Computer Science for All? The Impact of High School Computer Science Courses on College Majors and Earnings

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  - 450,000 open computing jobs in 2022, but only 90,000 students who received a computer science (CS) Bachelor degree (Code.org)
- Large gaps by gender, race/ethnicity, and socioeconomic backgrounds
  - Only 25% of all computing jobs are held by women (Ashcraft et al., 2016)
  - Large disparities by race/ethnicity and socioeconomic status as well

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- MD CS for All legislation passed in 2018
  - All high schools need to offer at least one "high-quality" CS course by school year 2021-22
- Little research on how the introduction of CS coursework affects student long-run outcomes

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  - Increasing secondary STEM course offerings raises educational attainment and likelihood of earning STEM degrees, especially for males (De Philippis 2021; Broecke 2013; Görlitz and Gravert 2018; Darolia et al., 2020)
  - Providing more advanced secondary math coursework increases educational attainment, math-intensive degree receipt, and earnings (Rose and Betts 2004; Goodman 2019; Levine and Zimmerman 1995; Joensen and Nielsen 2016)

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- This is the first causal study that evaluates how CS coursework affects student postsecondary and labor market outcomes

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  - Difference-in-Differences and Instrumental Variables

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  - Difference-in-Differences and Instrumental Variables
- Findings:
  - Taking a CS course did not change likelihoods of high school graduation or earning a BA degree, but significantly increased the chance of majoring in CS in first-/second-year of college and earning a CS BA degree
  - Unexpected exposure to HQ CS courses also raised students' chance of employment and annual earnings at age 24
  - Effects are larger for female, low-income, and Black students for CS BA degree receipt and labor market outcomes
  - However, take-up rates are lower for female, Black, Hispanic, and low baseline math scores students

Policy Background

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- MD HB 281 CS Education for All legislation required all HS to offer high-quality (HQ) CS by 2021-2022
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  - MCCE convened an expert panel to provide a streamlined HQ CS definition based on the alignment between School Codes for the Exchange of Data and the Maryland Computer Science Standards
  - HQ vs. Any CS

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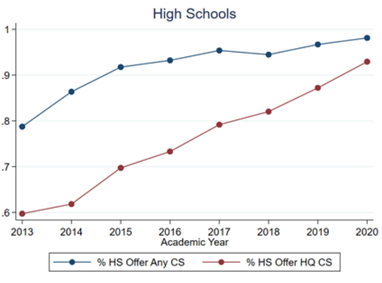
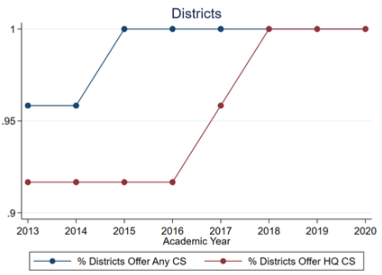
Table 1: Distribution of High-Quality Computer Science Course-Taking in Analytic Sample

SCED Code	SCED Course Title	CS Course Type	N	Percent
10971	Computer Science Essentials-CTE	Foundational CS	726	27.76%
10970	Foundations of Computer Science-CTE	Foundational CS	293	11.20%
10201	Web Page Design	Foundational CS	261	9.98%
10012	Exploring Computer Science	Foundational CS	136	5.20%
10171	Information Technology-Other	Foundational CS	75	2.87%
10952	Advanced Computing Concepts and Information Technologies-CTE	Foundational CS	-	-
10951	Introduction to Programming and Applications-CTE	Foundational CS	-	-
10972	AP Computer Science Principles-CTE	AP CS	597	22.83%
10973	AP Computer Science A-CTE	AP CS	182	6.96%
10157	AP Computer Science A	AP CS	104	3.98%
10011	Computer Science Principles	AP CS	85	3.25%
10019	AP Computer Science Principles	AP CS	33	1.26%
10155	Java Programming	Programming & Cybersecurity	51	1.95%
10152	Computer Programming	Programming & Cybersecurity	40	1.53%
10154	C++ Programming	Programming & Cybersecurity	-	-
10153	Computer Programming - Other Language	Programming & Cybersecurity	-	-
10108	Network Security	Programming & Cybersecurity	-	-
10020	Cybersecurity	Programming & Cybersecurity	-	-

