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Arkansas' Coding for All - Is it Really Reaching All Students?

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Arkansas' Coding for All – Is it Really Reaching All Students?

An Undergraduate Honors College Thesis

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by

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Introduction

Arkansas currently has over 1500 open computing jobs. However, Arkansas had only 328 computer science college graduates in 2015, and only 304 high school students in Arkansas took the AP Computer Science exam in 2016 (State Advocacy Sheet). Females and minorities were underrepresented in both groups (State Advocacy Sheet). Students who take AP Computer Science are eight times more likely to major in computer science (CS Education Statistics).

The Arkansas Computer Science Initiative required every high school to offer at least one computer science course by the 2015-16 academic year. Schools that did not have a qualified teacher were given access to online courses. It is important to point out that students do not need a computer science course to graduate, but credit in a computer science course could replace a 3rd science credit requirement or a 4th math credit requirement (ADE / ARCareerED Computer Science Fact Sheet). Some initial success has already been demonstrated. In 2014-15 there were sixty computer science classes offered in all of Arkansas. In the 2015-16 school year that number went up to 345 (ADE Data Center). However, this data does not indicate how many of those courses were offered online through Virtual Arkansas.

Due to this new legislation, the Arkansas education data provides a unique opportunity to track student progress before, during, and after the implementation of increased access to computer science curriculum. The goal of the program is computer science for ALL. It is well known, however, that women and racial minority groups are severely underrepresented in technology fields. According to the College Board, with respect to the nation as a whole, a higher percentage of women and minorities are enrolling in their new course, “AP Computer Science Principles,” than have traditionally enrolled in “AP Computer Science A.” For example, 16.2% of students taking Principles are black versus 4% of those taking AP Computer Science. For Latino and Hispanic students, 19% are taking Principles compared to 9% taking AP Computer Science A (Madda, 2017). This demonstrates the power of adding access to one course to make a positive change. Conversely, a single class can have a negative impact on participation. For example, Giannakos and colleagues (2016) cite Seymour and Hewitt (1997), who found that poor teaching, harsh grading, and heavy demands in a class were among the reasons college level STEM students gave for changing their majors.

In addition to lower female and minority enrollment in initial computer science courses, female and minority students are more likely to drop out of technology programs. Most studies looking at attrition focus on a college population. However, Greening (1999, cited in Wilson, 2002) concluded that, with regard to gender, “the biggest source of pipeline ‘leakage’ occurs prior to university admission.” Among those who begin a college major in computer science, 30 to 60 percent fail to finish it (Ohland et al. 2008). In addition, women who drop out of college level computer engineering programs tend to do so with a higher GPA than that of the men who drop out (Roberts, et al., 2011). Wasburn and colleagues (2008) found that lack of role models is another factor contributing to the attrition of women in IT. Nationally, 60.5 percent of secondary school teachers are female (Labor Force Statistics from the Current Population Survey 2016), so offering more computer science in high school could help solve the role model problem.

With these issues in mind, the main objective of this research thesis is to investigate to what extent – if any – has the Arkansas Computer Science Initiative increased student participation and diversity in high school computer science courses?

Data and Database Management Methods

Student level data from the Arkansas Department of Education was used to assess the impact of the Arkansas Computer Science Initiative. The data comprises information about Arkansas high school student participation in at least one computer science course with respect to demographics and grades from the 2007-08 academic year through the 2016-17 academic year. Given that the "initiative" was introduced in the 2015-16 academic school year, we have eight years of data prior to the "initiative," and two years of data post the "initiative". This is a very large and detailed dataset broken down by individual student and identifying demographic characteristics such as student gender and race as well as classifying each student in terms of their academic grades. It contains 1,283,319 observations over the 10-year period. Tables 1 and 2 summarizes all the individual student identifying characteristics. Table 1 categorizes all the demographic characteristics, and table 2 categorizes all the identifying characteristics with respect to each individual student's overall high school academic grades.

Table 1

Student Demographic Data
Research ID
Gender
Race
Gifted and Talented Status
Free and Reduced Lunch Status
Limited English Proficient Status
Grade Level
Fiscal Year
District LEA
District Description
School LEA
School Description
Primary Home Language Status

Table 2

Student Grades Data
Research ID
Gender
Race
District LEA
District Description
School LEA
School Description
Course Number
Course Section
1st Semester Grade
2nd Semester Grade
3rd Semester Grade
4th Semester Grade
Course Credit Earned

In order to conduct the analysis, the two data sets were combined to form an all-encompassing merged student data set (see table 3). Given the size of the data, which was too large for excel, all database management was conducted using the R software package and required a significant amount of programming to merge data across identifying student characteristics. Given that the demographic data is most pertinent and interesting for this research project, all of it was included in the final all-encompassing student data set. In order to distinguish whether a student is affected by the Arkansas Computer Science Initiative, the variable “Fiscal Year” was also included in the final data set. Given that the relative impact of the “initiative” across race was deemed to be of interest the final data set categorized students in terms of 7 distinct race groups (White, Black, Hispanic, Asian, Pacific Islander or Hawaiian native, Native American or Alaskan native, and students identifying with 2 or more races). To account for differential impacts of the “initiative” on economically disadvantaged students, a free and reduced lunch classification was used to identify such students. Finally, a new binary variable labelled “Computer Science Course” which was designated with a binary yes or no (“Y/N”) value was created to track participation across individual students. This indicator variable was constructed using information from the Arkansas Department of Education’s classifications for computer science course data, labelled “Course Number” in the initial data (see table 2).

Table 3

Student Data
Research ID
Freshman Year
Fiscal Year
Grade Level
Gender
Race
Gifted and Talented Status
Free and Reduced Lunch Status
Limited English Proficient Status
District LEA
School LEA
Computer Science Course

One of the most challenging aspects of this data was that students can move schools and/or districts within a given academic year, resulting in them being represented in the database multiple times. There are records of students moving up to three times in one year. It was decided that a student would get a separate row in the student data set for every district and school that they went to, that way the connection between taking of a computer science course and the location could be observed. This is important because there were some cases where a student would not be taking a computer science course in the first school they were in, but then would move schools and take a computer science course there.

Figures 1 through 6 summarize the raw student demographic data with respect to overall Arkansas high school student population (figures 1, 3 and 5) and with respect to computer science participation (figures 2, 4 and 6) over the 10-year period. Figures referring to computer science participation show the ratio of the number of student participants in at least one computer science class in a specific academic year to the total number of students attending high school in a specific academic year.

From figure 1 we can see the overall Arkansas high school student population increased by about 20,000 students over the 10-year period, while the ratio of females to males remained constant at about 50%.

