Who teaches high school computer science and does it matter?

Paul Bruno

Department of Education Policy, Organization and Leadership

University of Illinois Urbana-Champaign

Champaign, IL 61820

pbruno@illinois.edu

This is the accepted, uncorrected version of this paper. The Version of Record of this manuscript has been published and is available in *Computer Science Education* (2025). https://doi.org/10.1080/08993408.2025.2464489

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Background and Context: High schools have rapidly increased the number of computer science (CS) courses they offer. One challenge for these expansions is staffing CS classrooms with qualified teachers.

Objective: This study provides novel evidence about who teaches high school CS courses and what CS teacher attributes are important for ensuring that students have high-quality experiences in those courses.

Method: This study uses statewide longitudinal student- and teacher-level data from North Carolina high schools in descriptive and regression-based analyses.

Findings: CS courses are taught by teachers who are better qualified than teachers of other courses in terms of experience, education, and National Board Certification (NBC), though CS teachers often lack preparation to teach CS specifically. CS and non-CS courses have teachers with similar racial demographics, but CS courses are more likely to be taught by men. Teachers' observable qualifications and characteristics are not consistently related to whether their students take or are successful on Advanced Placement (AP) CS exams. However, there is some evidence that teachers with more experience generally, more experience teaching CS, or NBC have better student outcomes.

Implications: These findings suggest that stricter certification requirements for CS teachers may restrict CS course expansions unnecessarily, though they also point to important directions for future research on CS teacher quality.

Keywords: computer science education; teacher quality; teacher qualifications; Advanced Placement

Introduction

Computer science (CS) education is thought to provide economic opportunity and general thinking skills for students and to promote economic development (Armoni & Gal-Ezer, 2014; Grover & Pea, 2013; McGarr et al., 2023; Rothwell, 2014). These arguments have gained considerable traction, driving dramatic curricular shifts as schools, and especially high schools, offer rapidly-growing numbers of CS courses

(Code.org et al., 2022; Scott et al., 2019). For example, in California between 2003 and 2018 the number of high school CS courses offered increased from fewer than 1,000 to more than 5,000 (Bruno et al., 2022).

This proliferation of CS courses has outpaced state efforts to prepare and certify teachers to teach CS, raising questions about how these courses will be staffed. CS courses are often taught by teachers with preparation and experience in a wide range of loosely-related content areas, such as in other science, technology, engineering, and math (STEM) disciplines or in career technical education (CTE) (Bruno & Lewis, 2022; Century et al., 2013; Delyser et al., 2018; Ni, Tian, et al., 2023). Indeed, it has been a long-standing concern in CS education that, to the extent that staffing challenges result in CS courses being taught by teachers lacking CS subject matter knowledge or pedagogical content knowledge, the hoped-for benefits of CS course taking may not be realized (Poirot & Early, 1975; Statz & Miller, 1975). Moreover, new CS courses do not appear to substantially reduce other STEM course offerings in schools (Bruno & Lewis, 2022), so they may put additional strain on already-tight STEM teacher labor markets.

How schools navigate the tension between growing demand for CS courses and a limited supply of specialized CS teachers is poorly understood. In fact, little is known even about who teaches high school CS courses, let alone whether specific teacher characteristics are important for the success of students taking CS, and thus for the success of CS curricular expansions generally.

These considerations motivate my two research questions. First, what are the qualifications and characteristics of CS teachers, and how do they differ from teachers of non-CS courses? Like previous work I consider teacher race, gender, years of experience, highest level of education, and teaching licenses. I extend this work by also considering whether teachers hold a license related to CS specifically, their prior experience teaching CS, and their National Board certification (NBC). Second, are teachers' qualifications and characteristics important for students' success in CS courses? To answer this question, I consider whether those qualifications and characteristics are predictive of students' outcomes in a subset of CS courses for which there are standardized end-of-course assessments: Advanced Placement (AP) CS courses.

Background and previous research

Early efforts to expand secondary CS education recognized that a fundamental challenge to these expansions is the capacity of the teaching force (e.g., Deek & Kimmel, 1999). For instance, Poirot and Early (1975) recommended undergraduate CS pre-service preparation for teachers because CS-related content would be taught in schools in any case. The quality of that instruction would thus depend on teachers obtaining sufficient in-service training or pursuing graduate-level training in CS. Underlying these concerns was the belief that to teach CS effectively CS teachers – like teachers of other disciplines – would need to be proficient with both CS content and with methods of teaching CS (Statz & Miller, 1975; Yadav et al., 2016).

These concerns remain salient decades later because CS courses and course taking continue to proliferate in high schools (Bruno et al., 2022; Code.org et al., 2022) and CS-specific pre-service preparation remains relatively rare for teachers (Code.org et al., 2022; U.S. Department of Education, Office of Postsecondary Education, 2022). This raises questions about who is teaching high school CS courses and whether they have the attributes to do so effectively.

To date, there is little evidence about the qualifications and characteristics of high school CS teachers. This makes it difficult to know whether we should be concerned that these courses are being taught ineffectively or are putting strain on other areas of the teacher labor market (e.g., by increasing demand for STEM teachers). There is even less evidence on the extent to which specific teacher attributes matter for students' experiences and success in CS courses. I turn now to reviewing the literature on these topics.

Evidence about the qualifications and characteristics of CS Teachers

Evidence on the qualifications and characteristics of high school CS teachers is limited. Some nationwide evidence exists in the form of survey data. Perhaps the largest and most comprehensive of these are "landscape" surveys administered to CS teachers in the United States (U.S.) by the Kapor Center. In these surveys, less than one third of high school CS teachers report having an undergraduate or graduate "CS and tech sciences" degree (30% and 28% respectively), while 66% report a teaching credential in those fields and 57% report CS industry experience. Interpreting these figures is challenging given the range of experiences and skills these backgrounds might represent. For instance, "CS and tech sciences" is defined as any of CS, information and communications technology, information technology, engineering, networking, or cybersecurity (Koshy et al., 2022). Thus, the survey figures reported may represent an upper bound on CS teachers' CS-specific backgrounds, suggesting that many high school CS teachers have little CS-specific preparation. This may be why CS teachers frequently report low levels of confidence in their ability to teach CS (Ni, Tian, et al., 2023) even if they report high levels of confidence in their CS knowledge (Koshy et al., 2021).

Some teacher attributes appear to be important over and above the kinds of subject-specific specific skills that might be measurable to some extent by teachers' credentials (e.g., their degrees or teaching licenses). Perhaps most notably, a rapidly-growing body of research finds substantial benefits for students of same-race or same-gender teachers (Bottia et al., 2015; Dee, 2004; Gershenson et al., 2022; Holt & Gershenson, 2019; Lindsay & Hart, 2017). Given that evidence, and the prevailing underrepresentation of women and people of color in CS-related fields (John & Carnoy, 2019), CS teachers' races and genders may also represent important characteristics from a policy standpoint.

National surveys indicate that CS teachers in the U.S. may be more demographically representative than teachers generally of the student population. Specifically, 69% of high school CS teachers identify as white in the most recent of these surveys, and 65% as women (Koshy et al., 2022). For comparison, approximately 46% of high school students and 80% of secondary teachers are white (U.S. Department of Education, National Center for Education Statistics, 2021, 2022). Roughly 64% of secondary teachers are female (U.S. Department of Education, National Center for Education Statistics, 2021).

Other evidence on CS teacher qualifications and characteristics comes from analyses of administrative data that contain information about individual teachers and their classrooms. A limitation of these data is that they are restricted to a single U.S. state and can be difficult to compare across states (e.g., due to differences in teacher certification requirements). However, these data often provide a more detailed portrait of teachers and are often not as subject to concerns about various sorts of bias that might arise in surveys (e.g., non-response or social desirability biases).

Some of the most detailed of these analyses come from California (Bruno & Lewis, 2021, 2022). These studies find that high school CS teachers have strong general qualifications in terms of years of prior teaching experience and the probability of being fully licensed to teach or of holding a master's degree. In fact, teachers of CS courses compare favorably along these measures to teachers of other courses (Bruno & Lewis,

2022) and across racial subgroups of students (Bruno & Lewis, 2021). The authors suggest that the prevalence of teachers with strong general observable credentials may be attributable to the fact that credential requirements for CS teachers in California are very flexible. CS teachers in their data are licensed to teach a wide range of subjects other than CS, commonly including math, business, CTE, and science, among others (Bruno & Lewis, 2022).

However, these California studies also raise two additional concerns about the high school CS teacher workforce. First, though half or more of non-CS course enrollments in California are taught by women, more than two thirds of CS course enrollments are taught by men. This may be a concerning issue of gender representation in its own right, and it contributes to boys being twice as likely as girls to have a same-gender teacher when they enroll in CS (Bruno & Lewis, 2021). This suggests that girls may not be enjoying the benefits of student-teacher gender congruence that have been found in other contexts (Lim & Meer, 2017) as well as for female students in STEM specifically (Bottia et al., 2015; Carrell et al., 2010; Lim & Meer, 2020). For example, Carrell et al. (2010) find that while female undergraduates have lower grades than males in math and science courses by 0.15 standard deviations, about two-thirds of that gap is eliminated by random assignment to a female instructor. This high rate at which men teach CS courses in California is also somewhat at odds with the nationwide survey evidence discussed above (Koshy et al., 2022). This may indicate important variation in teacher characteristics across contexts or that survey respondents are not representative of teachers generally.

Second, depending on the year, between 60% and 80% of high school CS teachers in California are white. Consequently, while approximately 80% of white students in CS courses have a same-race teacher, that is true for at most 23% of students in other race groups, depending on the group and year. This again raises concerns that there are inequities in students' demographic congruence with their teachers. There is evidence that student-teacher race matches benefit students across a range of social, emotional, and academic outcomes (Dee, 2004; Egalite et al., 2015; Egalite & Kisida, 2018; Gershenson et al., 2022; Holt & Gershenson, 2019; Lindsay & Hart, 2017; Redding, 2019). These benefits often appear to be non-trivial and persistent. For instance, Dee (2004) finds that having a Black teacher boosts Black students' math and reading achievement by 3-6 percentile points. More strikingly, Gershenson et al. (2022) find that random assignment to Black teachers in elementary school increases the probabilities that Black students graduate high school and enroll in college by 6-9 percentage points (13-19%).