Policy Background: School and District Rollout





Data: Overview

- Linked administrative data from the Maryland Longitudinal Data System (MLDS) Center
  - 2008-2019 K-12 student enrollment data
  - 2013-2021 course data
  - 2008-2021 HS graduation
  - 2008-2022 postsecondary enrollment, graduation, majors, and earnings

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  - 2008-2022 postsecondary enrollment, graduation, majors, and earnings
- Outcome variables:
  - First-year "enroll" in college and CS major
  - Second-year "persist" in college and CS major
  - College graduation, CS degree, and degrees in other fields
  - Employment and income for ages 23-25

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  - 50,507 students in 58 high schools

Data: Summary Statistics

Table 2: Summary Statistics

	(1) Population	(2) Analytic Sample
Female	0.490	0.502
Free/Reduced Lunch	0.338	0.523
Black	0.348	0.498
Hispanic	0.126	0.118
White	0.410	0.312
Asian	0.060	0.025
Multiracial	0.052	0.042
English Learner	0.035	0.037
Special Education	0.123	0.162
Math Score	-0.056	-0.435
ELA Score	0.005	-0.318
Science Score	0.009	-0.385
School Total Enrollment	1,505	990
HQ CS Exposure	0.758	0.373
Took HQ CS	0.101	0.044
Any CS Exposure	0.859	0.594
Took Any CS	0.177	0.100
HS Grad in 4 Years	0.875	0.785
Enroll in College	0.631	0.509
Enroll and CS Major	0.034	0.020
Persist in College	0.545	0.408
Persist and CS Major	0.038	0.021
BA in 4 Years	0.190	0.104
CS BA in 4 Years	0.014	0.006
Earnings Age 23	$21,277	$20,198
Earnings Age 24	$24,885	$22,857
Earnings Age 25	$27,353	$24,699
N	635,771	50,507
N Schools	233	58

Treatment Timeline

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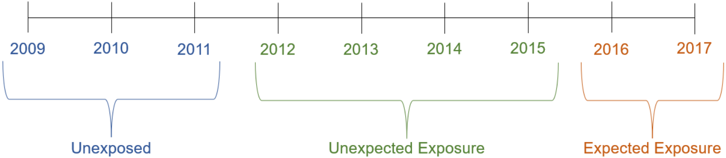
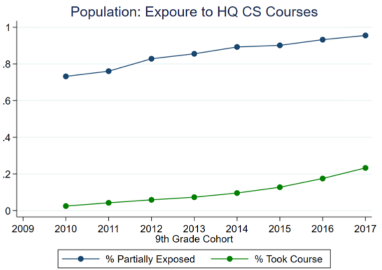
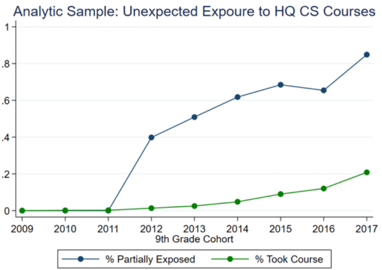
- Consider a school that begins offering HQ CS in 2015

