Increasing Capacity for Computer Science Education in Rural Areas through a Large-Scale Collective Impact Model

Jayce R. Warner
University of Texas at Austin
jaycewarner@utexas.edu

Carol L. Fletcher
University of Texas at Austin
carol.fletcher@utexas.edu

Ryan Torbey
University of Texas at Austin
ryan.torbey@utexas.edu

Lisa S. Garbrecht
University of Texas at Austin
lgarbrecht@utexas.edu

ABSTRACT

Students living in rural areas are less likely to attend schools that offer computer science (CS) courses largely because educational institutions in these remote areas lack the resources to staff teaching positions for these courses. This study investigated the impact of WeTeach_CS, a program designed to train teachers to become certified to teach high school CS in Texas. The WeTeach_CS collective impact model may be well suited to influence rural areas at scale because it utilizes an existing network of organizations across the state to bring high-quality professional development opportunities to teachers in remote areas. Results from a comparative interrupted time series analysis showed a significant, positive change in the rate in which the number of certified CS teachers in rural areas increased during the period of time after WeTeach_CS began compared to the period before the program was implemented, whereas the number of teachers certified in technology applications showed no such change. Furthermore, the growth rate in the number of certified CS teachers was much higher for rural schools than urban, suggesting that collective impact models like WeTeach_CS may be especially beneficial for rural communities.

KEYWORDS

rural education, teacher professional development, educator certification, high school teachers, equitable access to computer science education, broadening participation in computing

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1 INTRODUCTION

Schools in rural areas are behind their more urbanized counterparts in terms of access to CS education [12]. Rural schools constituted only 10% all U.S. public schools that offered an AP computer science course in 2017 [2], even though the latest estimates show that 28% of all public schools in the U.S. are designated as rural and 42% as rural or small-town [7]. At the core of this issue is that the lack of qualified CS teachers overall is exacerbated in rural areas, where schools have a relatively harder time funding new teaching positions and recruiting highly qualified teachers to fill those positions. Schools simply cannot offer courses for which they have no qualified teacher, implying that one crucial antecedent to increasing access to CS education for underserved students is increasing the CS teacher workforce in those areas.

Efforts to increase the number of qualified CS teachers are invariably met with challenges of scalability and sustainability. Collective impact models [13], which unite interdisciplinary partners towards a common goal, may be better suited to overcome these challenges than stand-alone interventions. A collective impact model has the potential to effect change in rural schools because it connects local education agencies with resources and expertise to which they may not otherwise have access. The WeTeach_CS program has worked extensively with rural schools and teachers over the past three years to build capacity for K-12 CS Education. Approximately 40% of the 640 schools served by WeTeach_CS in 2016-17 are in rural or small-town districts. WeTeach_CS, which serves teachers across multiple districts, is particularly helpful in creating an economy of scale for CS teacher professional development that is not possible to obtain for individual small, rural districts. WeTeach_CS supports sustainability of program effects by using a network of professional development partners to support local teachers before and after becoming certified to teach CS. This research project examines the effectiveness of the WeTeach_CS collective impact model for increasing the number of certified CS teachers in rural schools.

2 BACKGROUND

2.1 Equitable Access to CS Education in K-12

A growing consensus is emerging around the need for computer science (CS) education for all K-12 students. CSforAll as a national movement was catalyzed by President Obama's announcement in January of 2016 of a new initiative focused on making sure every student had the computer science and computational thinking experiences they needed to become "active citizens in our technology-driven world" [19]. Economic competitiveness in the United States rests in large part on the ability to develop and leverage technology to fuel progress and innovation. The CS field is booming, with jobs like Software Developer positioned to have hundreds of thousands of openings between now and 2026 [16]. The value for students who study CS is immense. Computer science majors earn an average of $1.67 million throughout their lifetimes, 40% greater than the average of all college graduates [18]. Even for those students who will not eventually pursue a post-secondary career specific to CS or information technology, learning to reason and solve problems computationally may be of value. Computational thinking has been marked as a transferable problem-solving skill, and computational literacy is seen as a modern way of learning and representing knowledge [1].