Evidence about whether qualifications or characteristics matter for teachers

One challenge for interpreting evidence about the qualifications and characteristics of CS teachers is that the evidence linking teachers' specific attributes to their effectiveness is limited. What evidence exists suggests that teachers' observable general qualifications and credentials – that is, those not specific to teachers' content areas – appear to be poor indicators of teacher quality. This includes qualifications that previous research on CS teachers has relied on, such as licensure and possession of a graduate degree (e.g., Bruno & Lewis, 2021, 2022). Studies consistently find that possession of a graduate degree *per se* says little about a teacher's instructional effectiveness (Buddin & Zamarro, 2009; Chingos & Peterson, 2011; Clotfelter et al., 2006, 2010; Goldhaber, 2007; Harris & Sass, 2011; Rockoff et al., 2011), and may be a negative signal if the degree is not in a teacher's subject area (Bastian, 2018). Similarly, teachers who have completed a traditional certification program, usually through a university and completing most or all of their certification coursework, internships, and exams prior to being certified, are not consistently more effective than those who have not (Cantrell et al., 2008; Henry et al., 2014; Rockoff et al., 2011). However, recent studies have complicated this story by highlighting changes over time and differences across contexts (e.g., STEM; Mansell, 2024; Penner, 2021).

Still, there are two general (i.e., not subject-specific) qualifications that appear to provide meaningful information about teacher effectiveness. First, teachers with more experience tend to be more effective than teachers with less experience. This seems to reflect both that individual teachers improve with experience, especially early career experience (Chingos & Peterson, 2011; Clotfelter et al., 2006, 2010; Harris & Sass, 2011), and that less effective teachers are more likely to exit the profession than their more effective counterparts in at least some contexts (Goldhaber et al., 2011; Harris & Sass, 2011). Second, there is consistent evidence that teachers who earn certification from the National Board for Professional Teaching Standards (NBC) or who do better on the associated performance assessment are more effective than other teachers (Cantrell et al., 2008; Chingos & Peterson, 2011; Clotfelter et al., 2010; Cowan & Goldhaber, 2016; Goldhaber, 2006; Horoi & Bhai, 2018).

There is also evidence that subject-specific preparation and experience can matter for teachers. For example, while possession of a graduate degree does not in general predict teacher effectiveness, there is some evidence that advanced degrees in a teacher’s subject area are more predictive (Bastian, 2018). Similarly, high school science teachers teaching multiple science courses make larger contributions to student learning in the courses aligned with their major of study (Sancassani, 2023). And while, as discussed above, the predictive value of licensure is weak, same-subject licensure and licensure exam scores are more predictive of high school teachers’ impacts on student achievement (Clotfelter et al., 2010). Similarly, CTE teachers’ subject-specific licensure exam performance is meaningfully related to their same-subject students' post-graduation incomes (Chen et al., 2022). Beyond formal training, there is also evidence that additional experience teaching specific subject matter improves teacher effectiveness in that subject, over and above the returns to general teaching experience (Bastian & Fortner, 2018; Cook & Mansfield, 2016). Consistent with this, CS teachers with more CS-specific teaching experience report higher levels of instructional confidence (Ni, Tian, et al., 2023).

Summary

In sum, the existing evidence suggests that high school CS teachers have relatively little subject-specific preparation or experience, and that such qualifications can be important for teacher effectiveness. This may be counterbalanced to some extent by relatively strong general qualifications, but many of these general qualifications appear to be poor indicators of teacher quality. CS teachers also appear to be disproportionately white and male, which raises additional concerns about the experiences of students from groups that have historically been marginalized in schools and in CS (e.g., girls and Black students). However, the evidence on the prevalence of these teacher characteristics is somewhat mixed, which may indicate data limitations or important variation across contexts. Previous work is also limited in the teacher characteristics it can consider and there is little research linking CS teacher characteristics to student outcomes. It is therefore hard to know the extent to which apparent limitations of school or teacher capacity to teach CS are translating into variation in students' experiences in CS classrooms.

This motivates my research questions. By using detailed and longitudinal data on teachers I can characterize CS teachers' characteristics in ways not possible in previous research (e.g., NBC or CS-specific previous teaching experience). I am also able to directly extend previous work using AP exam outcomes as indicators of students' experiences and success in CS educational opportunities (Warner et al., 2022). Because I can link teachers to students, I can estimate relationships between CS teacher characteristics and CS students' outcomes on AP CS exams. This means I can draw connections between schools' teaching capacities and student experiences in CS.

Data

I use statewide longitudinal teacher- and student-level data from the North Carolina Education Research Data Center (NCERDC). These data include a range of information on both students (e.g., demographic information, disability status, English learner status) and teachers (e.g., education, licensure, NBC). Identifiers allow students and teachers to be tracked over time, and students can be linked to teachers in "course membership" files. This level of detail is uncommon in previous research on CS teachers, allowing for analyses that would not otherwise be possible. Moreover, as I show below, when I conduct analyses like those in previous work, I get broadly similar results. This suggests that while my results are likely to generalize to contexts outside of North Carolina.

Course data

The NCERDC provided course enrollment data including the school years from 2005-2006 through 2018-2019. Because the 2005-2006 data are substantially less complete than in later years, my analyses begin with the 2006-2007 data. Because the same course may be offered multiple times within and across academic terms, I follow previous work in using many variables to identify course sections in which students are in the same classroom at the same time (Dalane & Marcotte, 2022). Specifically, I consider students to be enrolled in the same section of the same course at the same time if I observe them with the same school, semester/term, state and local course codes, course title, section number, meeting code, teacher, and total number of enrolled students. To focus on high school courses, I exclude courses in which the mean grade of enrolled students is below nine.

To isolate CS courses, I rely primarily on state course codes. I identify CS courses as those that have course codes indicating “Computer Science”, “Computer Programming”, “AP Computer Science”, and “Data Base Programming” courses in the state course catalogues. To accommodate cases where schools may have used more flexible course codes to offer CS courses outside of existing (and evolving) course codes, I identify other courses as CS courses if their titles reference “computer science”, “computer programming”, “python”, “java”, “network administration”, or “databases”. I present summary statistics for courses in online supplemental Table A1.

Though not a direct answer to my research questions, note for context that high school CS courses have proliferated rapidly in North Carolina during the period I consider. This reflects trends similar to other work elsewhere, as discussed above. These patterns in North Carolina are illustrated in Figure 1, which shows the total number of CS courses offered each academic year. Despite a drop in the period after the Great Recession – a pattern also observed in California (Bruno et al., 2022) – the number of CS courses offered has increased mostly steadily. By 2018-2019, high schools in North Carolina were offering nearly four times as many CS courses as in 2006-2007 (1619 vs. 423). Roughly 40% of this growth was driven by AP courses, especially AP CS Principles (first offered in 2016).

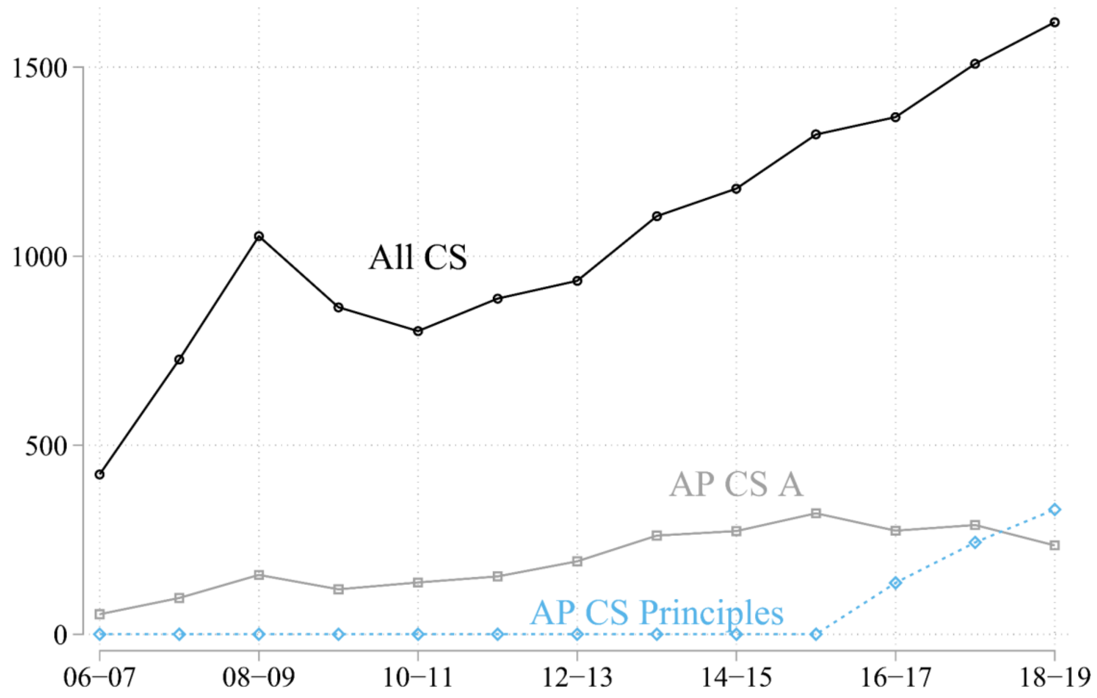

Figure 1. High school computer science (CS) courses in North Carolina. AP = Advanced Placement.