Figure 1

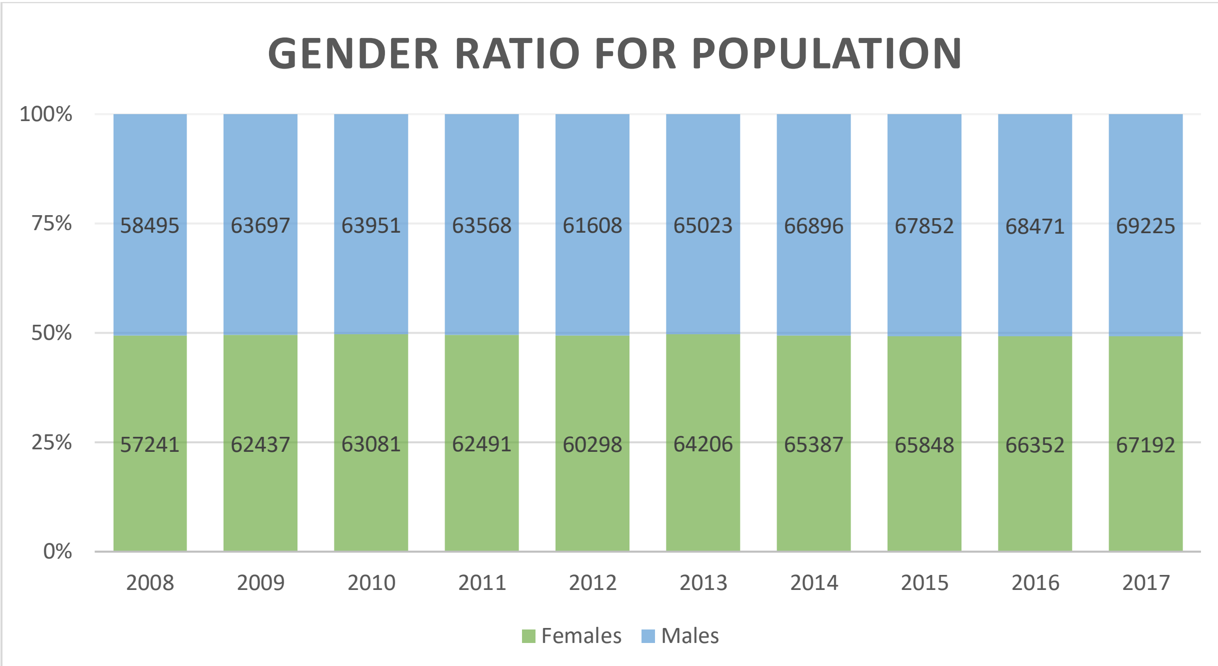


Figure 2 shows that the percentage of female students enrolled in at least one computer science class has stayed around 25% consistently over the eight years before the "initiative" (2007-08 – 2014-15). In the two years after the "initiative" (2015-16 – 2016-17), that percentage increased to around 30%. However, although this suggests that the "initiative" has had a positive impact on female student computer science participation, that figure is still far from the desired 50% consistent with the overall population ratio.

Figure 2

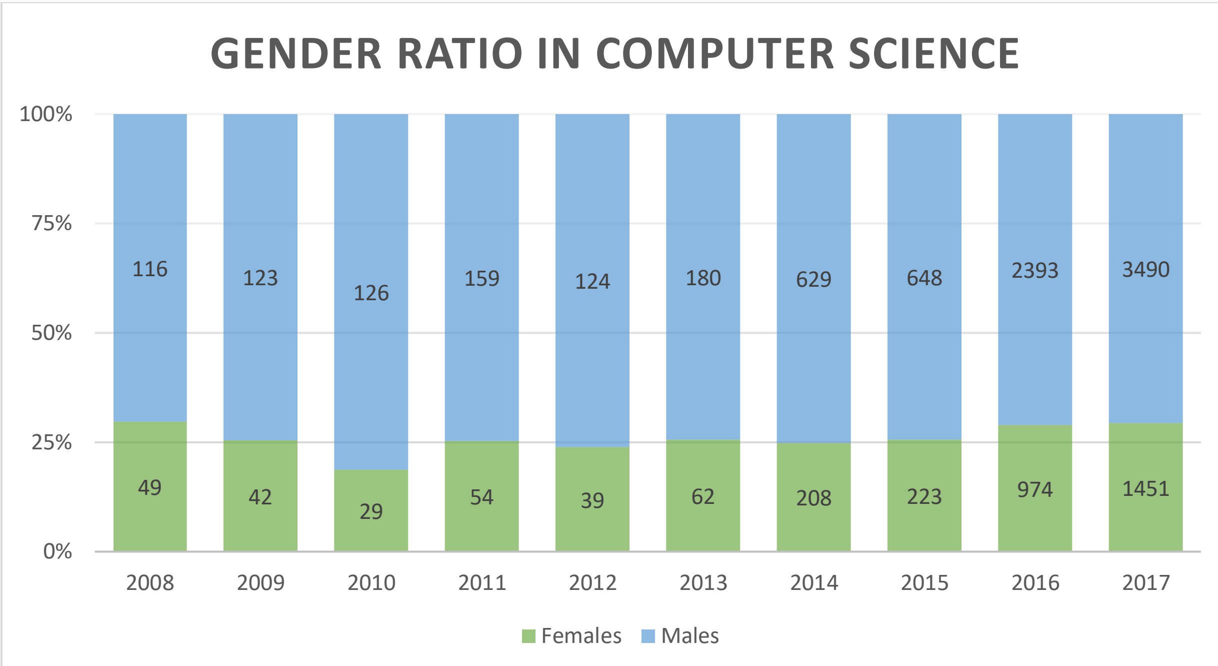
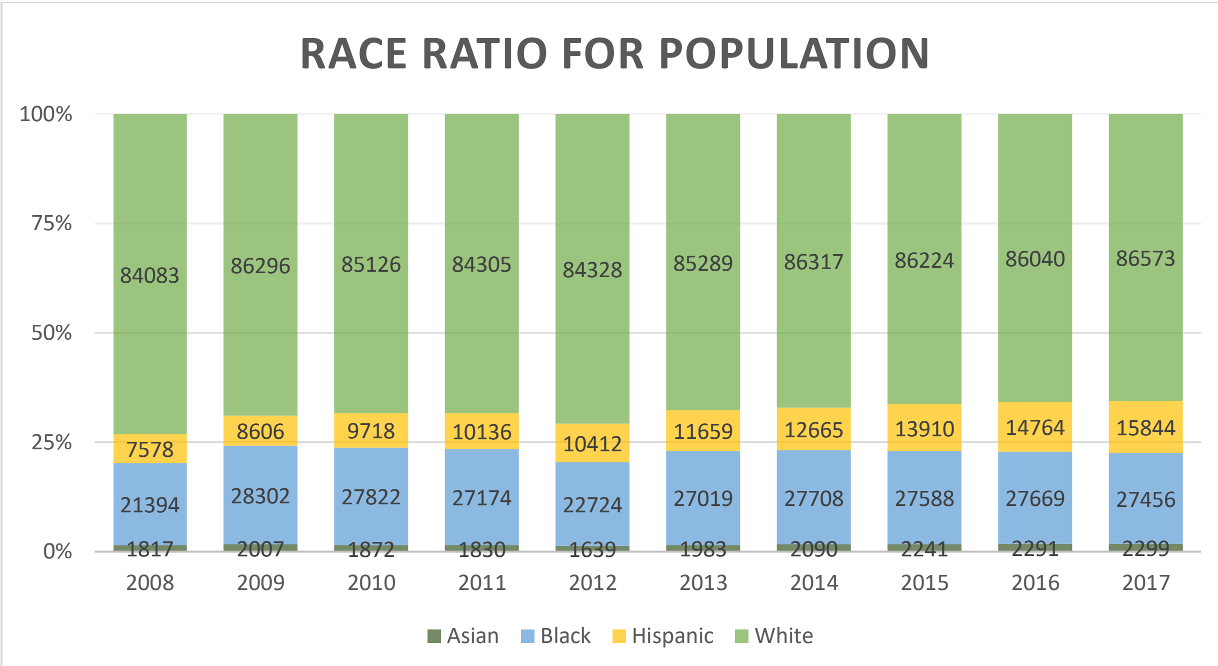


Figure 3 depicts the overall population by race, but only includes the four largest race categories (Asian, Black, Hispanic, and White). All these races increased in numbers over the 10-year period, but only the Hispanic population significantly increased their population percentage by practically doubling their population size over the 10 years.

Figure 3



In Figure 4 we see the race ratios (for the four largest race categories: Asian, Black, Hispanic, and White) for students enrolled in at least one computer science course in comparison to the overall student population. Overall, in the eight years prior to the "initiative," Asian students are highly overrepresented, Black students are highly underrepresented, White students are almost accurately represented, and Hispanic students increase to being slightly overrepresented in the last couple of years.

In the two years after the "initiative," although Asian students increase their overall participation in computer science, with respect to their overall population ratio they are no longer as overrepresented as they were prior to the "initiative". In contrast, Black students gain in both population and overall population representation. White students remain at about the same level of overall population representation, and finally Hispanic students have become slightly underrepresented compared with the overall population.