Equitable access to CS education is important since the opportunity to study CS opens doors to above-average earning potential and the ability to create, rather than simply consume, in the digital world. Schools, however, are struggling to adequately meet the challenge of providing equitable access to CS education opportunities for all students. Despite the fact that the majority of teachers and parents believe that CS should be a required part of K-12 education, only 40% of schools are estimated to offer at least one CS course [11]. Access to CS courses is even lower for students in rural areas, students of color, and students from low-income families [10]. One of the most significant barriers to the ability of schools to offer CS courses is the lack of certified teachers [6]. Many schools, especially those in poorer districts, simply lack the resources to train new CS teachers. For this reason, scalable interventions to incentivize and train teachers across a diverse range of schools and districts are needed to achieve the goals of increasing the number of certified CS teachers and providing all students opportunities to study CS. Little is known, however, about the effectiveness of such large-scale programs in relatively new subject areas like computer science and in rural areas.

2.2 Interventions to Increase the Teacher Workforce in High-Need Areas

District and state programs have utilized professional development and financial incentives as a means to influence teacher choices related to where they work and what they teach. For example, in New York City public schools, where teachers must have the relevant coursework to be qualified to teach a particular subject, the New York City Department of Education offers current teachers tuition reimbursement to gain additional certification in hard-to-staff subject areas [17]. Research on the effectiveness of similar programs has produced mixed results [4]. An analysis of Florida's Critical Teacher Shortage Program showed that tuition reimbursement programs and one-time bonuses had positive effects on the retention of teachers in math and special education [5]. Other research, however, calls into question the effectiveness of financial incentives that do not also provide teachers with professional support. Massachusetts and North Carolina implemented teacher bonus programs to incentivize teachers to teach hard-to-staff subjects at high-poverty schools. Over half of the Massachusetts teachers in the study ended up leaving before the four year program was complete [15], and the North Carolina program was mired by misunderstanding and low perceived value among teachers [3]. Another study showed that although a financial incentive increased the likelihood of having teachers to teach in low-performing schools, teachers who received the incentive were just as likely to leave the school as teachers who did not receive the incentive [20]. A common theme of the findings from these studies is that financial incentives alone may not be enough if not coupled with proper training and support. In addition, the majority of the studies in this field focus on the impact of incentives on the retention of teachers, whereas few studies take up the initial question of whether and how these incentives impact recruitment or the achievement of new certifications to teach additional, high-need subjects.

We have highlighted research regarding large, statewide programs because of their ability to effect change across a broad range of economically- and resource-diverse districts. Incentive and professional development programs designed for implementation by individual school districts can have the unfortunate result of perpetuating educational inequities since only those districts with adequate resources can successfully implement such programs. For example, one study found that larger school districts were more likely to implement incentive programs than smaller school districts [14]. Thus, to meet the needs of smaller, rural school districts, we need large-scale, collective impact programs that bring together educational institutions with similar goals, pool resources across geographic boundaries, and create a sustainable network of these institutions and resources to support efforts beyond the program's initial stages.

2.3 Collective Impact Models

Collective impact models have grown in prominence as viable solutions to complex social sector challenges. Projects applying a collective impact approach address a wide range of challenges including addressing worldwide malnutrition, reducing teenage binge drinking, combating childhood obesity, and tackling environmental cleanup efforts [8]. Other collective impact projects are addressing educational challenges. The Strive Partnership in Cinncinatti is a prime example of the potential of collective impact models to make significant and sustainable changes to student educational outcome measures, with 81% of its 34 measures of student achievement showing postive improvement over four years [8].

Collective impact models incorporate five key components: a backbone organization that supports the entire system, a common agenda regarding the problem to be solved, shared measurement systems to track progress toward goals, mutually reinforcing activities, and continuous communication across all stakeholders [13]. By leveraging the expertise of multiple players across the system, collective impact models can address a variety of variables that influence the problem of practice simultaneously. In the education sector, this includes building teacher content knowledge, developing administrator leadership, addressing school funding and teacher incentives, and identifying and modifying when possible state or local policies that impede progress.