Advanced Placement test data

To measure student success in CS courses, I take advantage of the fact that a subset of CS courses have standardized assessments: AP courses. AP courses include curriculum intended to provide students with college-level learning experiences in high school. Many colleges and universities offer students some course credit if they take the standardized end-of-course test associated with the course and receive a sufficiently high score (usually a 3) on a 1-5 scale. The AP program has offered three CS courses. AP CS A emphasizes object-oriented programming, currently in Java, and is intended to be like what would be included in the first semester of an introductory undergraduate CS course. AP CS Principles covers a variety of computing-related topics at more of a conceptual level, with less of an emphasis on programming, and is intended to be like what would be included in the first semester of an introductory undergraduate computing course. AP CS Principles was first offered in 2016-2017 and has expanded rapidly. As shown in Figure 1, in the 2018-2019 school year AP CS Principles courses outnumbered AP CS A courses. AP CS AB included the content of AP CS A as well as additional, related content, but was officially discontinued in 2008 due to low participation rates. I include these courses as CS courses, but do not use their associated test data due to the very small numbers of participating students. For all variables and their summary statistics used for AP CS course teachers and students, see online supplemental Table A2.

Methods

RQ1: What are CS teachers' qualifications and characteristics, and how do they differ from teachers of non-CS courses?

To answer my first research question, I rely first on basic descriptive techniques. I then use simple descriptive regressions to compare teachers across CS and non-CS courses. In their most basic form, these regressions take the form:

$$characteristic_{tcy} = \beta_0 + \beta_1 CS_c + \delta_y + \varepsilon_{tcy} \tag{1}$$

In model 1, I predict a *characteristic* for teacher *t* teaching course *c* in year *y*, such as whether they have NBC. My predictor of interest is an indicator for whether the course is a CS course (CS_c), with β_1 representing the difference between CS and non-CS courses. I additionally control for year fixed effects (δ_y) to account for year-to-year changes in the teaching force. β_0 can thus be interpreted as the mean of the teacher characteristics in non-CS courses in the omitted year (which I make the most recent year, 2018-2019). Previous work has highlighted differences between schools that offer CS courses and those that do not (Code.org Advocacy Coalition, 2020; Scott et al., 2019), which could drive differences in teacher characteristics between CS and non-CS courses. To explore this possibility, in iterations of model 1 I include school or school-by-year fixed effects. In all models I cluster standard errors on schools to allow for the possibility that errors are correlated within school.

RQ2: Do CS teachers' qualifications and characteristics matter?

To answer my second research question - Are teachers' qualifications and characteristics important for students' success in CS courses? – I begin by estimating the following model:

$$outcome_{ictesy} = \boldsymbol{X}_{ty}\boldsymbol{\alpha} + \boldsymbol{Y}_{iy}\boldsymbol{\beta} + \boldsymbol{Z}_{csy}\boldsymbol{\gamma} + \delta_{ey} + \varepsilon_{ictesy} \tag{2}$$

In model 2, I predict an AP exam *outcome* for student *i* in classroom *c* in year *t* in preparation for specific AP exam *e* in school *s* in year *y*. I consider two outcomes. First, I estimate linear probability models where the *outcome* of interest is whether the student took the AP exam (as indicated by whether they have an exam score reported in the NCERDC data). Results are similar when using logistic regression (not shown), so I present results from the linear probability models for ease of interpretation. Second, for students who took the exam, I predict the score that they received on the exam.

My predictors of interest are the teacher qualifications and characteristics included in the $\boldsymbol{X}_{ty}$ vector. These include the teacher's years of prior experience and years of prior experience squared, the number of prior years in which they taught a CS course (i.e., years of CS teaching experience), and indicators for their highest level of education, their NBC, and their teaching license areas. In some models, I also include teachers' race or gender and their interaction with analogous student characteristics to estimate effects of demographic congruence with students.

To account for some possible patterns along which students may sort to teachers (or vice versa), I control in the $\boldsymbol{Y}_{iy}$ vector indicators for students' race, gender, grade level, disability status, English learner status, and classification by North Carolina as economically disadvantaged. Given previous work finding important connections between students' math preparation and their subsequent participation and success in CS (Grover et al., 2016; Sadik & Ottenbreit-Leftwich, 2023; Torbey et al., 2020), I also control for students' 8th grade end-of-year statewide math assessment score, standardized within grade and year. For similar reasons, and to account for potential peer effects, I additionally control (in $\boldsymbol{Z}_{csy}$) for the classroom-level means of those student characteristics. δ_{ey} is an AP exam-by-year fixed effect, to account for mean differences between years and exams (e.g., AP CS A exam takers tend to receive lower scores than AP CS Principles exam takers). Because my predictors of interest are at the teacher level and I observe multiple students per teacher, I cluster standard errors on teachers. Because they include substantively different content, after pooling AP CS exams together, I estimate model 2 separately for AP CS A and AP CS Principles.

This approach to estimating teacher impacts differs from approaches relying on value-added modeling, which derive their credibility primarily from controlling for students' prior-year outcomes (Bacher-Hicks & Koedel, 2023). That is not possible here because students do not typically take an AP course in two consecutive years. (In rare cases where a student does take a given AP CS course more than once, I use only their first enrollment.) While I can control for prior math achievement, results derived from model 2 should be interpreted cautiously since there may be remaining unobserved differences between students that are correlated with both their exam outcomes and their teachers' attributes.

This uncertainty motivates three robustness checks to assess the sensitivity of my results to the assumption that, conditional on their observable characteristics, students are not sorting to teachers in their AP courses in ways that bias my estimates. First, I control for the mean score a student received on *any* AP exam they took in the previous year. Second, I account for potential student sorting across schools by adding school fixed effects. Third, I additionally allow for such between-school sorting to vary over time by replacing the school fixed effects with school-by-year fixed effects. All three approaches relax assumptions about student sorting in various ways. However, they reduce my estimation samples, respectively, to students who take AP CS in a year after taking at least one other AP exam or to students in schools employing multiple AP CS teachers with different characteristics (over time or in a given year, depending on the level of fixed effects).

Results

Results for RQ1: What are CS teachers' qualifications and characteristics, and how do they differ from teachers of non-CS courses?

Teaching licenses held by CS teachers

One of the most straightforward ways to understand the qualifications of CS teachers is to consider the licenses they hold to teach courses in specific content areas. Though teachers can have a wide range of specific licenses, I highlight licenses or groups of licenses that are either common among CS teachers or that have some substantive relationship to CS content.

As shown in Figure 2, across all years, most – 67% of – CS courses in North Carolina have been taught by teachers holding a CTE license to teach business and information technology (IT) education. This is not entirely surprising, as CS courses are commonly housed in Business and IT Education departments. However, other licenses are also common, including other CTE licenses. (Teachers can hold more than one license.)

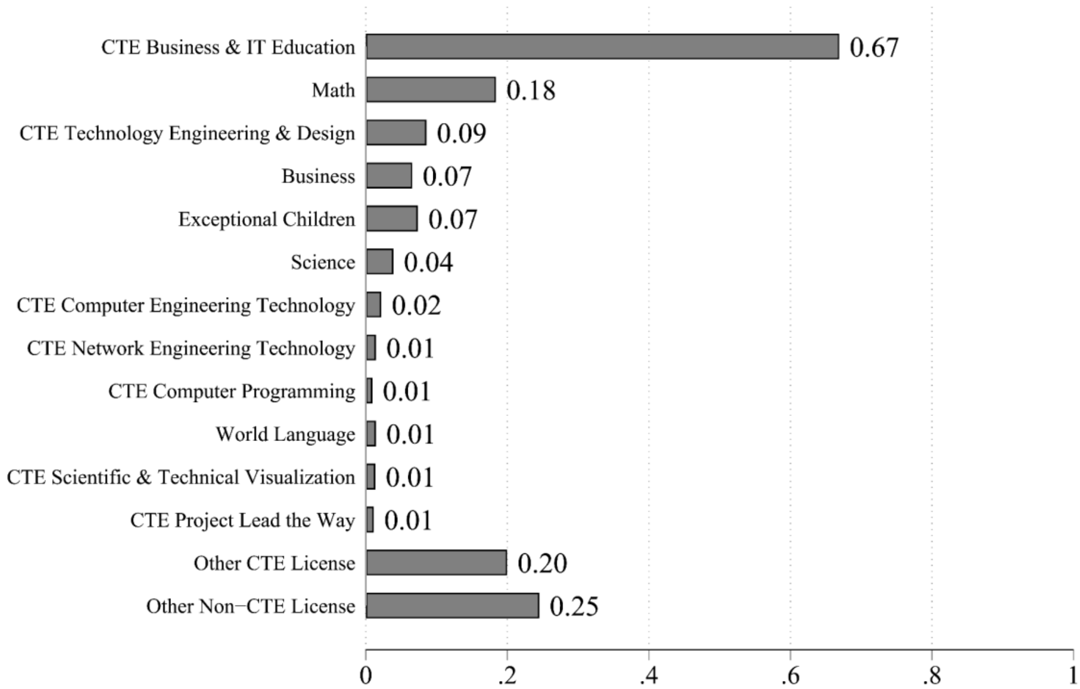

Figure 2. Share of computer science courses taught by teachers with various licenses. CTE=Career Technical Education. IT =Information Technology.

Non-CTE licenses are also common for teachers of CS courses, though they are less common than CTE licenses. Business (non-CTE) licenses are again common; their prevalence and that of CTE licenses may provide some information about the vocational orientation of many CS courses. However, CS courses during this period were roughly two-and-a-half times as likely to be taught by a teacher holding a math license (18%) as a by a teacher with a non-CTE business license (7%).

Though CS may intuitively be thought of as a science course, and is sometimes analogized to a world language (Jaschik, 2017), only a small fraction of CS courses are taught by teachers with any science (4%) or world language license (1%). In fact, neither category of license is as common among CS course teachers as licenses to teach exceptional children (i.e., students who have disabilities and/or are academically gifted).

These patterns of teacher licensure are broadly consistent with what has been observed in California over a similar period (Bruno & Lewis, 2022). These patterns also raise questions about the extent to which CS teachers have the required knowledge and skills to teach CS. For example, CS *per se* is not necessarily a fundamental or substantial component of other courses CTE business and IT education teachers may be eligible to teach. Nor is CS proficiency or coursework required to obtain that license. Indeed, the license most directly aligned with CS content – CTE computer programming – is very uncommon even among CS teachers during this period. Only roughly one high school CS course in 100 was taught by a teacher holding a CTE computer programming license. This in part reflects that CTE computer programming licenses have been available only in the latter few years of my data set, but it underscores the uncertain qualifications of CS teachers to teach CS courses.