Figure 4

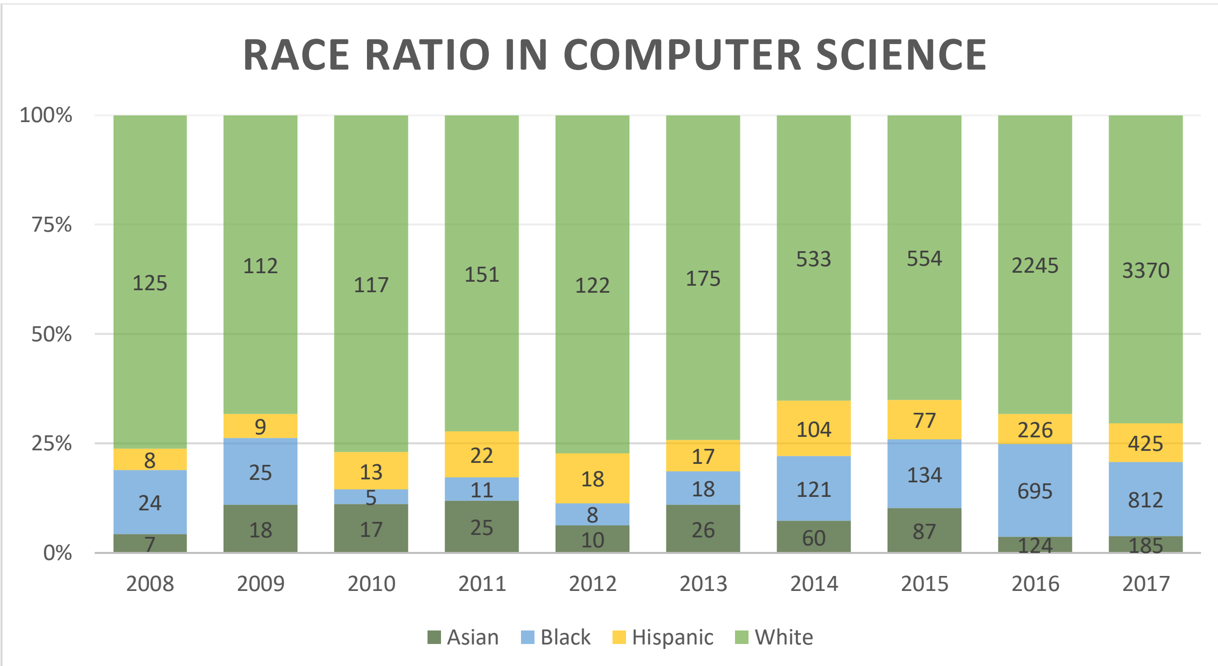


Figure 5 shows the population ratio for students who qualify for free and reduced lunch program – the economically disadvantaged – with respect to normal students who do not qualify for the program. Over the 10-year period the percentage of students who qualify for free and reduced lunch has increased from around 45% (less than half) to around 55% (more than half).

Figure 5

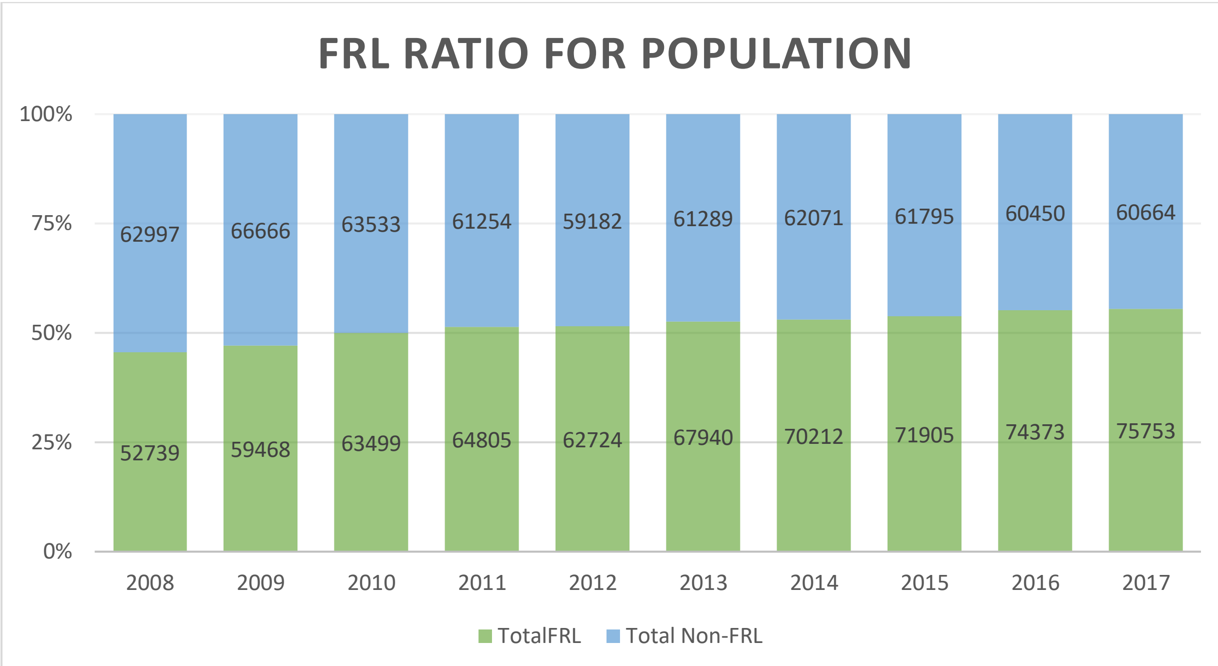
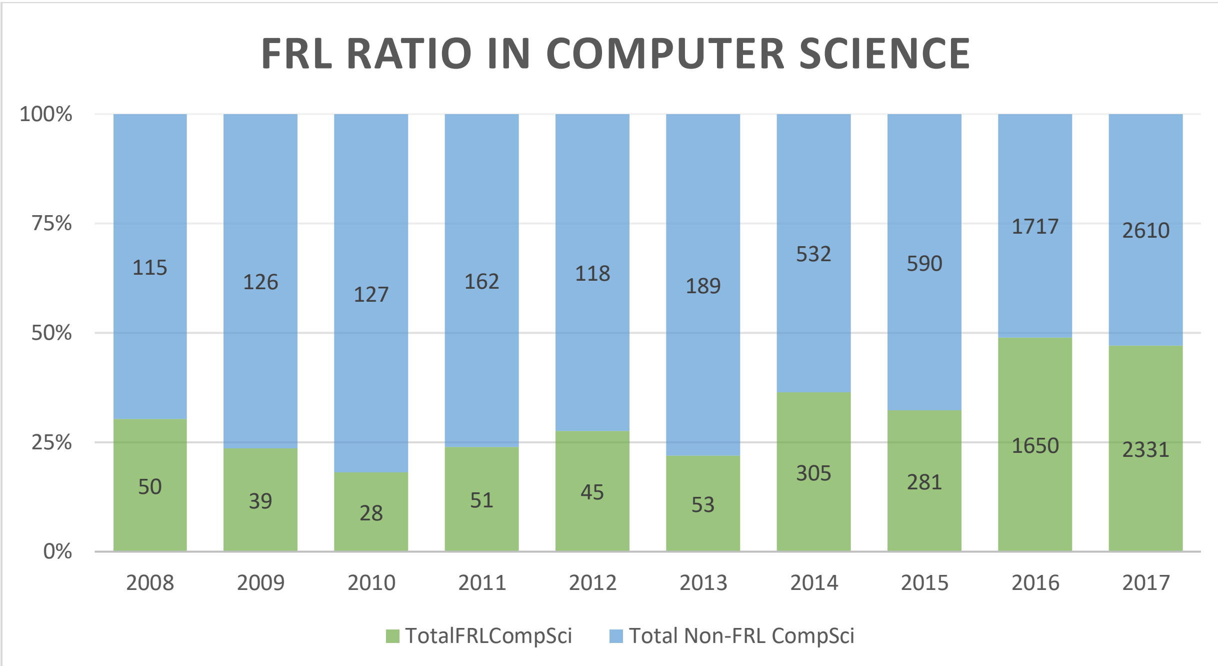


Figure 6 presents the ratio of students enrolled in at least on computer science course who also qualify for free and reduced lunch program with respect to normal students who do not qualify for the program. In the eight years before the "initiative," the percentage of students who qualify for free and reduced lunch and who are also enrolled in a computer science course are way less than half of the overall population, meaning that they were a very underrepresented group. However, encouragingly in the two years after the "initiative," that percentage increased to just under 50%, greatly closing the gap. It appears that the "initiative" has helped poorer students increase their participation in learning computer science skills.