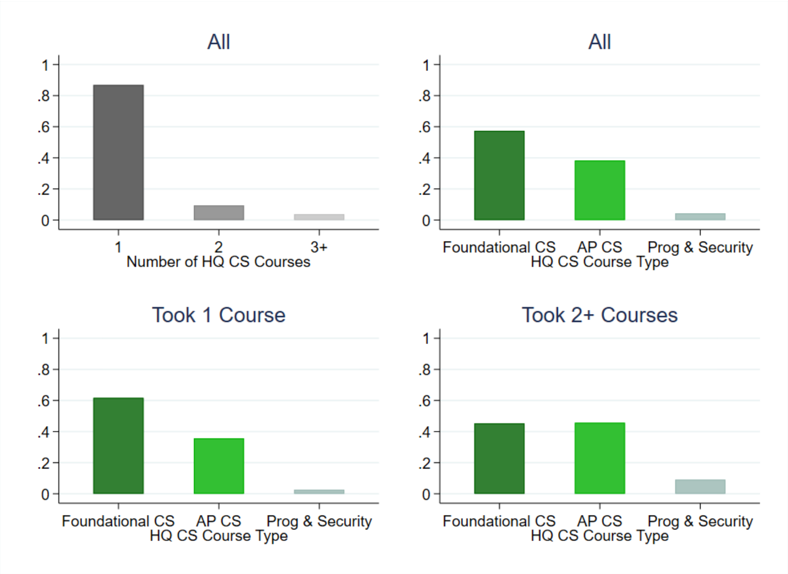


Student Access to HQ CS





Course-taking Patterns



Identification Strategy

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- Two layers of selection
  - Selection of students into high schools based on whether HQ CS is offered→exploit within-school cross-cohort variation in exposure to HQ CS
  - Selection of students into HQ CS within a high school→only use school-level variation through instrumenting CS course-taking with unexpected exposure (only varies at school-cohort level)

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- Within-school cross-cohort variation in exposure to HQ CS by comparing cohorts unexpectedly exposed to HQ CS to unexposed cohorts
- Estimate both reduced-form (RF) and Local Average Treatment Effects (LATE) in most cases

Empirical Strategy

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- Basic specification:

$$Y_{isc} = \gamma_s + \pi_c + \alpha_1 X_{isc} + \alpha_2 HQCS_{isc} + \eta_{isc} \tag{1}$$

  - Y_{isc} refers to the outcomes for student i in high school s and cohort c
  - γ_s and π_c refer to high school and cohort fixed effects, respectively
  - X_{isc} is a vector of individual and school characteristics
  - $HQCS_{isc}$ indicates whether student i took at least one HQ CS course in school s
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- 2SLS specification:

$$P(HQCS_{isc}) = \gamma_s + \pi_c + \beta_1 X_{isc} + \beta_2 PartialExpo_{sc} + u_{isc} \tag{2}$$

$$Y_{isc} = \gamma_s + \pi_c + \delta_1 X_{isc} + \delta_2 \widehat{HQCS}_{sc} + \epsilon_{isc} \tag{3}$$

  - δ_2 LATE of taking HQ CS for compliers

Effects of HQ CS on Typical Educational Attainment

Table 3: HQ CS Effects on Educational Attainment

	(1) HS Grad	(2) Enroll	(3) Persist	(4) BA Grad
Panel 1: RF Estimates				
Z	0.0108	0.0034	0.0006	0.0007
	(0.0095)	(0.0095)	(0.0085)	(0.0049)
Unexpo Mean	[.7675]	[.4933]	[.3918]	[.0991]
% Change	{1.41%}	{.70%}	{.15%}	{.71%}
N	50,507	50,507	50,507	43,871
N Schools	58	58	58	57
Panel 2: IV Estimates				
HQ CS	0.1751	0.0555	0.0097	0.0128
	(0.1738)	(0.1527)	(0.1362)	(0.0864)
Unexpo Mean	[.7675]	[.4933]	[.3918]	[.0991]
% Change	{22.81%}	{11.25%}	{2.48%}	{12.87%}
F-stat	16.5679	16.5679	16.5679	13.5183
N	50,507	50,507	50,507	43,871
N Schools	58	58	58	57

Results: CS Major

Table 4: HQ CS Effects on CS Majors

	(1) OLS CS Maj	(2) FS HQ CS	(3) RF CS Maj	(4) IV CS Maj	(5) IV CS Maj
Panel 1: Enroll and CS Major					
HQ CS	0.0654***			0.1019***	0.0738*
	(0.0130)			(0.0364)	(0.0434)
Z		0.0617***	0.0063***		
		(0.0153)	(0.0021)		
Unexpo Mean	[.0161]	[.0068]	[.0161]	[.0161]	[.0161]
% Change	{405.27%}	{911.22%}	{38.91%}	{630.99%}	{456.74%}
F-stat				16.3157	7.0743
N	48,196	48,196	48,196	48,196	48,196
N Schools	58	58	58	58	58
Panel 2: Persist and CS Major					
HQ CS	0.0704***			0.1200***	0.1253*
	(0.0139)			(0.0408)	(0.0693)
Z		0.0618***	0.0074***		
		(0.0154)	(0.0027)		
Unexpo Mean	[.0165]	[.0066]	[.0165]	[.0165]	[.0165]
% Change	{428.01%}	{944.08%}	{45.09%}	{729.13%}	{761.01%}
F-stat				16.2328	6.8163
N	49,181	49,181	49,181	49,181	49,181
N Schools	58	58	58	58	58
Panel 3: CS BA in 4 Years					
HQ CS	0.0338***			0.0547***	0.0753
	(0.0099)			(0.0185)	(0.0535)
Z		0.0551***	0.0030***		
		(0.0150)	(0.0010)		
Unexpo Mean	[.0043]	[.0039]	[.0043]	[.0043]	[.0043]
% Change	{783.12%}	{1410.15%}	{69.92%}	{1267.92%}	{1747.3%}
F-stat				13.5259	8.4135
N	43,849	43,849	43,849	43,849	43,849
N Schools	57	57	57	57	57
Trends					X