2.4 The WeTeach_CS Program

The University of Texas at Austin (UT Austin) STEM Center's WeTeach_CS program trains K-12 educators to improve access to high quality CS experiences for a broad and diverse range of students. The objectives of the WeTeach_CS program are to increase the number of CS certified high school teachers, increase the number of high schools offering CS courses, increase the number and diversity of students enrolled in CS courses, and expand access to computational thinking, coding and programming experiences for all students in K-8.

The WeTeach_CS program is a collective impact model currently serving the entire state of Texas. The program offers a $1,000 stipend to Texas teachers who successfully achieved certification in computer science. To help teachers learn the content, WeTeach_CS provides a 7-week online certification preparation course along with a 2-day in-person training that was offered at various locations around the state. In order to reach and serve teachers across all geographic and economic areas of the state, WeTeach_CS utilizes an existing network of 30 region-level organizations (e.g., education service centers, universities) within the state to publicize and implement the program.

The WeTeach_CS program reflects the five key characteristics of collective impact models mentioned above. The UT Austin STEM Center serves as the WeTeach_CS **backbone organization**, coordinating all state level professional development, CS Collaborative funding and support, data collection, and convening of leaders and teacher participants. Teachers, schools, universities, non-profits, industry partners, and professional development providers who participate in the WeTeach_CS program all share the **common agenda** of broadening participation in K-12 computing. The common goal is grounded in four key building blocks of broadening participation in K-12: 1) Capacity, 2) Access, 3) Participation, and 4) Equity. While the final goal is equitable participation of all students in CS-related experiences in K-12, the three prior components are necessary antecedents to reaching equity at scale. In this study we focus on the first of those components, capacity, operationalized here as the availability of qualified teachers certified to teach computer science. Partner organizations within WeTeach_CS all use the same **shared measurement systems**. For example, to become certified to teach computer science in Texas, all teachers must pass the same state certification exam specific to computer science. Additionally, public schools and districts across the state are all required to use one common data reporting system for all teacher and student data. **Mutually reinforcing activities** of the WeTeach_CS network include professional development related to teacher certification as well as other training that builds teacher content knowledge, equitable practices, and instructional skills. UT Austin also hosts an annual 3-day WeTeach_CS Summit, attended by over 400 educators in 2018, to provide professional development and build community across the statewide network. Finally, the WeTeach_CS community is connected through an ecosystem of support and **continuous communication**. The WeTeach_CS blog is a weekly online newsletter subscribed to by over 1,300 stakeholders focused on keeping teachers aware of various professional development opportunities, funding and policy updates related to CS education, instructional resources, and student opportunities. Over 2,400 people follow the WeTeach_CS Facebook and Twitter feeds. Each WeTeach_CS Collaborative teacher also receives regular communication from their own CS Collaborative Project Director related to their regional professional development program and meets regularly with the teachers in their CS Collaborative (20-40 teacher per cohort). WeTeach_CS Project Directors are supported by UT Austin staff through virtual and in-person meetings as well as CS workshops and training opportunities.

Many of the teachers and schools served by the collaborative organizations within this collective impact model were located in school districts that lacked the resources typical of larger districts in more affluent areas. The purpose of this study was to investigate whether and to what extent the WeTeach_CS program increased the number of certified CS teachers in rural areas of Texas.

3 METHOD

Comparative interrupted times series (CITS) analysis was used to investigate the impact of the WeTeach_CS program on the number of certified computer science teachers in rural schools. CITS is a quasi-experimental method that tests whether the introduction of an intervention produces a change in the target outcome over time for the treatment group to a greater degree than a comparison group. We refer to the periods of time before and after the introduction of the program as the pre-intervention and intervention phases, respectively. Two types of causal effects can be estimated with CITS: level change and slope change. In the current analysis, the presence of a level change would mean a change in the number of certified teachers immediately following the introduction of the WeTeach_CS program that could not be explained by the overall trend. A statistically significant slope change would indicate that the intervention phase trend differs from the pre-intervention phase trend. Similar level and slope changes for the comparison group would suggest that the observed changes for the treatment group were due to some other factor not accounted for in the model.