Figure 6



Methods

To statistically analyze the impact of the "initiative" on Arkansas students' computer science participation with respect to overall population and diversity, a forecasting regression is used to perform a counterfactual analysis. A counterfactual analysis measures the impact of a policy intervention – in this case the Governor's "initiative" – against the hypothetical situation in which the policy was never implemented. The counterfactual refers to the hypothetical outcomes that would have been expected if the policy had never been introduced and these outcomes are compared with the actual outcomes observed after the policy implementation. The forecasting regression is estimated using the data prior to the "initiative" and is subsequently used to forecast computer science participation for the overall population and student subcategories based on race, gender, and income in the absence of the "initiative" – the counterfactual situation.

The Ordinary Least Squares (OLS) forecasting regression only included a simple time trend as an explanatory variable and can be written as:

(1) $CSP_{it} = \alpha + \beta(trend) + e_{it}$,

Where CSP_{it} represents student participation by sub-group *i* in at least one computer science course in a given academic year t. The "trend" variable takes on the value of 1 for academic year 2007-08 and increases in unit increments for each subsequent year up to 2014-15, the year prior to the "initiative." The term a is constant and β is a regression coefficient measuring the percentage change in computer science participation for each sub-group by year. The term e_{it} is the regression error term.

Specifically, the various CSP_{it} sub-groups are:

(a) The ratio of students taking at least one computer science course over students in the overall population.

(b) The ratio of female students taking at least one computer science course over the total number of female students in the overall population.

(c) The ratio of male students taking at least one computer science course over the total number of male students in the overall population.

(d) The ratio of Asian students taking at least one computer science course over the total number of Asian students in the overall population.

(e) The ratio of Black students taking at least one computer science course over the total number of Black students in the overall population.

(f) The ratio of Hispanic students taking at least one computer science course over the total number of Hispanic students in the overall population.

(g) The ratio of White students taking at least one computer science course over the total number of White students in the overall population.

(h) The ratio of students who qualify for free and reduced lunch services taking at least one computer science course over the total number of students who qualify for free and reduced lunch services.

It was necessary to regress computer science participation by each sub-group on a trend variable to account for the natural increase in computer science participation over time, which would have occurred irrespective of whether the “initiative” was introduced.

Once the regressions were estimated the coefficient values (α and β) were used to forecast the hypothetical counterfactual situation of sub-group computer science participation over the last 2 years, assuming the “initiative” was not introduced. Then these counterfactual forecasts were compared to the actual observed sub-group computer science participation in the last 2 post-initiative years. A statistical difference in these two sets of values would indicate that the “initiative” had a significant impact.

To determine the statistical difference, prediction intervals were estimated for the various sub-group participation forecasts with respect to the last 2 years. Specifically, CSP_{it} forecasts and prediction intervals were constructed for the 2015-16 and 2016-17 years using the following formulas.

(2) $\widehat{CSP}_{i\,t} = \alpha + \beta(trend)$

(3) $LPI_{i\,t} = \widehat{CSP}_{i\,t} - (tstat * se)$

(4) $UPI_{i\,t} = \widehat{CSP}_{i\,t} + (tstat * se)$

Where $\widehat{CSP}_{i\,t}$ is the forecast of sub-group computer science participation for the 2015-16 and 2016-17 years. $LPI_{i\,t}$ represents the lower 95% prediction interval and $UPI_{i\,t}$ is the upper 95% prediction interval. The term *tstat* is the critical t-value statistic at the 5% level with n-2 degrees of freedom, and the term se is the standard error of the regression.

Results

The forecasting regression results for each of the sub-group computer science participation levels are reported in tables 4 through 11. Clearly the regressions do a reasonably good job explaining variation in sub-group computer science participation for the years prior to the "initiative". All the R-squared values range from 48% to 70% and all the trend variable coefficients are statistically different from zero.

Table 4 (Percentage of Students Taking a Computer Science Course)

Summary Output						
Regression Statistics						
Multiple R	0.7903					
R Square	0.6245					
Adjusted R Square	0.5619					
Standard Error	0.1522					
Observations	8					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	1	0.2312	0.2312	9.9791	0.01959	
Residual	6	0.1390	0.0232			
Total	7	0.3702				
	Coefficients	*Standard Error*	*t Stat*	*p-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.0627	0.1186	-0.5285	0.6161	-0.3529	0.2275
Trend	0.0742	0.0235	3.1590	0.0196	0.0167	0.1317

Table 5 (Percentage of Female Students Taking a Computer Science Course)

Summary Output						
Regression Statistics						
Multiple R	0.7751					
R Square	0.6007					
Adjusted R Square	0.5342					
Standard Error	0.0810					
Observations	8					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	1	0.0593	0.0593	9.0264	0.0239	
Residual	6	0.0394	0.0066			
Total	7	0.0987				
	Coefficients	*Standard Error*	*t Stat*	*p-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.0311	0.0631	-0.4932	0.6394	-0.1857	0.1234
Trend	0.0376	0.0125	3.0044	0.0239	0.0070	0.0682

Table 6 (Percentage of Male Students Taking a Computer Science Course)

Summary Output						
Regression Statistics						
Multiple R	0.7947					
R Square	0.6316					
Adjusted R Square	0.5702					
Standard Error	0.2219					
Observations	8					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	1	0.5064	0.5064	10.2866	0.0184	
Residual	6	0.2954	0.0492			
Total	7	0.8017				
	Coefficients	*Standard Error*	*t Stat*	*p-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.0926	0.1729	-0.5357	0.6114	-0.5156	0.3304
Trend	0.1098	0.0342	3.2073	0.01843	0.0260	0.1936

Table 7 (Percentage of Asian Students Taking a Computer Science Course)

Summary Output						
Regression Statistics						
Multiple R	0.8346					
R Square	0.6966					
Adjusted R Square	0.6460					
Standard Error	0.7234					
Observations	8					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	1	7.2092	7.2092	13.7738	0.0100	
Residual	6	3.1404	0.5234			
Total	7	10.3496				
	Coefficients	*Standard Error*	*t Stat*	*p-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.3355	0.5637	-0.5952	0.5734	-1.7149	1.0438
Trend	0.4143	0.1116	3.7113	0.0100	0.1411	0.6875

Table 8 (Percentage of Black Students Taking a Computer Science Course)

Summary Output						
Regression Statistics						
Multiple R	0.6956					
R Square	0.4838					
Adjusted R Square	0.3978					
Standard Error	0.1463					
Observations	8					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	1	0.1204	0.1204	5.6240	0.0554	
Residual	6	0.1284	0.0214			
Total	7	0.2488				
	Coefficients	*Standard Error*	*t Stat*	*p-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.0805	0.1140	-0.7063	0.5065	-0.3595	0.1984
Trend	0.0535	0.0226	2.3715	0.0554	-0.0017	0.1088

Table 9 (Percentage of Hispanic Students Taking a Computer Science Course)

Summary Output						
Regression Statistics						
Multiple R	0.7444					
R Square	0.5542					
Adjusted R Square	0.4799					
Standard Error	0.1896					
Observations	8					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	1	0.2681	0.2681	7.4591	0.0341	
Residual	6	0.2156	0.0359			
Total	7	0.4837				
	Coefficients	*Standard Error*	*t Stat*	*p-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.0777	0.1477	-0.5261	0.6177	-0.4392	0.2837
Trend	0.0799	0.0293	2.7311	0.0341	0.0083	0.1515

Table 10 (Percentage of White Students Taking a Computer Science Course)