Results: 2SLS for Other Majors

Table 5: HQ CS Course-Taking Effects on Other Majors

	(1) CS	(2) Other STEM	(3) Non-STEM	(4) Engi	(5) Health	(6) Bus	(7) Soc Sci	(8) Hum	(9) Edu
Panel 1: Enroll and Major									
HQ CS	0.1019***	-0.1301**	0.0860	-0.0876**	0.0366	0.0067	-0.0177	0.2444	-0.0489
	(0.0364)	(0.0589)	(0.1426)	(0.0347)	(0.0622)	(0.0663)	(0.0381)	(0.1703)	(0.0453)
Unexpo Mean	[.0161]	[.0434]	[.4029]	[.0166]	[.046]	[.0399]	[.0189]	[.2665]	[.0213]
% Change	{631%}	{-300%}	{21%}	{-526%}	{80%}	{17%}	{-93%}	{92%}	{-229%}
F-stat	16.3157	16.3157	16.3157	16.3157	16.3157	16.3157	16.3157	16.3157	16.3157
N	48,196	48,196	48,196	48,196	48,196	48,196	48,196	48,196	48,196
N Schools	58	58	58	58	58	58	58	58	58
Panel 2: Persist and Major									
HQ CS	0.1200***	-0.1005*	0.0239	-0.0585**	0.0512	-0.0278	-0.0502	0.1065	-0.0337
	(0.0408)	(0.0536)	(0.1242)	(0.0245)	(0.0518)	(0.0532)	(0.0381)	(0.1178)	(0.0416)
Unexpo Mean	[.0165]	[.043]	[.3128]	[.0144]	[.0399]	[.041]	[.0256]	[.1759]	[.0222]
% Change	{729%}	{-234%}	{8%}	{-405%}	{128%}	{-68%}	{-196%}	{61%}	{-152%}
F-stat	16.2328	16.2328	16.2328	16.2328	16.2328	16.2328	16.2328	16.2328	16.2328
N	49,181	49,181	49,181	49,181	49,181	49,181	49,181	49,181	49,181
N Schools	58	58	58	58	58	58	58	58	58
Panel 3: BA Grad in 4 Years and Major									
HQ CS	0.0547***	-0.0494	0.0206	-0.0115	0.0516*	0.0227	-0.0656	-0.0517	-0.0140
	(0.0185)	(0.0461)	(0.0871)	(0.0253)	(0.0303)	(0.0296)	(0.0428)	(0.0395)	(0.0229)
Unexpo Mean	[.0043]	[.0154]	[.0792]	[.0038]	[.008]	[.0117]	[.024]	[.0175]	[.0066]
% Change	{1268%}	{-321%}	{26%}	{-302%}	{646%}	{194%}	{-274%}	{-296%}	{-211%}
F-stat	13.5259	13.5259	13.5259	13.5259	13.5259	13.5259	13.5259	13.5259	13.5259
N	43,849	43,849	43,849	43,849	43,849	43,849	43,849	43,849	43,849
N Schools	57	57	57	57	57	57	57	57	57

