(0.00018)	(0.00018)	(0.00015)
Pct. Effect	24.8	28.8	4.9	3.9
Outcome Mean	0.00463	0.00344	0.00450	0.00325
N	124,927	122,285	130,679	127,403

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Standard errors are clustered at the employee-level. In all columns, the outcome is a binary indicator for becoming AP in the next academic year. In columns (1)-(2), only math teachers and math VA are used. In columns (3)-(4), only reading teachers and reading VA are used. Both math and reading VA are normalized to have a mean of zero and standard deviation of one. In columns (1) and (3), there are indicators for race/ethnicity, gender, education, national board certification, licensing level, school type, and academic year, as well as a second order polynomial of age and indicators for teaching experience in 5 year intervals. In columns (2) and (4), there the same controls except for school type.

A Appendix

Table A1: Summary Statistics for Teachers 2012-2018 with Math and Reading VA

	Math VA	Reading VA	P-value
Female	0.8846	0.9113	0.000
	(0.320)	(0.284)	
White	0.8476	0.8468	0.000
	(0.359)	(0.360)	
Black	0.1230	0.1266	0.673
	(0.328)	(0.333)	
Hispanic	0.0118	0.0115	0.000
	(0.108)	(0.107)	
Other race/ethnicity	0.0177	0.0151	0.000
	(0.132)	(0.122)	
Age	40.3841	40.6116	0.000
	(10.612)	(10.707)	
Experience	12.2836	12.3568	0.000
	(8.085)	(8.115)	
Bachelors	0.6259	0.6074	0.000
	(0.484)	(0.488)	
Masters	0.3681	0.3865	0.000
	(0.482)	(0.487)	
Advanced deg	0.0036	0.0035	0.042
	(0.060)	(0.059)	
Doctorate	0.0024	0.0025	0.180
	(0.049)	(0.050)	
National board cert	0.1194	0.1288	0.000
	(0.324)	(0.335)	
Teaching license	0.9617	0.9621	0.000
	(0.192)	(0.191)	
Principal license	0.0368	0.0365	0.000
	(0.188)	(0.188)	
Superintendent license	0.0015	0.0013	0.560
	(0.039)	(0.036)	
Elem school	0.6891	0.6850	0.000
	(0.463)	(0.465)	
Elem and middle	0.0361	0.0370	0.104
	(0.186)	(0.189)	
Middle school	0.2748	0.2780	0.000
	(0.446)	(0.448)	
AP next year	0.0034	0.0032	0.005
	(0.058)	(0.057)	
Observations	120,653	125,615	
Teachers	26,074	27,241	

Note: This table contains the sample of teachers in the years 2012-2018 who worked at elementary, middle, or combined elementary and middle schools. Means are presented with standard deviations below in parentheses. P-value comes from a regression of the variable of interest on an indicator for having math or reading VA. Standard errors are clustered at the teacher level since there are multiple observations per teacher, and p-value comes from the statistical test of whether the coefficient on the indicator for having math or reading VA is different from zero.

Table A2: VA and Becoming AP - Heterogeneity by Gender and Race/Ethnicity

	Math Teachers		Reading Teachers	
	(1)	(2)	(3)	(4)
VA	0.00359***	0.00082***	0.00118*	0.00023
	(0.00078)	(0.00017)	(0.00071)	(0.00015)
Female	-0.00450***		-0.00344***	
	(0.00079)		(0.00083)	
Female X VA	-0.00281***		-0.00103	
	(0.00080)		(0.00073)	
Black		0.00261***		0.00236***
		(0.00074)		(0.00072)
Hispanic		0.00038		-0.00017
		(0.00163)		(0.00141)
Other race/ethnicity		-0.00184*		0.00011
		(0.00108)		(0.00155)
Black X VA		0.00224***		0.00012
		(0.00081)		(0.00060)
Hispanic X VA		-0.00020		-0.00091
		(0.00119)		(0.00119)
Other X VA		0.00149		0.00041
		(0.00122)		(0.00102)
Pct. Effect - Women	23.2		4.8	
Pct. Effect - Men	106.8		36.5	
Pct. Effect - Black		91.0		10.7
Pct. Effect - Hispanic		18.5		-21.2
Pct. Effect - Other		68.6		19.9
Pct. Effect - White		24.4		7.0
Outcome Mean	0.00337	0.00337	0.00323	0.00323
N	120,653	120,653	125,615	125,615

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Standard errors are clustered at the teacher-level. For brevity, the variables Black, Hispanic, and Other race/ethnicity are used in the regressions in columns (1) and (3) but the coefficient is not reported in this table. Similarly, the variable for Female is used in the regressions in columns (2) and (4) but the coefficient is not reported in this table. In all columns, the outcome is a binary indicator for becoming AP in the next academic year. In columns (1) and (2), only math teachers and math VA are used. In columns (3) and (4), only reading teachers and reading VA are used. Both math and reading VA are normalized to have a mean of zero and standard deviation of one. In all columns, there are also indicators for education, national board certification, licensing level, school type, and academic year, as well as a second order polynomial of age and indicators for teaching experience in 5 year intervals.