CS teachers' CS-specific qualifications

To consider how CS-specific qualifications have changed over time as CS courses have proliferated, Figure 3 presents three characteristics of the teachers of CS courses over time. First, the prevalence of CTE computer programming licenses has increased since they were first offered, though they remain uncommon even in the latest year for which I have data. In 2016-2017, 1.9% of CS courses were taught by a teacher holding a CTE computer programming license, rising to 3.6% by 2018-2019.

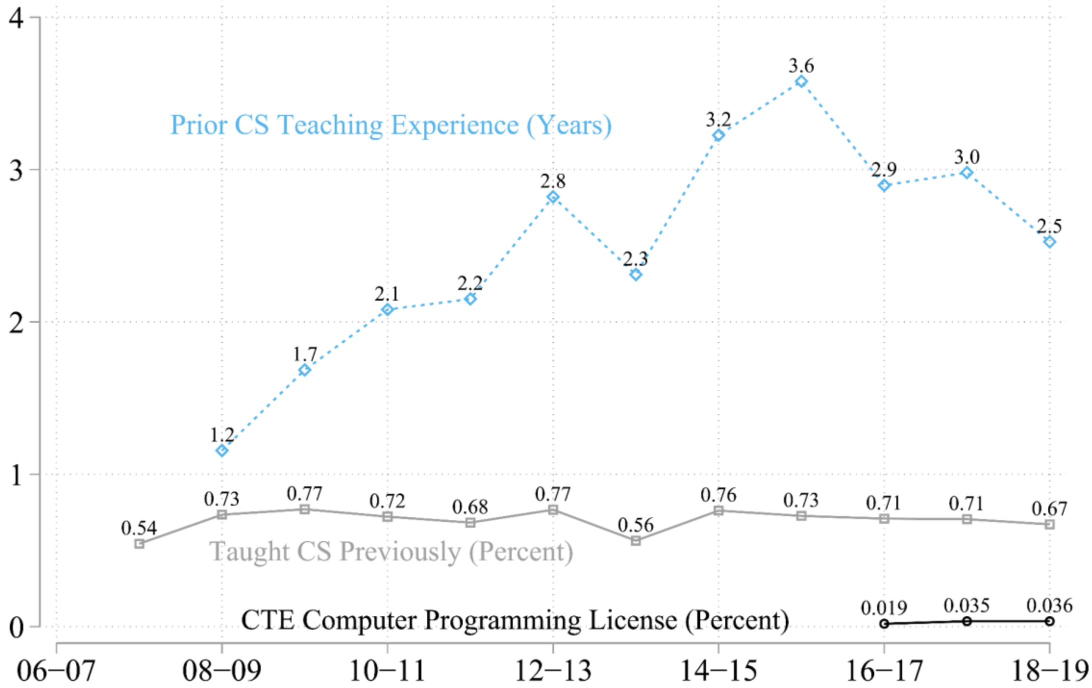

Figure 3. Computer science (CS)-specific qualifications of teachers of CS courses. The license for Career Technical Education (CTE) Computer Programming was offered only in recent years. Teachers' prior teaching experiences are observed only as far back as 2006-2007.

Second, as discussed above, licenses held by teachers are imperfect indicators of quality. I therefore also consider in Figure 3 the extent to which CS courses are taught by teachers with prior experience teaching CS courses. As was also discussed above, such subject-specific experience seems to matter for teachers and could mitigate gaps in teacher knowledge that might be inferred from their licensure. Perhaps encouragingly, even in 2007-2008, over half of CS courses were taught by teachers I also observed teaching CS in the previous year (i.e., the first year of my data). That rate if anything has increased somewhat, suggesting teachers who begin teaching CS often stay. This is also reflected in the mean number of prior years in which I observe them teaching CS courses, which increased from 1.2 in 2008-2009 to a high of 3.6 in 2015-2016. These figures are necessarily underestimates since teachers may have accumulated experience prior to 2006-2007 that I do not observe.

CS teachers' prior teaching experience declines after 2015-2016. That does not obviously correspond to a sudden increase in the availability of CS courses (Figure 1). However, it does correspond to the introduction and growth of AP CS Principles courses. Given that this course was designed to broaden participation in CS coursework among students (Sax et al., 2020), it may be similarly attracting a different group of teachers.

Teachers of CS courses compared to teachers of non-CS courses

If recruiting and retaining teachers with strong CS backgrounds is a challenge, flexible licensure requirements for CS teachers may be appropriate even if they result in patterns of licensure that raise doubts about CS teachers' CS-specific teaching ability. This is because stricter authorization requirements may prevent CS courses from being offered at all, and more flexible requirements may provide a larger pool of potential teachers to draw from who have other strong qualifications or other important characteristics. I test for these other qualifications and characteristics by comparing the characteristics of teachers (at the course level) between CS courses and other courses. Table 1 presents associated regression results for teachers' races, gender, prior teaching experience, possession of a graduate degree, and NBC accounting for year, school and year, or school-by-year fixed effects. I indicate statistical significance at p values as high as $p <$ .1. This does not necessarily indicate substantive importance, particularly with the large samples I use to answer my first research question. However, this allows me to convey information about marginal statistical significance and maintains consistency with the results for my second research question (which relies on substantially smaller samples, with consequently reduced statistical power).

Table 1. Linear regressions comparing characteristics of CS and non-CS course teachers

	Asian			Black			Hispanic			White		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
CS Course	0.011	0.008	0.008	0.017	0.030	0.030^{+}	-0.006	-0.008^{+}	-0.007	-0.017	-0.033	-0.034^{+}
	(0.009)	(0.009)	(0.009)	(0.025)	(0.018)	(0.018)	(0.005)	(0.005)	(0.005)	(0.028)	(0.020)	(0.020)
Constant	0.009^{***}			0.173^{***}			0.029^{***}			0.777^{***}		
	(0.001)			(0.008)			(0.001)			(0.010)		
Year FEs	X	X		X	X		X	X		X	X	
School FEs		X			X			X			X	
School-by-Year FEs			X			X			X			X
Courses	3392244	3392095	3391967	3392244	3392095	3391967	3392244	3392095	3391967	3392244	3392095	3391967
Schools	1019	870	844	1019	870	844	1019	870	844	1019	870	844
Adj. R-sq.	0.00	0.02	0.04	0.00	0.19	0.21	0.00	0.01	0.02	0.00	0.20	0.22

	Female			Years Prior Teaching Experience			Has MA+			Is National Board Certified		
	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)
CS Course	-0.092^{**}	-0.084^{**}	-0.086^{**}	3.190^{***}	3.123^{***}	3.002^{***}	0.236^{***}	0.197^{***}	0.194^{***}	0.078^{***}	0.059^{**}	0.057^{**}
	(0.031)	(0.031)	(0.031)	(0.558)	(0.521)	(0.514)	(0.028)	(0.029)	(0.028)	(0.019)	(0.020)	(0.020)
Constant	0.598^{***}			13.447^{***}			0.416^{***}			0.122^{***}		
	(0.004)			(0.102)			(0.006)			(0.004)		
Year FEs	X	X		X	X		X	X		X	X	
School FEs		X			X			X			X	
School-by-Year FEs			X			X			X			X
Courses	3457979	3457826	3457699	3382105	3381951	3381819	3303785	3303631	3303503	3507645	3507487	3507363
Schools	1024	871	845	1020	866	842	1020	866	842	1030	872	846
Adj. R-sq.	0.00	0.02	0.03	0.00	0.04	0.06	0.00	0.03	0.05	0.01	0.04	0.06

Note. Standard errors clustered on schools in parentheses. All models are linear regressions and predict dummy variables indicating the teacher of the course has a given characteristic except teacher experience (measured in years). The predictor of interest is a dummy variable indicating computer science courses. Most coefficients can therefore be interpreted as differences in the probability that the teacher of a CS course has a given attribute (e.g., is Black or has a graduate degree [MA+]), compared to the teacher of a non-CS course. In the case of prior teaching experience, the coefficient represents the mean difference in prior teaching experience for teachers in CS courses relative to non-CS courses. Because 2018-2019 is reference group, the constant term indicates the mean value of the dependent variable for teachers in non-CS courses in 2018-2019. FEs = Fixed effects. p<.1, * p<.05, ** p<.01, *** p<.001

As shown in the top panel of Table 1, teachers of CS and non-CS courses are largely similar in terms of race. Because 2018-2019 is the omitted category of year fixed effects, the constant can be interpreted as the mean for non-CS courses in the most recent year for which I have data. Roughly 78% of non-CS teachers were white in 2018-2019, and the difference with CS courses is statistically and practically insignificant (column 10). Differences for other race groups are similarly small and insignificant. These patterns also don't change when comparing courses within school or school-and-year. The lone exception is that when controlling for school or school-by-year fixed effects, CS courses are about 3 percentage points less likely than other courses to be taught by white teachers (columns 11 and 12) and equivalently more likely to be taught by Black teachers (columns 5 and 6). Though these differences are at most marginally statistically significant, they represent a non-trivial increase in the probability that CS courses are taught by a Black teacher relative to the 2018-2019 baseline for non-CS courses (17 percentage points).

These results suggest that teacher diversity challenges are not uniquely serious in CS courses. Still, this lack of diversity may deter students from groups historically marginalized in CS-related fields from participating in CS courses and echoes previous work finding that even when students of color enroll in CS courses they are highly unlikely to enjoy a same-race teacher match (Bruno & Lewis, 2021). This also previews challenges I encounter when estimating the effects of such matches for CS students when addressing my second research question, discussed further below.