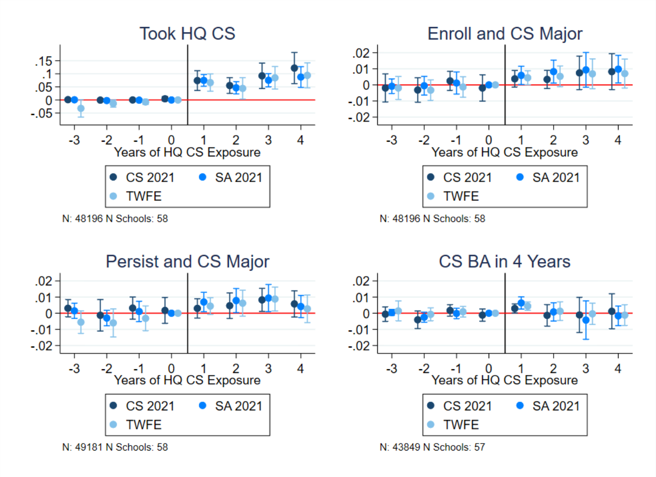
Specification for Event Study

- Nonparametric event study specification:

$$Y_{isc} = \gamma_s + \pi_c + \phi_n \sum_{n=-3}^{4} \mathbb{1}(EventTime_{sc} = n) + v_{isc} \tag{4}$$

  - ϕ_n is the effect of HQ CS exposure n cohorts before or after course is first offered

Results: Event Study



TWFE: Two-way fixed effects; SA: Sun & Abraham (2021); CS: Callaway & Sant'Anna (2021)

Complier Analysis

Table 6: Characterizing Compliers with First-Stage Coefficients

	(1)	(2)	(3)	(4)
Panel 1: Gender and Socioeconomic Status				
	Females	Males	FARMS	Not FARMS
Z	0.0502***	0.0726***	0.0532***	0.0638***
	(0.0128)	(0.0191)	(0.0126)	(0.0208)
Ratio wrt Full FS	.8137	1.1765	.8617	1.0341
N	24,035	24,161	25,583	22,613
Panel 2: Race				
	Black	Hispanic	White	Asian
Z	0.0620***	0.0389**	0.0582***	0.1320**
	(0.0144)	(0.0182)	(0.0193)	(0.0653)
Ratio wrt Full FS	1.0041	.6303	.9432	2.1393
N	24,100	5,795	14,861	1,175
Panel 3: Quartiles of Math Achievement				
	1st Q	2nd Q	3rd Q	4th Q
Z	0.0396***	0.0496***	0.0323***	0.1052***
	(0.0126)	(0.0132)	(0.0111)	(0.0303)
Ratio wrt Full FS	.6419	.8036	.5243	1.7045
N	12,081	10,727	13,332	12,056

Complier Analysis and Heterogeneity for CS Majors

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- Male, students not eligible for free or reduced price meals, Asian, and higher-achieving students are more likely to take HQ CS when offered the opportunity compared to their peers

Complier Analysis and Heterogeneity for CS Majors

- Male, students not eligible for free or reduced price meals, Asian, and higher-achieving students are more likely to take HQ CS when offered the opportunity compared to their peers
- Inconsistent heterogeneity comparing first-year CS major vs. CS BA degree receipt
  - Positive, large, and significant effects for traditionally overrepresented or higher-achieving students (e.g., 12.6 pp for white student but null result for Black students)
  - underrepresented subgroups and lower-achieving students benefit more on CS BA receipt (e.g., 30% bigger for Black students compared to white students, with both coefficients significant)

Heterogeneity: CS Majors

Panel 2: Race

	Black	Hispanic	White	Asian
Enroll and CS	0.0908	0.0264	0.1260**	0.3118
	(0.0607)	(0.1310)	(0.0510)	(0.2685)
F-stat	15.9496	5.3779	8.8700	4.1392
N	24,100	5,795	14,861	1,175
Persist and CS	0.0821	0.0165	0.1651***	0.4532
	(0.0619)	(0.2139)	(0.0466)	(0.3076)
F-stat	16.2913	5.7607	8.4297	4.1839
N	24,623	5,854	15,183	1,205
CS BA in 4 Years	0.0709**	0.0532	0.0557*	0.1172
	(0.0315)	(0.0713)	(0.0324)	(0.1237)
F-stat	11.9692	9.0688	10.1801	5.8367
N	21,677	5,276	13,648	1,108

