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Teacher retention in early college high schools and STEM academies: understanding the positive impacts of college and career readiness school models

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ABSTRACT

Several experimental studies find that high schools using College and Career Readiness School Models (CCRSM) produce positive postsecondary outcomes for students. Yet little research explores the internal mechanisms of these schools. We study teacher turnover in two CCRSMs implemented in Texas, called Early College High Schools and inclusive Science, Technology, Engineering, and Math Academies. We find (a) CCRSM schools have lower teacher turnover compared to traditional public high schools, (b) charter versions of CCRSM schools have higher turnover, but (c) non-CCRSM charters have the highest overall teacher turnover. We discuss implications for improving high school-based college readiness reforms.

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Teacher labor market; college readiness; charter schools; small schools; Early College High Schools; STEM academies

High school contexts play a key role in shaping students' postsecondary educational outcomes (e.g. Perna et al. 2008). In response, policymakers have designed new high school models aimed at improving conditions for teaching and learning. A growing area of quantitative, causal research finds long-term educational benefits for students attending Early College High Schools, small, specialized high schools where students earn a high school diploma and up to 60 credits toward a college degree (Atchison et al. 2021; Berger, Adelman, and Cole 2010; Berger et al. 2009; 2013; Edmunds et al. 2012; 2013; 2017). Related research highlights improved student outcomes associated with inclusive Science, Technology, Engineering, and Math (STEM) schools, small high schools with a STEM-oriented curriculum (Bicer et al. 2014; National Research Council 2011; Sahin et al. 2015; Saw 2017; 2019; Young, Adelman, Bier, Cassidy, House, et al. 2010; Young, Adelman, Bier, Cassidy, Keating, et al. 2010; Young, Adelman, Cassidy, et al. 2011). Both types of high schools represent a growing trend to embed high schools with an explicit college and career readiness mission. Texas administers the largest network of these schools nationally, where Early College High Schools and Texas STEM Academies fall under a statewide program called College and Career Readiness School Models (CCRSM). Since their inception in Texas in 2005, the state has maintained a detailed blueprint that identified schools must follow in exchange for extra resources and notoriety as a member of the statewide CCRSM program. Despite evidence of positive impacts, little quantitative research explores the inner working of these schools and policymakers have limited evidence about why these schools might be effective.

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To provide greater clarity around the mechanisms of positive impacts of CCRSM schools in Texas, we examine changes over time in teacher retention in these schools, from when they first open, up to the 2017–2018 school year. Our theoretical framework positions a stable teacher workforce as both an outcome of the CCRSM blueprint school design and a cause of previously observed positive impacts. Both traditional public school districts and charter networks have opened new CCRSM schools. We compare teacher turnover in the charter and non-charter versions of these schools to that of similar traditional non-CCRSM high schools. In most cases, new schools are opened as CCRSM schools, but in other cases, an existing traditional public school converts to an ECHS or T-STEM academies.

As hypothesized, we find that some CCRSM high schools have greater teacher retention than similar non-CCRSM high schools, but that results depend on the specific model and governance structure. Newly opened traditional (non-charter) ECHSs have especially high retention rates, whereas teacher turnover in newly opened charter ECHSs is similar to that of traditional public high schools (and significantly lower than non-CCRSM charter high schools). Newly opened charter T-STEM Academies have turnover rates similar to that of non-CCRSM charter schools. Using a difference-in-difference event-study approach, we find a small, but not statistically significant reduction in teacher retention for ‘conversion schools’ that convert from non-CCRSM into a CCRSM school. In what follows, we present in turn, background policy and research, our data and analytic approach, findings, and discussion of policy implications and conclusions.

1. Background policy and research

1.1. Policy context

Student experiences in high school influence postsecondary matriculation and success, yet historically underserved students often attend high schools that do not offer educational opportunities that promote college readiness (Bettinger et al. 2009; Castleman, Owen, and Page 2015; Engberg and Wolniak 2010; The National Academies 2007; Perna et al. 2008; Rowan-Kenyon, Perna, and Swan 2011; Schneider, Kirst, and Hess 2003; U.S. Department of Education 2013). CCRSM is a state-wide policy initiative that redesigns existing high schools and encourages the establishment of new innovative high school designs. The goal of CCRSM is to expand the number of high school graduates in Texas – especially historically underserved students – who are ready to succeed in college and in a career. According to the Texas Education Agency (2022), the network currently includes 482 campuses and continues to grow. Expansion of CCRSM since the program began has focused primarily on two school models, Early College High Schools (ECHS) and Texas STEM or T-STEM Academies.