Unlike with race, the gender of CS course teachers is substantially different than in non-CS courses. Overall, CS courses during this time are about nine percentage points less likely to be taught by a woman than are non-CS courses (for which about 60% of teachers were women in 2018-2019, column 13). That difference shrinks only slightly when comparing courses in the same school (column 14) or school-and-year (column 15). This is a substantially smaller gender gap between CS and non-CS courses than is observed in California, which is sometimes as large as 30 percentage points (Bruno & Lewis, 2021). Indeed, this gap implies that in North Carolina the CS teacher population is more like the high school student population in terms of gender – roughly 50/50 – than is the high school teacher population as a whole. Given the potential benefits of student-teacher gender match for girls in STEM education and society-wide patterns of female underrepresentation in CS-related fields, the relative gender parity of CS teachers in North Carolina – both overall and compared to California – warrants further study.

Previous work has found in California that CS courses are taught by teachers who are about as experienced as teachers of other courses, and somewhat more likely to have a graduate degree (Bruno & Lewis, 2022). In North Carolina, I find that CS courses are taught by teachers with even stronger relative qualifications by these measures, as well as by NBC. The mean CS course in 2018-2019 was taught by a teacher with more than three additional years of prior teaching experience than the mean non-CS course (column 16). CS courses were also 24 percentage points more likely than non-CS courses to be taught by a teacher with a graduate degree (column 19) and almost eight percentage points more likely to be taught by a teacher with NBC (column 22). These gaps are also quite large in proportional terms, amounting to differences favoring CS courses of 24% for years of experience, 57% for graduate degrees, and 64% for NBC. Moreover, this does not simply reflect CS courses being offered disproportionately at more advantaged schools with more highly qualified staff. In no case does controlling even for school-by-year fixed effects reduce these gaps by even one third, and the gap in teacher experience is almost entirely unaffected by this adjustment (columns 18, 21, and 24). In other words, even compared to other courses being taught at the same time in the same school, CS courses are taught by teachers who are substantially more experienced, more highly educated, and more likely to be NBC than teachers of other courses.

Taken together, these results suggest that even when CS courses are new, they are not being taught by new teachers. Rather, they are taught by relatively veteran staff transitioning into a new content area. Consequently, CS teachers look like other teachers in many respects (e.g., race), and often have relatively strong general qualifications (e.g., experience and NBC) even if they do not necessarily have CS-specific background or formal preparation (e.g., in terms of licensure). Whether this pattern is good or bad on balance is not obvious, in part because it is not clear which attributes are most important in CS teachers. I turn now to my second research question, which explores precisely this issue.

Results for RQ2: Do CS teachers' qualifications and characteristics matter?

The remaining tables predict student outcomes in AP CS courses as a function of teacher characteristics. I assume that positive impacts on student exam taking with non-negative impacts on exam scores indicate a net improvement in student outcomes because the marginal AP exam taker is less well prepared for the exam than the average exam taker. Considering test taking separately from scores may provide suggestive evidence about the nature and mechanism of teacher impacts, if any (e.g., whether impacts are on student learning or attitudes). Each table presents results for AP CS A and AP CS Principles courses combined, as well as separately, and then presents results with my additional controls as robustness checks, as described above. However, because there are fewer AP CS Principles students in my sample, I am unable to estimate models for students in those courses that include school or school-by-year fixed effects. Even my other estimates for AP CS Principles students should be interpreted cautiously since they include relatively small numbers of students and, especially, teachers. For similar reasons, my estimates when combining both AP courses are driven primarily by students and teachers in AP CS A courses.

Teacher qualifications

Tables 2 and 3 present results from model 2, predicting whether students in AP CS courses take the associated AP exam (Table 2) and, if they take the exam, their score (Table 3). Column numbers represent the same model specification in both tables.

Teaching experience. Consistent with prior work, my primary results (column 1 in Tables 2 and 3) suggest that there are positive-but-diminishing returns to teacher experience. Given the presence of the squared experience term, the coefficient on years of prior teaching experience can be roughly interpreted as implying that a teacher's first year of experience is associated with an increase of 1.6 percentage points in the probability that their AP CS students take the associated AP exam and 0.05 points higher scores among exam takers on the 1-5 scale. For comparison, 74% of AP CS enrollments in my sample result in an exam being taken, with a mean exam score of about 2.5 (see supplemental online Table A2). The coefficients on the squared experience terms are small and negative, consistent with smaller experience returns in later years, though that estimate is statistically significant only for exam scores. These results are mostly quantitatively and qualitatively consistent across the two AP exams, though less precisely estimated (columns 5 and 9).

Table 2. Regressions predicting whether students in Advanced Placement computer science (AP CS) courses take the AP exam.

	Both Tests				APCS A				APCS Principles	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Prior Experience (Years)	0.016^{+}	0.021*	0.011	0.016	0.013	0.015	0.012	0.001	0.020	0.039^{+}
	(0.008)	(0.009)	(0.010)	(0.020)	(0.009)	(0.009)	(0.010)	(0.022)	(0.021)	(0.019)
Experience Squared	-0.000	-0.001*	-0.000	-0.001	-0.000	-0.000	-0.000	-0.000	-0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
CS Teaching Experience (Years)	0.015*	0.019**	0.010	0.009	0.018*	0.023**	-0.010	0.007	0.031	0.038^{+}
	(0.007)	(0.006)	(0.014)	(0.029)	(0.007)	(0.007)	(0.015)	(0.038)	(0.019)	(0.022)
Has Graduate Degree	-0.110*	-0.131**	-0.097	0.360^{+}	-0.130*	-0.163**	-0.008	0.293	0.343**	0.188^{+}
	(0.049)	(0.045)	(0.075)	(0.185)	(0.053)	(0.054)	(0.077)	(0.205)	(0.120)	(0.097)
National Board Certification	0.110*	0.108*	0.061	-0.114	0.105*	0.105*	0.053	-0.189	-0.061	-0.041
	(0.043)	(0.044)	(0.071)	(0.108)	(0.047)	(0.051)	(0.066)	(0.181)	(0.103)	(0.073)
Career Technical Education (CTE) Licenses Relative to CTE Business & IT Education Only										
Programming + Business & IT	-0.101	-0.306***	0.023		-0.077	-0.220**	0.024		0.299	-0.129
	(0.091)	(0.074)	(0.134)		(0.089)	(0.070)	(0.149)		(0.242)	(0.241)
Technology Engineering & Design Only	-0.066	-0.092	0.319^{+}		0.124	0.104	0.283		-0.111	-0.069
	(0.134)	(0.141)	(0.182)		(0.076)	(0.072)	(0.192)		(0.206)	(0.205)
No CTE Licenses	-0.059	-0.080	-0.042	-0.061	-0.054	-0.038	-0.055	0.223*	0.350^{+}	0.130
	(0.060)	(0.054)	(0.119)	(0.127)	(0.070)	(0.066)	(0.137)	(0.089)	(0.177)	(0.171)
Other CTE License Combinations	-0.106^{+}	-0.011	-0.105	-0.274*	-0.069	0.040	-0.096	-0.125	0.105	0.022
	(0.055)	(0.048)	(0.083)	(0.105)	(0.066)	(0.066)	(0.079)	(0.082)	(0.128)	(0.112)
Non-CTE Licenses										
Math	0.009	0.093^{+}	-0.131	-0.037	-0.006	0.038	-0.163	-0.356*	-0.270**	-0.048
	(0.058)	(0.048)	(0.115)	(0.118)	(0.070)	(0.057)	(0.118)	(0.162)	(0.096)	(0.085)
Science	-0.278*	-0.309	-0.293^{+}	-1.123**	-0.234	-0.451*	0.086	-0.345	-0.604***	-0.453**
	(0.134)	(0.191)	(0.158)	(0.391)	(0.148)	(0.190)	(0.065)	(0.353)	(0.100)	(0.157)
Exceptional Children	-0.073	-0.031	0.290*	-0.099	-0.058	-0.016	0.305**	-0.116		
	(0.052)	(0.061)	(0.119)	(0.158)	(0.056)	(0.072)	(0.106)	(0.137)		
World Language	0.200*	0.033	0.632***	0.315	0.224*	0.070	0.572***	0.010	-0.064	-0.131
	(0.093)	(0.055)	(0.144)	(0.201)	(0.092)	(0.072)	(0.140)	(0.248)	(0.151)	(0.107)
Business	-0.255***	-0.254**	0.126	-0.188	-0.314***	-0.300**	0.142	-0.003	0.108	0.004
	(0.064)	(0.079)	(0.098)	(0.155)	(0.071)	(0.091)	(0.108)	(0.172)	(0.205)	(0.235)
Other	0.080^{+}	0.148**	-0.040	-0.189	0.092^{+}	0.151**	-0.103	-0.350^{+}	0.013	0.073
	(0.047)	(0.047)	(0.090)	(0.154)	(0.052)	(0.049)	(0.096)	(0.198)	(0.094)	(0.092)
Mean Prior Year AP Scores		-0.013^{+}				-0.015^{+}				0.005
		(0.007)				(0.008)				(0.021)
School FEs			X				X			
School-by-Year FEs				X				X		
Observations	5361	2559	5166	5048	4600	2213	4401	4291	760	346
Teachers	169	135	157	142	149	117	135	122	37	33
Adj. R-sq.	0.20	0.21	0.40	0.48	0.20	0.20	0.41	0.49	0.41	0.51

Note. Standard errors clustered on teachers in parentheses. All models are linear regressions and control for exam-by-year fixed effects (FEs); student race, gender, grade level, disability status, economic disadvantage, English learner status, and 8th grade math scores, as well as classroom means for those variables. + p<.1, * p<.05, ** p<.01, *** p<.001

Table 3. Regressions predicting scores on Advanced Placement computer science (AP CS) exams.