We hypothesized that the WeTeach_CS program would positively impact the number of certified CS teachers in rural schools but that this effect would happen gradually over time. Accordingly, we expected results to reveal a statistically significant, positive change in slope but no significant level change. We further expected null results for changes in the level and slope of the number of certified teachers in the comparison group.

In contrast to standard interrupted time series (ITS) analyses, CITS seeks to rule out the possibility of unknown confounders by including a comparison group that is similar to the treatment group such that it would be influenced by the same unknown confounding factors as the treatment group but remain unaffected by the treatment. We included teachers who obtained certification in technology applications to serve as the comparison group for a couple reasons. First, technology applications is the certification most similar to the computer science licensure in terms of the content knowledge covered on the certification exam and the curricular content of the courses that a teacher holding that certification would be qualified to teach. Second, technology applications and computer science had relatively similar slopes for the pre-intervention phase. For both computer science and technology applications, the number of certified teachers steadily increased over the four years prior to the start of WeTeach_CS, whereas other certification fields (e.g., mathematics) showed less stable increases or no increases during that time period.

3.1 Data Sources

Education data were collected through the Texas Educational Research Center, a data clearinghouse that contains a broad range of data on every public school and public school teacher and student in the state. This clearinghouse includes data maintained by the State Board of Educator Certification (SBEC), which oversees and administers educator certifications for the state. To obtain a certification for a particular subject area in Texas, teachers are required to hold a bachelor's degree, complete an approved certification program, and pass the appropriate certification exam for that subject. Teachers who already hold certification in one area can become certified in another area by passing the appropriate content exam and applying for certification. The SBEC maintains records of all exam administrations and all certifications issued. Access to these data allowed us to determine precise counts of the number of active CS certifications each month across several years. By merging these data with data on teacher assignment, we were able to determine for all certified teachers the name and location of the school in which they were teaching at the time they became certified and each time point thereafter. We included data spanning six years, from the beginning of the 2011-12 school year through the end of 2016-17.

To determine whether teachers taught in rural or urban/suburban school districts, we used the district type designations developed and assigned by the Texas Education Agency (TEA). These include eight categories, which we list here in order from the largest, most urban type of school districts to the smallest, most remote type of districts: major urban, major suburban, other central city, other central city suburban, independent town, non-metropolitan fast-growing, non-metropolitan stable, and rural. (A ninth category, charter school districts, was excluded from the analysis because the criteria for inclusion in this category was entirely unrelated to geographic location. Computer science teachers in this category comprised approximately two percent of the total population of certified CS teachers employed in the state at the start of the intervention.) Because the TEA designation of "rural" includes only the smallest, most remote school districts, we further grouped these eight categories into two super categories: urban-suburban and rural. To determine whether each of the eight TEA district types should be classified as urban-suburban or rural, we considered several factors, including average district size (in terms of student enrollment), average number of campuses per district, and remoteness. Clear distinctions were evident between the first three categories and the latter five in terms of district size and number of campuses per district, as shown in Table 1. Visual inspection of the districts within each category confirmed the remoteness of the latter five district types. Thus, these five district types were designated as rural in the current study.