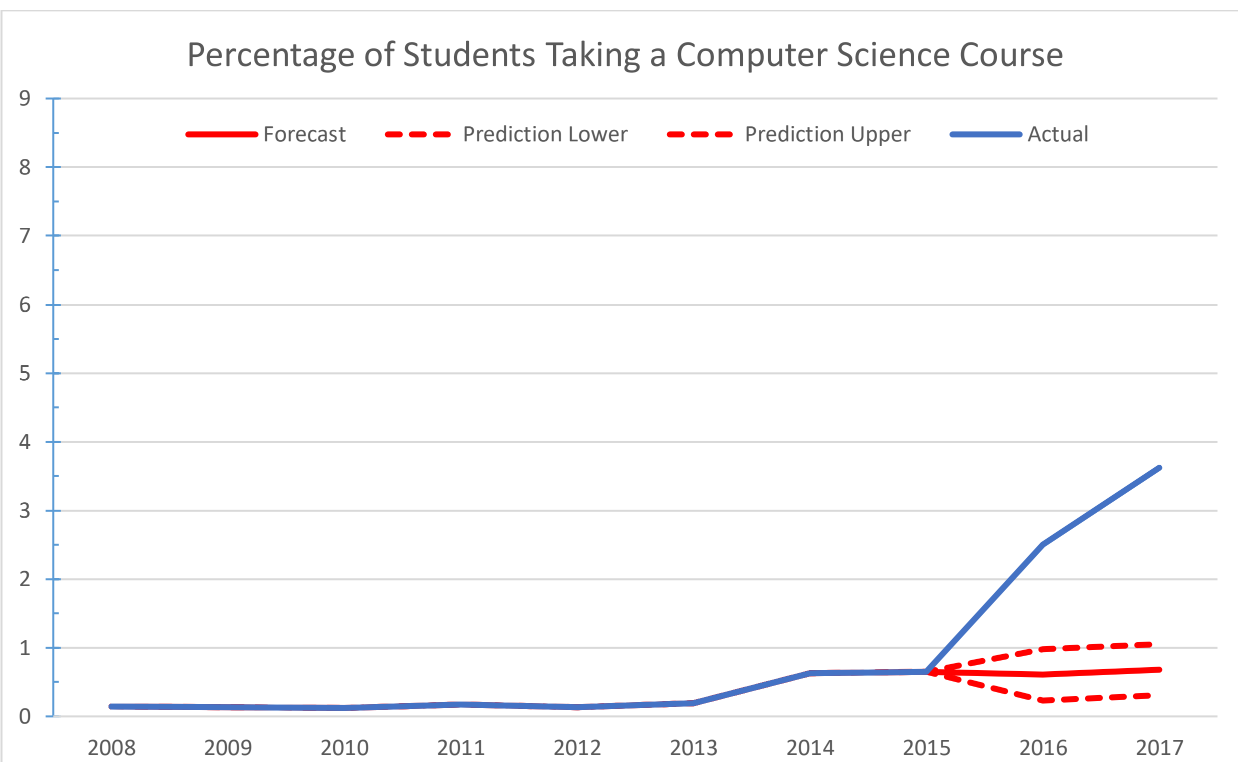
Summary Output						
Regression Statistics						
Multiple R	0.8031					
R Square	0.6450					
Adjusted R Square	0.5858					
Standard Error	0.1417					
Observations	8					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	1	0.2189	0.2189	10.9009	0.0164	
Residual	6	0.1205	0.0201			
Total	7	0.3394				
	Coefficients	*Standard Error*	*t Stat*	*p-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.0493	0.1104	-0.4462	0.6711	-0.3195	0.2209
Trend	0.0722	0.0219	3.3016	0.0164	0.0187	0.1257

Table 11 (Percentage of FRL Students Taking a Computer Science Course)

Summary Output						
Regression Statistics						
Multiple R	0.7371					
R Square	0.5434					
Adjusted R Square	0.4673					
Standard Error	0.1158					
Observations	8					
ANOVA						
	df	*SS*	*MS*	*F*	*Significance F*	
Regression	1	0.0958	0.0958	7.1396	0.0369	
Residual	6	0.0805	0.0134			
Total	7	0.1762				
	Coefficients	*Standard Error*	*t Stat*	*p-value*	*Lower 95%*	*Upper 95%*
Intercept	-0.0576	0.0902	-0.6383	0.5469	-0.2784	0.1632
Trend	0.0477	0.0179	2.6720	0.0369	0.0040	0.0915

The counterfactual forecasts of sub-group computer science participation are shown in figures 7 – 14. From figure 7, we can see that the ratio of student computer science participation to the overall student population was extremely low at around 0.15% and had a flat trend, indicating no noticeable increase until the 2013-14 academic year, which corresponds with the beginning of the Governor's campaign for office, and when he began talking about his proposed "initiative." Governor Asa Hutchinson was running for office in 2013 and 2014 and was elected in November of 2014 (Asa Hutchinson). Noticeably, we can see that the level of student participation in computer science courses increases dramatically after the "initiative," jumping up to 2.5% in 2015-16 and then to 3.6% in 2016-17. This increase is clearly statistically significant as the actual levels of participation are much higher than the 95% upper prediction interval. The Governor's "initiative" undoubtedly had a positive impact on overall computer science participation.

Figure 7



Figures 8 – 14 depict a similar story with again the Governor's "initiative" having a statistically significant and positive impact within each sub-group on computer science participation. However, there are some interesting differences across the sub-groups. For example, as seen in figures 8 and 9, while both the female and male student sub-groups follow the same pattern as the overall students (figure 7) of beginning their increase around the time of the Governor's campaign and then increasing much more quickly at the start of the "initiative," the percentage of female students taking at least one computer science course only makes it up to 2.2% while the percentage of male students taking at least one computer science course rises all the way to 5%.