	Both Tests				APCS A				APCS Principles	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Prior Experience (Years)	0.047*	0.051*	-0.001	-0.005	0.037^{+}	0.036^{+}	0.004	0.027	0.005	-0.015
	(0.020)	(0.021)	(0.023)	(0.049)	(0.019)	(0.019)	(0.024)	(0.059)	(0.062)	(0.081)
Experience Squared	-0.001*	-0.002**	-0.000	0.001	-0.001*	-0.001*	-0.000	0.000	-0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)
Prior CS Teaching	0.060**	0.069**	0.048	-0.153**	0.080***	0.086***	0.064*	-0.198*	-0.061	-0.052
Experience (Years)	(0.022)	(0.022)	(0.029)	(0.057)	(0.023)	(0.021)	(0.030)	(0.092)	(0.072)	(0.102)
Has Graduate Degree	-0.024	0.087	-0.315	0.985*	-0.095	0.001	-0.407^{+}	0.827	0.037	0.182
	(0.150)	(0.152)	(0.221)	(0.486)	(0.153)	(0.155)	(0.205)	(0.524)	(0.254)	(0.307)
National Board Certification	0.129	0.080	-0.085	-0.119	0.154	0.133	-0.074	0.337	-0.044	-0.107
	(0.147)	(0.130)	(0.127)	(0.197)	(0.182)	(0.139)	(0.130)	(0.428)	(0.282)	(0.360)
Career Technical Education (CTE) Licenses Relative to CTE Business & IT Education Only										
Programming +	0.244	0.730**	-0.859***		0.743***	1.569***	-0.546*		0.670	1.524^{+}
Business & IT	(0.219)	(0.228)	(0.239)		(0.220)	(0.217)	(0.215)		(0.595)	(0.815)
Technology Engineering	0.684***	0.750***	-0.026		0.748***	0.742***	-0.036		-0.460	-0.212
& Design Only	(0.185)	(0.156)	(0.333)		(0.213)	(0.161)	(0.350)		(0.655)	(0.815)
No CTE Licenses	0.687***	0.721***	-0.082	0.351^{+}	0.792***	0.834***	-0.137	-0.007	0.495	0.495
	(0.176)	(0.171)	(0.211)	(0.184)	(0.182)	(0.183)	(0.201)	(0.462)	(0.328)	(0.453)
Other CTE License	0.160	0.150	-0.334*	-0.002	0.261^{+}	0.243^{+}	-0.491**	-0.045	-0.063	0.140
Combinations	(0.136)	(0.142)	(0.167)	(0.352)	(0.145)	(0.140)	(0.152)	(0.395)	(0.337)	(0.451)
Non-CTE Licenses										
Math	0.309^{+}	0.293^{+}	0.297^{+}	0.116	0.241	0.275	0.275	0.680	0.314	0.070
	(0.174)	(0.155)	(0.163)	(0.473)	(0.189)	(0.169)	(0.174)	(0.768)	(0.246)	(0.249)
Science	-0.363	-0.273	-0.105	-2.400**	-0.254	0.325	-0.194	-3.124**	-1.060^{+}	-1.159
	(0.246)	(0.450)	(0.263)	(0.778)	(0.205)	(0.371)	(0.326)	(0.952)	(0.557)	(0.733)
Exceptional Children	0.906***	0.658**	-0.033	-0.407	0.898***	0.669**	0.060	-0.276		
	(0.192)	(0.248)	(0.337)	(0.559)	(0.197)	(0.239)	(0.369)	(0.619)		
World Language	-0.323	-0.570*	-0.068	-1.394^{+}	-0.440^{+}	-0.642**	0.127	-0.755	0.216	-0.020
	(0.261)	(0.282)	(0.291)	(0.788)	(0.227)	(0.227)	(0.334)	(0.910)	(0.467)	(0.539)
Business	0.091	0.185	-0.162	1.203*	0.072	0.162	0.014	0.953	-0.795	-0.024
	(0.214)	(0.174)	(0.221)	(0.510)	(0.196)	(0.170)	(0.241)	(0.604)	(0.633)	(0.903)
Other	0.132	0.002	0.245	-0.997**	0.204	0.108	0.277	-0.451	-0.513^{+}	-0.602^{+}
	(0.159)	(0.139)	(0.217)	(0.352)	(0.161)	(0.130)	(0.219)	(0.404)	(0.262)	(0.340)
Mean Prior Year AP Scores		0.419***				0.422***				0.347***
		(0.031)				(0.037)				(0.047)
School FEs			X				X			
School-by-Year FEs				X				X		
Observations	3997	2186	3836	3740	3476	1908	3311	3221	520	278
Teachers	147	116	137	125	127	97	115	105	32	30
Adj. R-sq.	0.45	0.52	0.52	0.54	0.46	0.54	0.52	0.54	0.39	0.41

Note. Standard errors clustered on teachers in parentheses. All models are linear regressions and control for exam-by-year fixed effects (FEs); student race, gender, grade level, disability status, economic disadvantage, English learner status, and 8th grade math scores, as well as classroom means for those variables. + p<.1, * p<.05, ** p<.01, *** p<.001

Even net of overall teaching experience, additional years of CS teaching experience are also positively related to AP CS student outcomes. An additional year of CS teaching experience for an AP CS teacher predicts that their students are 1.5 percentage points more likely to take the AP exam and to score another 0.06 points higher. These estimates are very similar in magnitude to what I estimate for very early-career experience suggesting that subject-specific experience is very important for CS teachers. This may not be surprising if, as discussed above, CS teachers enter their classrooms without substantial CS backgrounds and need to learn a great deal on the job.

Estimates from models that consider each AP course separately suggest some differences between them. CS-specific teaching experience is positively related to test taking for both courses; the estimate for AP CS Principles is substantially larger in magnitude, but also much less precisely estimated. At the same time, the estimated impact on scores for exam takers is driven by AP CS A. This may reflect the relatively more technical nature of AP CS A content (compared to AP CS Principles) requiring more on-the-job learning.

These results are highly robust to controlling for students' mean prior-year AP exam scores (column 2 in each table). That my estimates of the impacts of teacher experience are cleanly in line with prior research is reassuring since I cannot otherwise give them a straightforward causal interpretation. Yet these results are quite sensitive to the inclusion of additional fixed effects (columns 3 and 4). This suggests some reason to be concerned that my estimated impacts of teacher characteristics are biased by unobserved differences between students. However, given previous research consistently finding positive returns to teacher experience, this may also suggest that I do not have sufficient within-school variation to credibly fit these models.

Graduate degrees. Despite estimating numerous models for multiple outcomes, I find little evidence that a teacher's graduate degree is important for student outcomes. In my baseline models combining AP CS courses, when a student's teacher has a master's degree (or more) they are 11 percentage points less likely to take the AP exam, with essentially no apparent difference in exam scores. Controlling for prior AP exam scores or school fixed effects (i.e., comparing only students in the same school, but exposed to different teacher characteristics) makes little difference. This suggests limited bias from unobserved differences between students and is very consistent with the previous work discussed above. However, I note two exceptions. First, controlling for school-by-year fixed effects (i.e., comparing only students in the same school in the same year) makes the estimated impacts of a graduate degree large and positive, both overall and for AP CS A specifically. Second, teacher graduate degrees are associated with substantially higher test taking rates for AP CS Principles students (though not higher scores). In both cases, limited identifying variation makes the estimates hard to interpret, but they recommend at least some degree of caution about interpreting my other estimates, and may be consistent with previous research (also discussed above) finding that the importance of graduate degrees may vary (e.g., based on the content of the degree).

National Board Certification. Consistent with previous research, I find some evidence that NBC is a meaningful predictor of AP CS students' outcomes. In my baseline models (columns 1 of Tables 2 and 3), students whose teacher is NBC are 11 percentage points more likely to take the AP exam than other students. Teacher NBC is not significantly related to student exam scores, but perhaps more importantly the coefficient is large and positive and this is at least consistent with increases in student exam taking not being driven by additional unprepared students taking the exam. These results are robust to controlling for students' prior AP exam scores, but two important caveats are in order. First, these results are again sensitive to the inclusion of additional fixed effects, which cause my estimates to become smaller or switch sign. This suggests students may differ between schools or over time in important ways that I do not observe and that are correlated with these teacher attributes. Second, any apparent benefits of NBC are driven by AP CS A; I find no (or even slightly negative) relationships to student outcomes in AP CS Principles. It could be that AP CS A's more technical content is more instructionally demanding, raising the salience of the teacher skills reflected in NBC.

Licensure areas. Because potential combinations of teacher licenses are numerous, I simplify their inclusion in my models by grouping licenses. First, I consider all CTE licenses, and group teachers into five mutually exclusive groups based on which combination of CTE licenses (if any) they hold, each represented with a dummy variable. I omit teachers holding only a business and IT education license (and no other CTE licenses) as a comparison group, since this represents a somewhat "typical" CS teacher. I then include dummy variables for the salient groups of non-CTE licenses I consider above, indicating if teachers hold any math, science, exceptional children, world language, business, or other non-CTE license, respectively.

To summarize briefly, I find at most mixed evidence that teachers' licenses matter for student outcomes in AP CS courses. Compared to students of teachers holding no CTE licenses except business and IT education, students of teachers with other combinations of CTE licenses (or no CTE licenses) are not consistently more or less likely to take the AP CS exam in their course. A possible exception is that students whose teachers instead have a CTE technology engineering and design license are perhaps more likely to take the exam in AP CS A courses (columns 5-7 of Table 2). Those students also have higher exam scores on average, particularly in AP CS A (columns 5-7 of Table 2). However, I lack sufficient variation to estimate those relationships in the presence of school-by-year fixed effects and, if anything, the opposite is true in AP CS Principles.

Though they are not more likely (and are perhaps less likely) to take the exam, compared to students whose teacher has only a CTE business and IT education license, students who take the exam have higher scores on average when their teacher either additionally has a CTE computer programming license or has no CTE licenses at all. Given the somewhat ambiguous relationship between business and IT education license requirements and CS proficiency, this is perhaps what would be expected. However, it is less obvious why holding – or being able to hold – these licenses would improve student test scores but not their test taking rates and these estimates are again sensitive to the inclusion of additional fixed effects (if they can be estimated at all; as noted above, CTE computer programming licenses are rare).

I also do not find clear evidence that non-CTE licenses provide meaningful information about the effectiveness of CS teachers. I find some evidence that students whose teachers hold business and science licenses are less likely to take the AP exam at the conclusion of their courses. And I find some suggestive evidence that students whose teachers hold math or exceptional children licenses receive higher scores when they take their AP exams. However, estimates for these licenses are not consistently robust across model specifications.