Results: Earnings

Table 8: HQ CS Effects on Employment and Log Earnings

	(1)	(2)	(3)	(4)
Panel 1: Employment and Log Earnings for Full Sample				
	Employed at 23	Employed at 24	Employed at 25	Earnings at 24
RF	0.0001	0.0263**	0.0295**	0.0802**
	(0.0103)	(0.0100)	(0.0117)	(0.0365)
IV	0.0021	0.9603	1.1505	3.1215
	(0.2337)	(0.5844)	(0.7879)	(2.0772)
F-stat	9.8193	8.7282	4.5333	6.5259
Panel 2: Log Earnings at 24 by Gender and Socioeconomic Status				
	Females	Males	FARMS	Not FARMS
RF	0.0999*	0.0580	0.1409***	-0.0079
	(0.0580)	(0.0510)	(0.0508)	(0.0455)
IV	5.0463	1.8333	5.0519	-0.3526
	(4.3223)	(1.7939)	(3.2892)	(1.9501)
F-stat	3.5764	7.5234	4.242	6.8144
N	10,777	9,475	10,532	9,720
Panel 3: Log Earnings at 24 by Race				
	Black	Hispanic	White	Asian
RF	0.1203**	-0.0957	0.0115	-0.1147
	(0.0501)	(0.1097)	(0.0505)	(0.2222)
IV	3.4022	-43.6498	0.5863	-1.9591
	(2.3983)	(103.4302)	(2.5920)	(3.6836)
F-stat	4.2231	.1907	3.5624	1.6394
N	10,449	1,572	6,742	414
Panel 4: Log Earnings at 24 by Quartiles of Math Achievement				
	1st Q	2nd Q	3rd Q	4th Q
RF	0.0514	0.0809	0.0605	0.1184*
	(0.0734)	(0.0614)	(0.0714)	(0.0660)
IV	2.0740	3.2961	4.3554	3.5933
	(3.5059)	(2.8401)	(6.1913)	(2.4497)
F-stat	2.3709	4.1064	3.2505	5.6907
N	5,072	5,072	5,045	5,063

Discussion

- This paper finds that taking secondary HQ CS increases the likelihood of majoring in CS in the first- and second-year of college and receiving a CS degree
- Positive effects on early career labor market outcomes
- Substantial heterogeneity
  - Traditionally underrepresented groups, including female, low-SES, and Black students show stronger benefits on employment and earnings
  - However, their take-up rates of HQ CS are lower than their peers
- Policy implications:
  - "CS for All" initiatives are promising in increasing the supply of CS majors
  - More efforts to enhance underrepresented groups' participation in CS courses
- Future research:
  - CS teacher workforce
  - Explore why take-up rates are low for underrepresented groups and potential solutions

Thank You!

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Appendix: Balance Test

Table A8: Balance Tests for Changes in Observable Characteristics

	(1) TWFE	(2) CS 2021	(3) SA 2021
Female	-0.0118	-0.0243	-0.0300**
	(0.0103)	(0.0162)	(0.0138)
Free/Reduced Lunch	-0.0092	0.0283	0.0051
	(0.0129)	(0.0210)	(0.0212)
Black	-0.0144	0.0255	-0.0160
	(0.0140)	(0.0305)	(0.0206)
Hispanic	0.0180	0.0205	0.0259
	(0.0154)	(0.0217)	(0.0196)
White	-0.0020	-0.0220	0.0057
	(0.0100)	(0.0223)	(0.0152)
Asian	-0.0001	-0.0061	-0.0018
	(0.0033)	(0.0054)	(0.0039)
Multiracial	0.0017	-0.0098	-0.0062
	(0.0038)	(0.0074)	(0.0070)
English Learner	0.0092**	0.0060	0.0090**
	(0.0044)	(0.0051)	(0.0039)
Special Education	-0.0204**	-0.0140	-0.0284**
	(0.0097)	(0.0152)	(0.0141)
Math Score	0.0126	-0.0598	0.0363
	(0.0398)	(0.0615)	(0.0430)
ELA Score	0.0150	-0.0663	0.0240
	(0.0246)	(0.0572)	(0.0336)
Science Score	0.0604	-0.0661	0.0256
	(0.0385)	(0.0504)	(0.0477)
Joint Test P-Value	.1216		
N	50,506	50,506	50,506
N Schools	57	57	57