Figure 8

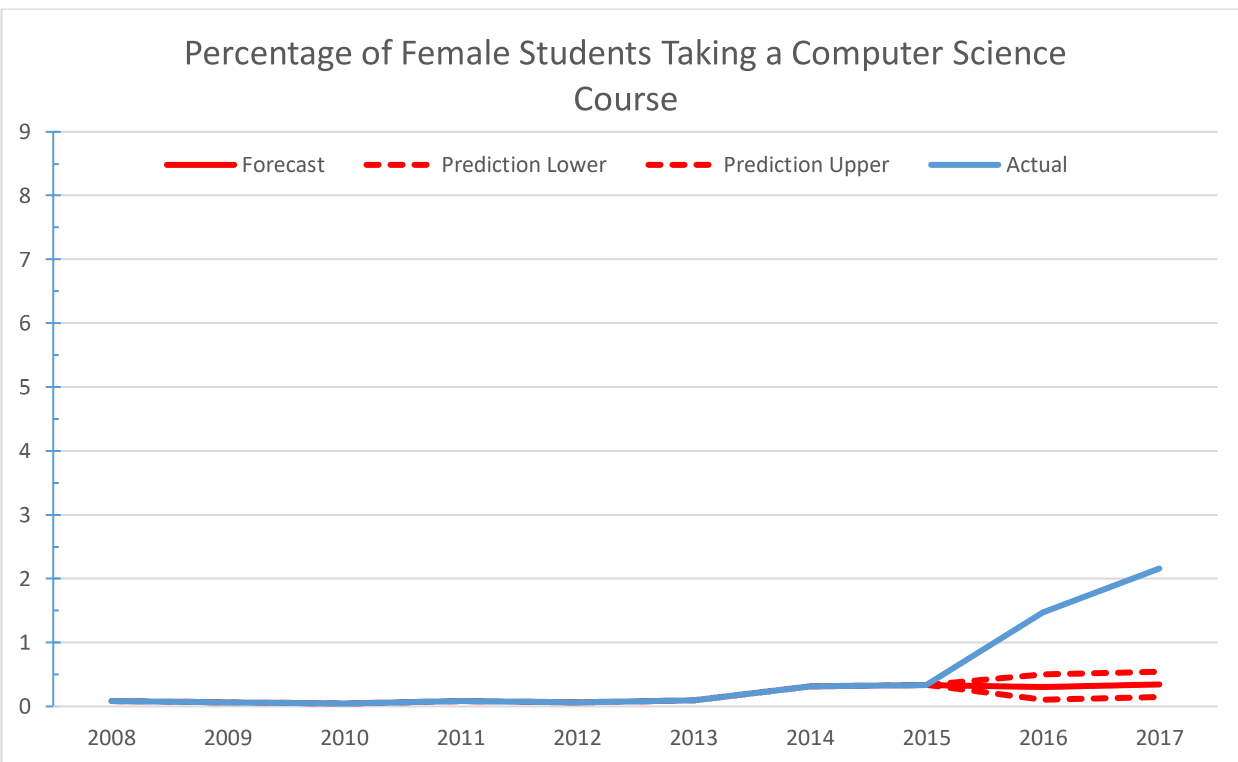
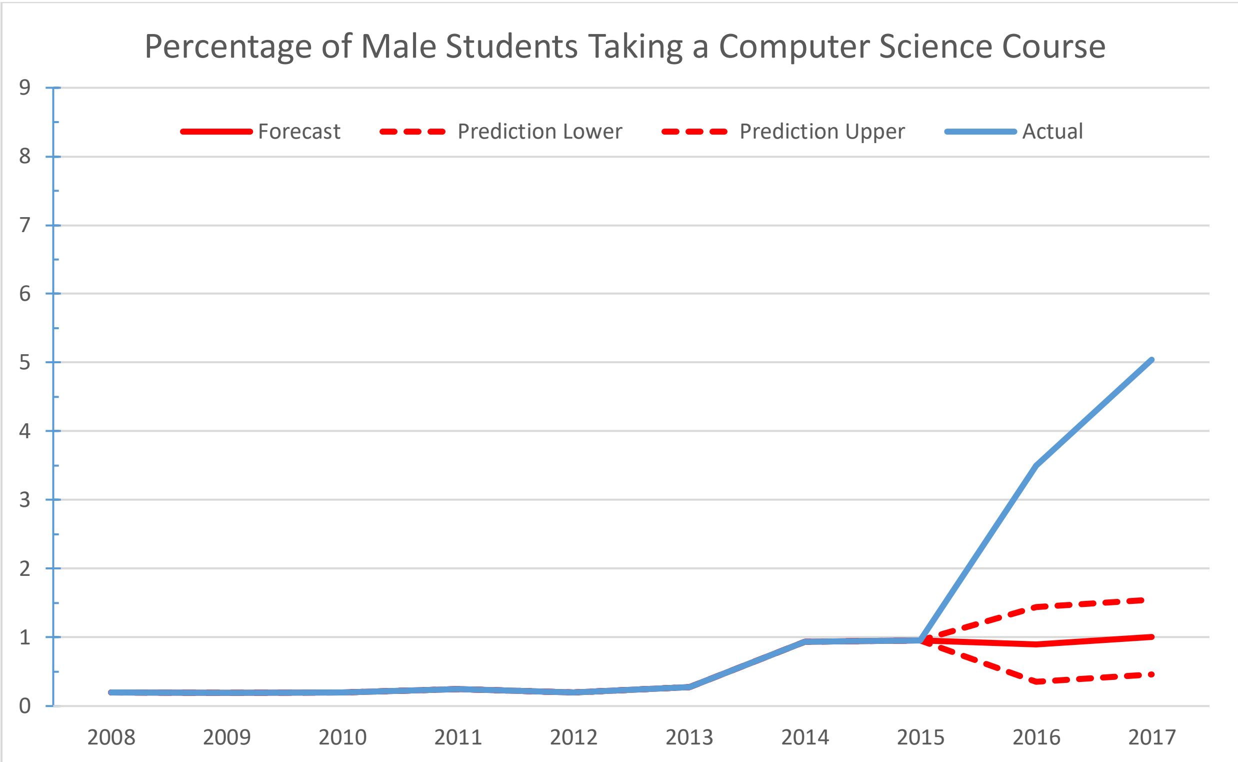


Figure 9



Similarly, figures 10 – 13 show that while the percentage of Black and Hispanic students taking at least one computer science course rise to about 3%, the percentage of White students taking at least one computer science course almost reaches 4%, and the percentage of Asian students nearly doubles that by reaching 8%. Indeed, the number of Asian students taking computer science courses showed a remarkable trend over the 2 years immediately before the "initiative." These disparities show that while the "initiative" is increasing participation in all sub-groups, White and Asian males are still dominating the classroom.

Figure 10

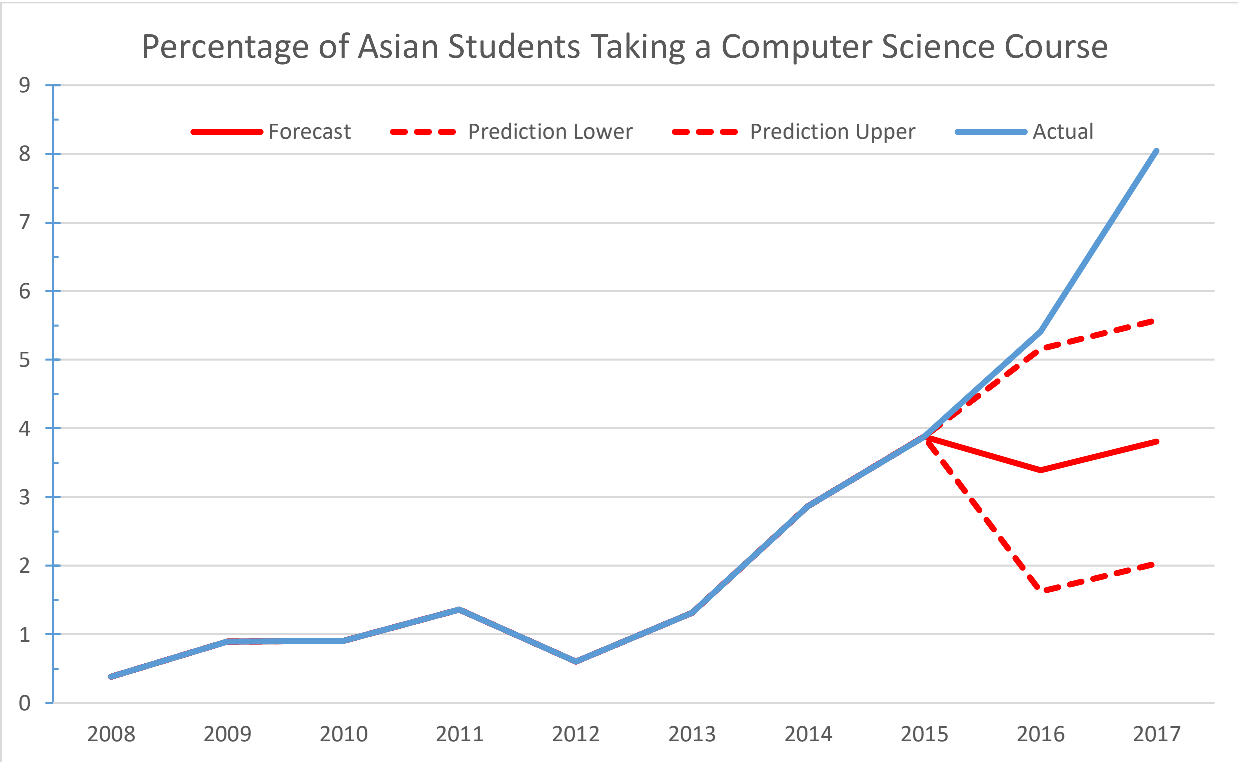

Percentage of Asian Students Taking a Computer Science Course
Forecast
Prediction Lower
Prediction Upper
Actual
0
1
2
3
4
5
6
7
8
9
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