Student-teacher demographic congruence

Finally, I consider whether, over and above teachers' more "objective" qualifications to teach CS, their demographic congruence with their students matters for their students' outcomes. I consider congruence separately for gender and for race. In each case, I add two terms to model 2: an indicator of the teacher's gender or race and a term interacting the teacher's gender or race with the student's. Results are presented in Tables 4 (for gender) and 5 (for race). For simplicity, I include only the gender and race predictors, though models are otherwise specified as before. The top panel of each table presents results predicting whether students took the AP exam, and the bottom table presents results predicting scores among students who took the exam.

Table 4. Students' Advanced Placement computer science (AP CS) outcomes as a function of student-teacher gender congruence.

	Both Tests				APCS A				APCS Principles	
Took AP Exam	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Teacher is Female	0.028	0.020	-0.001	-0.125	0.059	0.069	0.002	-0.212	0.106^{+}	0.013
	(0.048)	(0.056)	(0.054)	(0.141)	(0.053)	(0.059)	(0.064)	(0.136)	(0.060)	(0.064)
Student is Male	0.021	0.045	0.019	0.020	0.041	0.054	0.028	0.035	-0.064	0.005
	(0.022)	(0.029)	(0.020)	(0.020)	(0.025)	(0.033)	(0.022)	(0.023)	(0.049)	(0.046)
Male Student x Female Teacher	-0.055^{+}	-0.058	-0.046^{+}	-0.050^{+}	-0.074^{*}	-0.066	-0.052^{+}	-0.065^{*}	0.022	-0.051
	(0.030)	(0.036)	(0.025)	(0.026)	(0.034)	(0.040)	(0.029)	(0.029)	(0.060)	(0.056)
Mean Prior Year AP Scores		-0.014^{+}				-0.015^{+}				0.007
		(0.008)				(0.008)				(0.022)
School FEs			X				X			
School-by-Year FEs				X				X		
Observations	5356	2556	5161	5043	4595	2210	4396	4286	760	346
Teachers	168	134	156	141	148	116	134	121	37	33
Adj. R-sq.	0.20	0.21	0.40	0.48	0.20	0.20	0.41	0.49	0.41	0.51
	Both Tests				APCS A				APCS Principles	
AP Exam Score	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Teacher is Female	-0.109	-0.173	-0.021	0.615	-0.031	-0.097	0.033	0.706	-0.597^{*}	-1.072^{***}
	(0.148)	(0.137)	(0.137)	(0.401)	(0.151)	(0.139)	(0.153)	(0.758)	(0.234)	(0.220)
Student is Male	0.157^{**}	0.155^{*}	0.196^{***}	0.211^{***}	0.176^{**}	0.160^{*}	0.215^{***}	0.234^{***}	0.163	0.194
	(0.056)	(0.062)	(0.042)	(0.042)	(0.057)	(0.063)	(0.045)	(0.047)	(0.127)	(0.119)
Male Student x Female Teacher	0.051	0.059	-0.025	-0.073	0.010	0.027	-0.053	-0.110	0.001	0.022
	(0.081)	(0.092)	(0.064)	(0.072)	(0.078)	(0.093)	(0.069)	(0.080)	(0.209)	(0.222)
Mean Prior Year AP Scores		0.415^{***}				0.420^{***}				0.350^{***}
		(0.032)				(0.038)				(0.049)
School FEs			X				X			
School-by-Year FEs				X				X		
Observations	3996	2186	3835	3740	3475	1908	3311	3221	520	278
Teachers	146	116	136	125	126	97	115	105	32	30
Adj. R-sq.	0.45	0.52	0.52	0.54	0.46	0.53	0.52	0.54	0.42	0.46

Note. Standard errors clustered on teachers in parentheses. All models are defined as in tables 2 and 3 except that teacher gender and its interaction with student gender are included as predictors.
+ p<.1, * p<.05, ** p<.01, *** p<.001

Table 5. Students' Advanced Placement computer science (AP CS) outcomes as a function of student-teacher race congruence.

	Both Tests				APCS A				APCS Principles	
Took AP Exam	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Teacher is Black	-0.044	-0.174	0.136^{+}	-0.023	0.036	-0.091	0.179*	-0.055	-0.486**	-0.501**
	(0.096)	(0.114)	(0.071)	(0.087)	(0.115)	(0.100)	(0.073)	(0.086)	(0.167)	(0.156)
Student is White	0.013	-0.022	0.037	0.049*	0.018	0.001	0.036	0.046^{+}	0.029	-0.178*
	(0.026)	(0.031)	(0.025)	(0.024)	(0.027)	(0.031)	(0.026)	(0.026)	(0.058)	(0.076)
White Student x	-0.032	0.037	-0.063	-0.092*	-0.039	0.065	-0.065	-0.095^{+}	0.048	0.196*
Black Teacher	(0.075)	(0.104)	(0.042)	(0.043)	(0.089)	(0.102)	(0.048)	(0.051)	(0.099)	(0.074)
Mean Prior Year		-0.008				-0.008				0.006
AP Scores		(0.009)				(0.009)				(0.027)
School FEs			X				X			
School-by-Year FEs				X				X		
Observations	3980	1828	3817	3707	3452	1573	3284	3181	528	254
Teachers	147	118	137	121	129	101	117	103	33	29
Adj. R-sq.	0.19	0.22	0.40	0.46	0.20	0.22	0.42	0.49	0.41	0.55
	Both Tests				APCS A				APCS Principles	
AP Exam Score	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
Teacher is Black	0.149	-0.163	0.298	1.012**	0.238	-0.099	0.282	0.861*	-1.040^{+}	-1.175
	(0.251)	(0.312)	(0.209)	(0.327)	(0.301)	(0.410)	(0.207)	(0.339)	(0.560)	(0.804)
Student is White	0.285***	0.307*	0.272**	0.270**	0.252**	0.322*	0.238**	0.226*	0.569**	0.442
	(0.082)	(0.127)	(0.084)	(0.098)	(0.085)	(0.135)	(0.086)	(0.105)	(0.175)	(0.324)
White Student x	-0.315	-0.150	-0.285	-0.344	-0.334	-0.175	-0.277	-0.325	2.122**	1.702^{+}
Black Teacher	(0.204)	(0.252)	(0.209)	(0.252)	(0.219)	(0.297)	(0.218)	(0.264)	(0.741)	(0.989)
Mean Prior Year		0.429***				0.437***				0.338***
AP Scores		(0.041)				(0.047)				(0.075)
School FEs			X				X			
School-by-Year FEs				X				X		
Observations	2949	1550	2808	2725	2563	1342	2419	2339	386	207
Teachers	128	101	120	108	111	84	102	91	27	26
Adj. R-sq.	0.44	0.51	0.52	0.54	0.44	0.52	0.51	0.54	0.43	0.46

Note. Standard errors clustered on teachers in parentheses. All models are defined as in tables 2 and 3except that teacher race and its interaction with student race are included as predictors, and estimation samples are limited to white and Black students with white or Black teachers.
+ p<.1, * p<.05, ** p<.01, *** p<.001

Gender congruence. As shown in Table 4, I find little evidence that girls in AP CS courses benefit from having a female teacher. Because of the presence of the term interacting student and teacher gender, the coefficient on the indicator for female teachers can be interpreted as the relationship between having a female teacher and course outcomes for girls. For girls, having a female teacher rather than a male teacher is only positively and marginally significantly related to exam taking in AP CS Principles (column 9), and even that result is sensitive to the inclusion of student's prior exam scores (column 10). The relationship for girls between having a female teacher and exam scores (the bottom panel of Table 4) is if anything more negative.

The evidence for boys is less clear. The coefficients on the indicator for male students estimates differences in outcomes between boys and girls in the presence of a male teacher. When taught by male teachers, boys are perhaps more likely than girls to take the AP exam, at least in AP CS A, where the difference amounts to 2.8-5.4 percentage points depending on the model but is at most marginally significant statistically (columns 5-8). However, as shown in columns 11-20, in male teacher's classrooms boys have substantially higher AP exam scores, by 0.16-0.23 points, and this is consistent across models and exams (though estimates for AP CS Principles are much more imprecise). In the presence of a female teacher, the test taking advantage for boys is substantially and statistically significantly smaller. In fact, the coefficients on the interaction terms in the top panel of Table 4 imply that the gap switches directions in most models (i.e., favors girls) when the teacher is female, though is not consistently significantly different from zero. This is consistent with boys deriving some benefit from a same-gender CS teacher but this does not appear to translate into higher exam scores for exam takers. As shown by the coefficients on the interaction terms in the bottom panel of Table 4, the higher scores observed for boys, relative to girls, who take the AP exams are not significantly different when the teacher is female.

Race congruence. Table 5 presents analogous results for student-teacher race match. These models include only white and Black students and teachers because the number of matches for other groups of students is extremely small. As with gender, I find little evidence of race congruence effects.

Similar to Table 4, because of the presence of the interaction term the coefficient on the indicator for Black teachers in Table 5 estimates the effect for Black students of having a Black, rather than white, teacher. Thus, for Black students, having a Black teacher often predicts no change in the probability of taking the AP exam and, if anything, the coefficients are more likely to be negative than positive. This is particularly true for AP CS Principles, where Black students are 49 percentage points less likely to take the exam when they have a Black teacher (column 9), and to score more than 1 point lower if they do take the exam (column 19). Given the small size of my estimation samples for AP CS Principles, these results should be interpreted particularly cautiously; a plausible takeaway from Table 5 is that the race of Black students' AP CS teachers is mostly unrelated to their AP exam outcomes.