Table 1: District Type Designations

Designation in Current Study	TEA District Type	Avg. No. of Campuses Per District	Avg. Student Enrollment
Urban-Suburban	Major Urban	124	89,059
	Major Suburban	26	22,066
	Other Central City	29	21,142
Rural	O.C.C. Suburban	7	4,603
	Independent Town	6	3,744
	Non-Met Growing	3	1,057
	Non-Met Stable	4	1,687
	Rural	2	388

4 RESULTS

Huitema's [9] guidelines for two-stage model selection were followed to conduct model fit tests to identify the appropriate parameters to include in the model and determine correct model specifications. Results from these tests suggested that a four-parameter model that accounted for autocorrelated errors would be the best fit to analyze the data. The resulting model assumed this form:

$$Y_t = \beta_0 + \beta_1 T_t + \beta_2 L_t + \beta_3 S_t + \phi_1 e_{t-1} + u_t \tag{1}$$

where Y_t is the number of certified teachers at time t; β_0 is the intercept; β_1 is the pre-intervention slope; β_2 is the level-change at the time of the intervention; β_3 is the change in slope from pre-intervention phase to intervention phase; T_t is the value of the time variable at time t; L_t represents the level-change and is a dummy-code variable that denotes the phase at time t; S_t represents the slope-change variable and is defined as $[T_t - (n_1 + 1)]L$; n_1 is the number of observations in the first phase; ϕ_1 is the first-order autoregressive coefficient; e_{t-1} is the residual at time $t-1$; and u_t is the residual at time t.

Inspection of scatter plots of the data revealed evidence of seasonal trends recurring annually. Specifically, the number of certified teachers decreased slightly each year between the months of August and September. These decreases are likely the result of some teachers allowing their certifications to lapse before renewing them again, since certifications are often set to expire at the end of the school year. To account for this seasonality, we added 11 dummy-coded variables to the model to indicate the month of the year for each time point. Due to space constraints, we omitted these variables from the results tables.

Table 2: Time Series Regression Results: Rural CS Teachers

	B	SE	t	p
Pre-intervention slope	0.33	0.15	2.14	.037
Level change	3.09	3.79	0.82	.418
Slope change	6.46	0.44	14.59	.000
Constant	56.47	4.91	11.48	.000

ρ=.83

Results showed that, as expected, the level change was not statistically significant ($t(57)=0.82$, $p=.418$), indicating that there was no immediate change in the number of certified CS teachers that could not be explained by the overall trend (see Table 2). However, the slope change was statistically significant ($t(57)=14.59$, $p<.001$), signaling that the intervention slope differed from the pre-intervention slope. The coefficient for this estimate (B=6.46) suggests that an average of approximately 6 more teachers were certified each month in the intervention phase than in the pre-intervention phase. By adding the slope-change coefficient to the coefficient for the pre-intervention slope (B=0.33), we can calculate the actual slope for the intervention phase. In doing so, we note that an average of about 7 new teachers were certified each month during the time after WeTeach_CS began compared to an average of less than 1 new teacher per month during the time before WeTeach_CS was implemented. Figure 1 illustrates these trends.

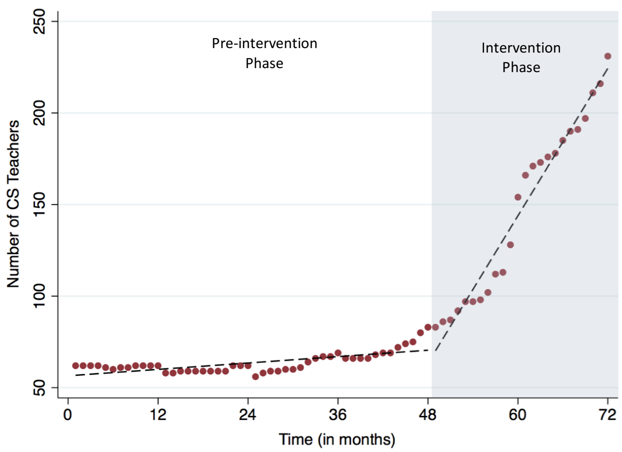

Figure 1: The number of certified CS teachers in rural areas before and after the start of the WeTeach_CS program

To check whether these trends were similar or dissimilar to the trends for urban-suburban school districts, we conducted the same analysis for CS teachers in those areas. The statistical significance of this analysis was similar to that of rural schools in that there was no level change but there was a significant change in slope from the pre-intervention to the intervention phase ($t(57)=9.11$, $p<.001$), indicating that there was a significant increase in the rate at which teachers in urban-suburban districts became certified after the start of WeTeach_CS compared to the period of time before the program. However, the rate at which teachers became certified in rural areas was substantially larger than urban-suburban areas. Whereas the number of certified CS teachers in urban-suburban areas increased by 88% during the intervention phase, it increased by 169% in rural areas during the same period (see Figure 2).