Figure 11

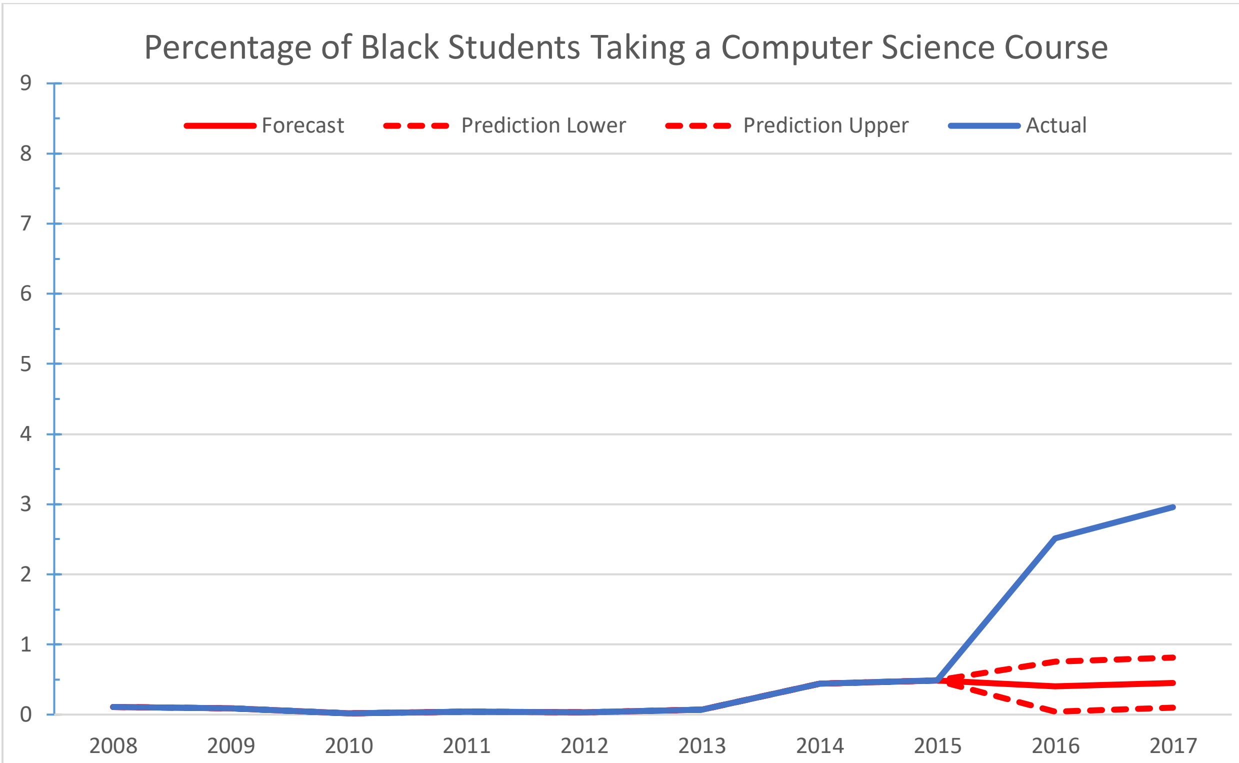
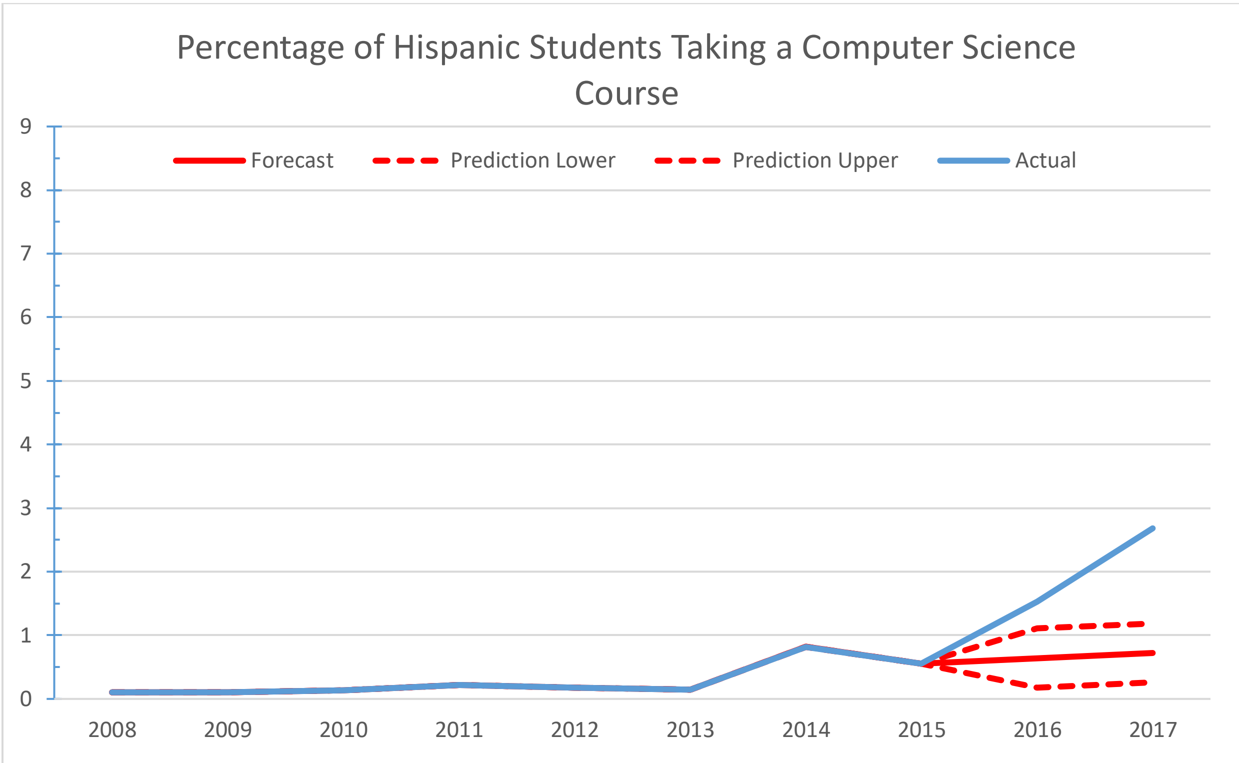
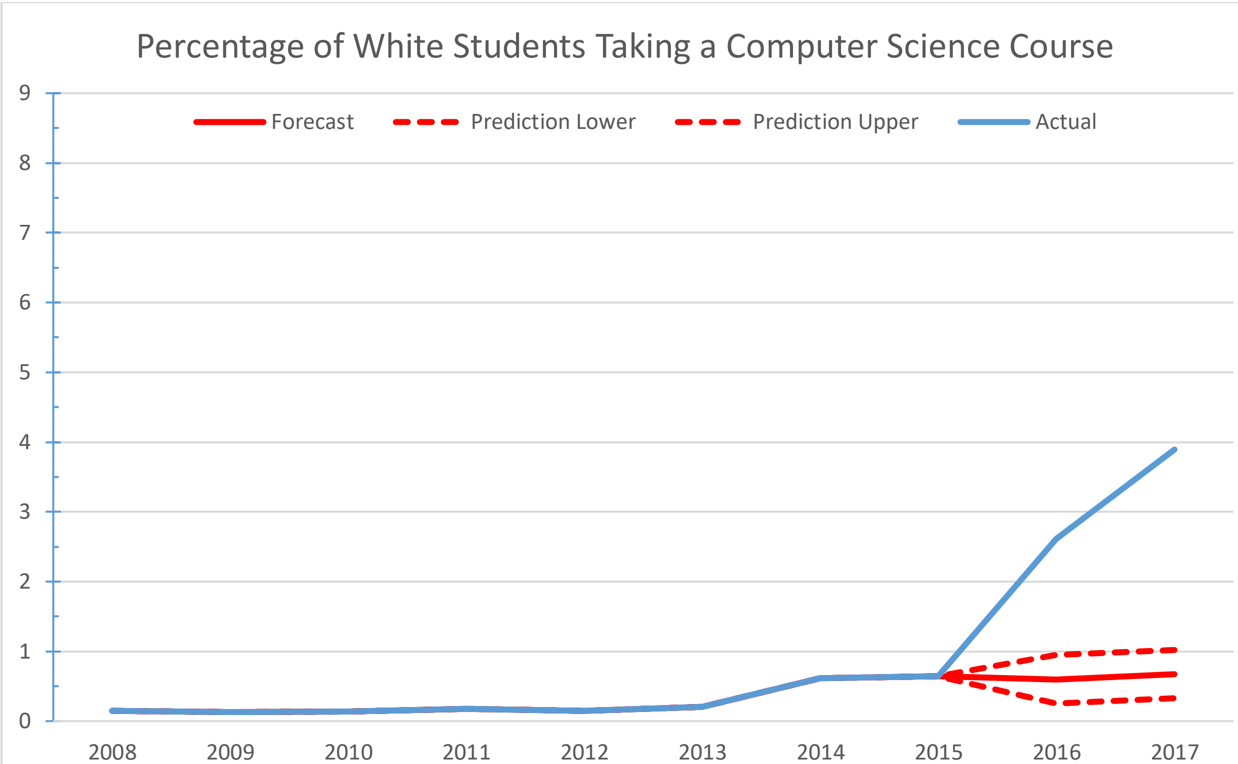