The coefficients on the indicators for white students illustrate that, *ceteris paribus*, white students are perhaps slightly more likely than Black students to take the AP exam in the presence of a white teacher (columns 1-10) and to score 0.23-0.57 points higher on average when they take the exam (column 11-20). This reflects generally better exam outcomes, rather than any particular racial match benefits, for white students. The coefficients on the interaction terms are generally small and statistically insignificant when predicting exam taking. Coefficients are somewhat larger when predicting exam scores, in some cases erasing the Black-white gap indicated by the coefficients on the white student dummy variable. However, these estimates vary substantially in magnitude and rarely reach statistical significance. They thus present at most suggestive evidence of any race-match effects.

Discussion and conclusion

I contribute to a nascent body of literature studying policy, administration, and implementation issues in the expansion of CS education in high schools. I present some of the most detailed evidence to date about who teaches CS courses and whether their attributes matter for students' experiences. I motivate my analysis in terms of prior research on teacher effectiveness, but my research questions are important from a policy perspective because the success of CS curricular expansions may hinge on how CS courses are staffed and how effectively CS teachers are able to deliver students the intended benefits of CS education. My results therefore have implications for both research and practice.

A longstanding concern among educators and researchers has been that there is a tension between offering additional CS opportunities to students and needing to find teachers who are sufficiently qualified to provide those opportunities effectively. I find that despite being relatively new courses, CS courses tend to be taught by relatively veteran teachers. This is a plausible way to navigate the tensions associated with a limited supply of teachers with specialized CS knowledge and skills. Though veteran teachers may lack formal experience with or preparation in CS, they may have other attributes that make them effective instructors. Indeed, I find that, in part because of their reliance on veteran teachers, CS courses are taught by teachers of above average experience who are more likely to have a graduate degree and to be NBC. And, at least in North Carolina, CS teachers are as or more demographically representative of the student population compared to teachers of other courses.

Previous research suggests that many of these attributes are important in teachers, and I find some evidence consistent with this in the case of AP CS courses. For example, in at least some models, teachers' years of prior experience and NBC are predictive of students either taking AP exams or scoring higher on those exams. However, these results are not entirely consistent, especially in models isolating within-school variation, and like many previous studies I do not find that a teacher's possession of a graduate degree benefits their students.

Additionally, I do not find clear evidence that teachers' licensure areas predict their students' outcomes, even licensure in computer programming specifically. This is again in line with some previous research looking at teacher licensure in other subject areas. However, two important caveats bear emphasizing. First, most licenses have little substantive alignment to CS content. Thus, even if they are unimportant for student outcomes, that does not imply that licenses better aligned to CS course content would not matter. Second, the limited number of teachers I observe with the most closely aligned license – computer programming – should urge caution when interpreting results for that license specifically.

The detailed data available in North Carolina allow me to investigate these issues in ways that have not been possible in previous work on CS teachers. And the fact that my results often align with previous findings in other contexts suggests that they are likely to generalize to other settings. This, in turn, suggests that my findings can inform policymakers and researchers elsewhere.

Taken together these results suggest that schools' current approaches to CS course staffing are largely reasonable, at least to the extent that CS curricular expansions are desirable in the first place. The current approach of many states (including North Carolina) to allow CS courses to be taught by teachers without CS-specific licensure appears to be a reasonable way to allow CS coursework to expand in the absence of a dedicated supply of CS teachers. Indeed, this conclusion is bolstered by the fact that I explore the importance of teacher qualifications in the context of AP courses. To the extent that AP courses are especially advanced, qualifications like licensure may matter even less in less advanced, but more common, CS courses.

This is not to say that investing in a more specialized CS teacher workforce would not be worthwhile for states and school districts. I find some evidence that prior CS teaching experience matters for CS teacher effectiveness. Thus, supporting teachers as they transition into CS teaching, so that they can accumulate subject-specific experience, may be a useful way for schools to develop their CS teaching capacities. And, as discussed above, previous research has found in at least some cases that subject-specific preparation can matter for teachers.

Moreover, investing in the CS teacher supply might help to relieve stress on the supply of other teachers who appear, in the status quo, to be doing “double duty” as teachers of both CS and other subjects. For example, as I show above, a substantial minority of CS courses are taught by teachers holding math licenses. Given widespread concerns about shortages of math teachers, it is not obvious that schools and students benefit on balance from assigning veteran and well-qualified math educators to CS classrooms. Alternatively, veteran teachers of other subjects denied the opportunity to teach CS may, as a result, exit their school or the profession. In any case administrators need to weigh the trade-offs of specific curricular and staff assignment options carefully, particularly in cases where the supply of CS, STEM, or CTE teachers is tight.

I conclude with a final caveat regarding estimates of relationships between teacher characteristics and student outcomes, especially in CS contexts. Recent years have seen a dramatic increase in the availability of in-service supports for CS teachers. These supports are varied and often lack evidence on uptake and effectiveness, so their impacts are difficult to describe or anticipate in a general way (Menekse, 2015; Ni, Bausch, et al., 2023). While individual programs may be effective, on the whole participation in activities like professional development does not appear to have consistently large effects on teacher effectiveness (Harris & Sass, 2011; Kirsten et al., 2023), suggesting that in-service programs will not substantially affect my analyses. However, I cannot rule out the possibility that the availability of in-service training for CS teachers – like other unobserved differences between teachers – might affect my results.

This kind of uncertainty, as well as difficulties associated with staffing trade-offs faced by administrators, point to important areas for future research. My results are broadly in line with findings across many studies that teacher effectiveness is not easy to predict using observable teacher characteristics. But my results are by no means definitive. Most notably, I do not observe teachers being randomly assigned to students, nor can I estimate value-added models of teacher effectiveness. I therefore cannot rule out the possibility that my estimates of the importance of teacher characteristics for student outcomes are biased (e.g., by the availability of in-service supports for CS teachers). Indeed, my results are often sensitive to my choice of model specification. Future research should investigate CS teacher effectiveness more thoroughly, especially since many schools continue to expand – or seek to expand – their CS course offerings. This research would especially benefit from explorations of students' longer-term outcomes since CS curricula are so commonly justified in terms of student access to specific college curricula and employment opportunities.

Declaration of Interest Statement: The authors report there are no competing interests to declare.

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Who teaches high school computer science and does it matter?

Online supplementary materials

Table A1. Summary statistics: courses' teacher characteristics

	N	Mean	SD	Min	Max
Female	3457979	0.61	0.49	0	1
Asian	3392244	0.01	0.09	0	1
Black	3392244	0.15	0.36	0	1
Hispanic	3392244	0.02	0.14	0	1
Native American	3392244	0.01	0.10	0	1
White	3392244	0.81	0.39	0	1
Prior Experience (Years)	3382105	13.33	9.65	0	59
Prior CS Teaching Experience (Years)	3331108	0.02	0.25	0	12
MA+	3303785	0.39	0.49	0	1
National Board Certified	3507645	0.10	0.30	0	1
Career Technical Education (CTE) Licenses					
CTE Business and IT Education	3384727	0.07	0.25	0	1
CTE Technology Engineering and Design Education	3384727	0.02	0.13	0	1
CTE Computer Engineering Technology	3384727	0.00	0.02	0	1
CTE Network Engineering Technology	3384727	0.00	0.01	0	1
CTE Computer Programming	3384727	0.00	0.01	0	1
CTE Scientific and Technical Visualization	3384727	0.00	0.03	0	1
CTE Project Lead the Way	3384727	0.00	0.04	0	1
Other CTE	3384727	0.14	0.35	0	1
Non-CTE Licenses					
Math	3384727	0.15	0.35	0	1
Business	3384727	0.01	0.11	0	1
Exceptional Children	3384727	0.13	0.34	0	1
Science	3384727	0.13	0.33	0	1
World Language	3384727	0.05	0.23	0	1
Other Non-CTE	3384727	0.53	0.50	0	1

Note. CS=Computer science.

Table A2. Summary statistics: Advanced Placement computer science (AP CS) courses' teacher and student characteristics

	N	Mean	SD	Min	Max
Teachers					
Female	854	0.54	0.50	0	1
Asian	845	0.02	0.14	0	1
Black	845	0.08	0.26	0	1
Hispanic	845	0.00	0.05	0	1
Native American	845	0.01	0.11	0	1
White	845	0.89	0.31	0	1
Prior Experience (Years)	761	19.35	9.79	0	41
Prior CS Teaching Experience (Years)	868	2.51	2.42	0	10
MA+	758	0.71	0.45	0	1
National Board Certified	868	0.22	0.41	0	1
Career Technical Education (CTE) Licenses					
CTE Business and IT Education	756	0.45	0.50	0	1
CTE Technology Engineering and Design Education	756	0.10	0.31	0	1
CTE Computer Engineering Technology	756	0.05	0.21	0	1
CTE Network Engineering Technology	756	0.01	0.10	0	1
CTE Computer Programming	756	0.01	0.07	0	1
CTE Scientific and Technical Visualization	756	0.03	0.18	0	1
CTE Project Lead the Way	756	0.02	0.13	0	1
Other CTE	756	0.15	0.36	0	1
Non-CTE Licenses					
Math	756	0.26	0.44	0	1
Business	756	0.02	0.13	0	1
Exceptional Children	756	0.03	0.18	0	1
Science	756	0.04	0.19	0	1
World Language	756	0.03	0.18	0	1
Other Non-CTE	756	0.48	0.50	0	1
Students					
Grade Level	6457	11.45	0.74	9	12
Female	6461	0.23	0.42	0	1
Native American	6439	0.00	0.06	0	1
Asian	6439	0.14	0.35	0	1
Hispanic	6439	0.06	0.23	0	1
Black	6439	0.10	0.30	0	1
White	6439	0.67	0.47	0	1
With Disability	6458	0.02	0.14	0	1
English Learner	6458	0.00	0.06	0	1
Economically Disadvantaged	6458	0.14	0.35	0	1
Took AP Exam	6462	0.74	0.44	0	1
Score on AP Exam	4759	2.51	1.47	1	5
Mean AP Exam Score in Prior Year	3064	3.31	1.15	1.00	5.00
Standardized End-of-Grade-8 Math Test Score	5572	1.23	0.84	-2.03	2.97

Note. Teacher data includes one observation per teacher per course. Licenses included in Table 1 but not observed for APCS teachers are not shown.