To ensure this difference between rural and urban-suburban areas was unique to the intervention phase and not simply a continuation of differences that existed prior to the intervention, we calculated the percent change for comparable periods of time before and after the start of the WeTeach_CS program. Because the intervention phase comprised a two-year period and the pre-intervention phase comprised a period of four years in the analysis, we calculated the pre-intervention percent change using just the two years prior to the start of WeTeach_CS and found that the number of CS teachers increased by 31% in urban-suburban areas and 34% in rural areas during this time period. Thus, whereas the rate in which teachers became certified in urban-suburban areas was twice as large during the two years of the intervention phase than the last two years of pre-intervention phase (63% vs 31%, respectively), it was over five times greater in rural areas (178% vs 34%).

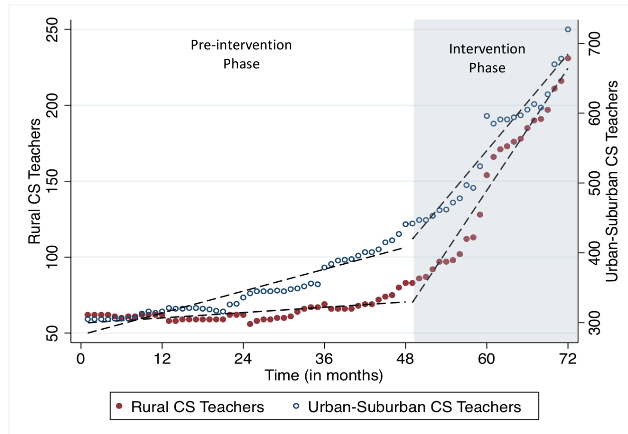

Figure 2: The number of certified CS teachers in rural and urban-suburban areas before and after the start of the WeTeach_CS program

To aid in ruling out the presence of unknown confounding factors, an interrupted time series analysis was run on the comparison group, rural teachers obtaining certification in Technology Applications. In conducting this analysis, we followed the same procedures used to conduct the analysis for rural CS teachers. We followed Huitema's [9] two-stage model selection guidelines to determine appropriate model specification, tested and accounted for autocorrelation, and included month dummy variables to control for seasonality. Results showed no statistically significance change in level or slope (see Table 3). Thus, we conclude that there were no changes in the number of certified Technology Applications teachers immediately after the start of the intervention phase that could not be accounted for by the overall trend, nor was there any difference between the trends in the intervention and pre-intervention phases.

Table 3: Time Series Regression Results: Rural Technology Applications Teachers

	B	SE	t	p
Pre-intervention slope	4.33	0.63	6.83	.000
Level change	-2.24	11.55	-0.19	.847
Slope change	1.27	1.73	0.73	.467
Constant	1060.44	20.70	51.24	.000

5 DISCUSSION

The results of this study demonstrate that large-scale collective impact interventions can be effective in increasing the number of certified CS teachers. Moreover, given the statistically significant change in slope between the pre-intervention and intervention phases, this study shows that program effects can be sustained over time. Perhaps most importantly, the WeTeach_CS program seemed to have had an even greater impact in rural schools, where the number of certified CS teachers increased by 178% compared to 63% in urban-suburban areas. As advocates make the case for expanding K-12 CS education for all students in the United States, initiatives that demonstrate success in rural locations will be of great importance. There has been a focus on closing the digital divide, in which rural schools have lagged behind urban-suburban institutions in gaining access to technical advances. Unless effective strategies in broadening participation in CS in rural districts are developed and implemented, there is a risk that this divide will perpetuate and even widen.