Percentage of Black Students Taking a Computer Science Course
Forecast
Prediction Lower
Prediction Upper
Actual
0
1
2
3
4
5
6
7
8
9
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

Figure 12



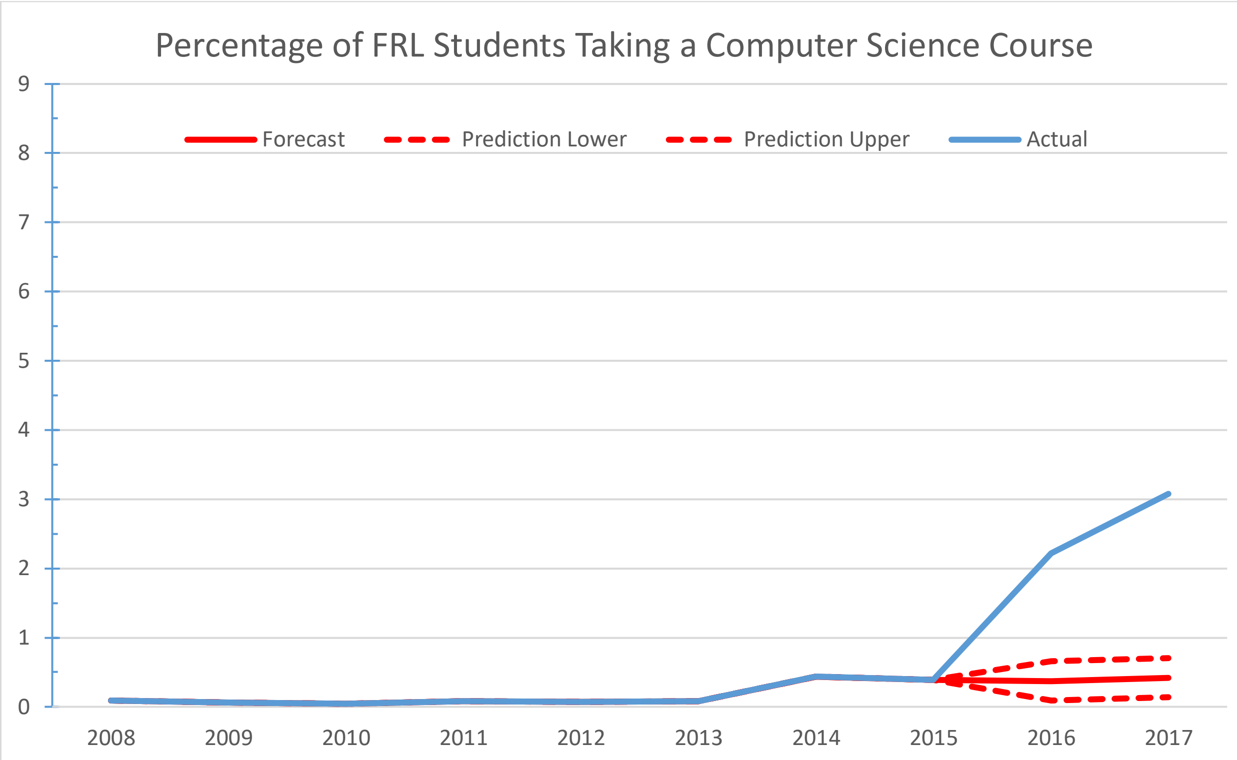
Percentage of Hispanic Students Taking a Computer Science Course
Forecast
Prediction Lower
Prediction Upper
Actual
9
8
7
6
5
4
3
2
1
0
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017

Figure 13



Finally, figure 14 shows that the "initiative" tripled the percentage of students enrolled in at least one computer science course who are also enrolled in the free and reduced lunch program. This is particularly heartening as hopefully computer science skills will help this group break the poverty cycle.

Figure 14



Summary and Conclusions

Perhaps most importantly, this research shows that Governor Asa Hutchinson's "Computer Science Initiative" significantly increased the number of students enrolling in at least one computer science course across gender, racial, and economic sub-groups. However, regardless of these increased levels, participation is still much less than desired levels. Participation within each sub-group is still very low with Asian students recording the largest participation levels of 8% relative to their overall student body size. Given the importance of computer science skills in the modern world, desirable levels of participation for all students and across sub-groups should probably be closer to at least 20%, with much higher levels optimal. In fact, in an ideal world every high school student irrespective of race, gender, or economic background would be exposed to at least one computer science course. Therefore, it is imperative that the "initiative" should be continued.

In addition, to some extent the "initiative" also improved diversity in computer science participation by improving the representation of some groups of students. Students with free and reduced lunch services made great improvements, most likely because the "initiative" gave students in more rural districts, and therefore higher populations of students with free and reduced lunch services, access to computer science courses that they wouldn't have received otherwise. Black students also saw huge improvements in their representation, beginning with less 0.1% of Black students taking a computer science course in the 2007-08 school year, to nearly 3% in the 1016-17 school year. This increase led to Black students becoming closer to their appropriate level of computer science participation relative to their overall size in the population. The initiative also resulted in Asian students in computer science losing some of their overrepresentation, but they still grew the most of any sub-group.

However, notwithstanding these improvements in diversity, there is still much room for improvement, with female students requiring far greater participation to raise them to the appropriate levels commensurate with their overall size in the population. Although female students saw great improvement in numbers of students participating in computer science courses, male student participation increased even more. In fact, female representation in comparison to males – the ratio of female to males – only increased modestly from around 25% prior to the "initiative" to around 30% following the "initiative." Also, although Hispanic students did grow in their overall percentage of participation, they lost representation, staying marginally underrepresented. However, this can likely be explained by the districts that have historically had computer science courses being the districts with the largest Hispanic population in the state (i.e. Northwest Arkansas).

In summary, the “initiative” has had a positively significant influence on Arkansas student computer science participation and should be continued in the years to come. Given that participation numbers across sub-groups have experienced large positive trends in the aftermath of the “initiative” one might expect that over time the “initiative” may well help increase participation far beyond current levels for all students and improve diversity in participation.

The results of this research are of relevance to educators at all levels from high schools to universities and community colleges, as well as to state policy makers and private industry. A well-educated student body entering the workforce with computer science skills is imperative to fostering higher economic growth within the State. A better understanding of how well education policy – such as the “initiative” – is helping students achieve these skills is important so that the policy can be tweaked if necessary. Similarly, high school educators can better design computer science curricula if they know current and trending levels of student participation. In addition, at higher education levels, colleges such as the College of Engineering at the University of Arkansas, should find the results of interest, as it indicates likely future demand for computer science courses and how diverse might be their future student body.

On a final note, a future research direction might look at the underlying causes as to why certain population sub-groups remain underrepresented and how overall numbers of participation might be increased. It would also be interesting to examine grade performance to see if certain sub-groups are doing better than others in computer science classes. Additionally, grade performance could be analyzed to see if better grades in computer science classes result in subsequent participation in additional higher-level computer science courses.

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