Whereas previous research on increasing the teacher workforce in high-need areas focused on interventions enacted on relatively smaller scales (typically at the district level), this study provides evidence for the effectiveness of a large-scale intervention as it was implemented across an entire state. WeTeach_CS appears to be implementing a promising strategy yielding positive results across a state which has large socioeconomic and geographic diversity. We believe the distinguishing factors that have contributed to the success of the WeTeach_CS program lay in its utilization of the collective impact model as well as its combination of financial incentives with ample available training. The results of this study provide strong evidence for the value of collective impact models for effecting change in rural areas and across large geographic regions generally.

The unique impact on rural areas may have been due to three challenges that rural school districts face to a greater degree than urban and suburban districts. First, while many school districts, regardless of geography, lack computer science expertise, school districts in urban and suburban areas can often tap into nearby institutions of higher education and industry partners to access resources. Second, administrators and teachers in rural communities often have overlapping responsibilities due to the small school size and simply lack the bandwidth to launch and support new initiatives in which they lack personal expertise. Finally, it if often the case that rural school districts simply lack the ability to afford expensive initiatives, such as implementing new courses and training teachers in new content areas.

We theorize that WeTeach_CS has been more successful in rural communities because it addresses these specific challenges. Collective impact models like WeTeach_CS, which function at a large scale and create collaborative networks of like-minded organizations, can be especially beneficial for educational institutions in remote areas. With the collective impact model, small rural schools can leverage the expertise of the network to compensate for limited CS expertise within their organizations. While these schools are geographically isolated, through collective impact they become connected to institutions of higher education, industry partners, and other teachers and schools all focused on addressing the same challenges. Because rural schools have relatively few teachers, it is difficult for individual school districts to achieve an economy of scale to support the creation and growth a CS program. However, in a collective impact model the investment can be distributed across an entire statewide network, thus achieving the economy of scale that would be too inefficient for rural districts to do on their own. The CS certification preparation training provided by the WeTeach_CS program purposefully leverages the strengths of the collaborative network, allowing the local organizations to utilize their existing relationships with teachers to propagate the online course and promote in-person training sessions. This allowed the initiative to scale more quickly into all areas of the state while keeping the financial cost to schools and districts at manageable levels.

Another distinguishing feature of the WeTeach_CS program is its focus on training and incentivizing inservice teachers as opposed to preservice teachers. This approach may have provided additional benefits to rural districts since training existing teachers who are already serving in rural schools means reducing the need to recruit CS teachers to remote areas.

5.1 Limitations

Despite the fact that we used a comparative design to strengthen claims of causal inference, it is important to consider the possibility of other confounding factors. The existence of unknown confounding factors would be more plausible if other programs or interventions were implemented at the same time as WeTeach_CS that were likely to influence the number of certified CS teachers but not the number of certified Technology Applications teachers. However, we believe the presence of such factors to be highly unlikely given the fact that the WeTeach_CS program was the only statewide CS program in effect at the time.

One limitation of this study is the fact that rules and regulations concerning teacher certification vary from state to state in the United States and country to country worldwide. Texas teacher certification rules enable currently certified teachers to take a subject-matter certification exam and then add that subject to their teaching certificate. This can be done without any additional coursework, allowing for a relatively flexible teacher workforce in terms of adding additional academic subjects to teaching credentials. Where certification requirements differ in other states, interventions like the one examined in this study may need to be altered to be effective.

5.2 Conclusion

A major strength of this study lies in the fact that it was done at scale, as the intervention canvassed the entire state of Texas and the analysis took into account the whole of certification data in the state. This has important implications for efforts to improve equitable access to CS education. The lack of qualified teachers is one of the foremost barriers to students' access to CS courses in their schools. This study is an important step forward in understanding how to improve equitable access to CS education for all students because it examines and demonstrates the effectiveness of a large-scale collective impact model to build capacity in rural communities.

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