The Texas Education Agency created a blueprint that describes the required elements of each school model (Texas Education Agency 2015; 2017). As described in the blueprint, ECHSs are generally smaller schools (e.g. 300–600 students) that specialize in dual credit coursework, where students take courses that provide credit toward both high school graduation and postsecondary education. Students in ECHSs can earn up to 60 credits leading to an associate’s degree and take many of their courses on community college campuses. ECHSs were initially established as a national initiative with support from the Bill & Melinda Gates Foundation, Carnegie Corporation, the Ford Foundation, and W. K. Kellogg Foundation. T-STEM Academies provide specialized coursework and activities related to STEM. As with ECHSs, students attending T-STEM Academies receive additional academic and career counseling supports through reduced support staffing ratios. T-STEM Academies reflect a broader national policy initiative to create ‘inclusive’ STEM schools designed to foster inclusive learning environments for women and people of color, who are underrepresented in STEM industries (Saw 2017).

Both school models are typically implemented in stand-alone high schools but can also be embedded as a school-within-a-school high school. School-within-school models are more common in larger, comprehensive high schools, where a section of the school that serves about

500 students is designated as an ECHS or T-STEM Academy. High schools sometimes use both models, but we exclude these from our sample since that approach is rare (fewer than five schools in any year) and schools using both models may have unique contexts that differ from typical settings. Stand-alone CCRSM schools are typically smaller high schools (about 500 students) where the entire campus is designated as an ECHS or T-STEM Academy (Texas Education Agency 2015; 2017). Because ECHS and T-STEM Academies can be either stand-alone or school-within-school, and can either be charter or non-charter, there are potentially eight different CCRSM school types. However, in practice charter schools do not use the school-within-school model and only five models are widely implemented. Three ECHS models are common: stand-alone charter and non-charter high schools and school-within-school non-charters. Two T-STEM models are common: stand-alone charter high schools and school-within-school non-charters. In general, T-STEM academies are more common among the charter sector, while ECHS are more often part of traditional public school districts, although there is overlap between CCRSM type and governance structure (see Table 1). School districts and charter networks interested in opening a new CCRSM school, or converting an existing high school, go through an application process leading to an initial approval, a five-year probationary period where the school is monitored more closely for implementation fidelity, and a final approval.

Figure 1 shows the number of high schools in Texas from 2004–2005 to 2017–2018, including our comparison group schools, which consist of traditional comprehensive and charter high schools (Panel A), newly opened (non-converting) CCRSM schools, and conversion CCRSM schools, which are high schools that initially open as a non-CCRSM, but then convert to a CCRSM high school.¹ This figure shows consistent growth in new stand-alone CCRSM models for both the charter and non-charter sector. The figure also shows consistent growth of newly opened non-CCRSM charter schools and traditional comprehensive high schools, both of which serve as comparison groups for our analyses of teacher turnover in CCRSM schools.

1.2. Research on the CCRSM and related models

As noted earlier, researchers have extensively studied CCRSM high school models. Extant research on ECHSs and T-STEM academies shows these high school models produce positive impacts on students (Berger et al. 2009; Berger, Adelman, and Cole 2010; Bicer et al. 2015; Sahin et al. 2015; Song et al. 2021; Young, Adelman, Bier, Cassidy, House, et al. 2010; Young, Adelman, Bier, Cassidy, Keating, et al. 2010; Young, Adelman, Cassidy, et al. 2011). In addition to several correlational studies, two lottery-based experimental studies of ECHSs by AIR (Berger et al. 2013; 2014; Haxton et al. 2016) and the SERVE Center (Edmunds et al. 2012; 2013; 2017) link attendance at these schools with positive postsecondary outcomes including enrollment and completion of both two and four-year colleges. Atchison et al. (2021) show that ECHSs produce monetary benefits to society that far outweigh social costs, producing at least an additional \$4.60 per \$1 of taxpayer investment.

Related research highlights improved student outcomes associated with inclusive STEM high schools in general, and T-STEM Academies in particular (Almus, Sahin, and Almus 2016; Bicer et al. 2014; Sahin et al. 2015; Saw 2017; 2019). Fewer studies of inclusive STEM schools or T-STEM Academies use causal methods and existing findings are more mixed. Means et al. (2016) examine inclusive STEM schools in North Carolina. They find enrollment in these schools is linked to a greater number of STEM courses completed prior to graduation and higher grade point averages, relative to a matched sample of students attending traditional high schools. However, the authors find no significant differences in students' average ACT scores. Gnagey and Lavertu (2016) similarly find limited effects of attending inclusive STEM schools, although their study focused solely on test score achievement. Young, Adelman, Bier, Cassidy, House, et al. (2010), Young, Adelman, Bier, Cassidy, Keating, et al. (2010), and Young, Adelman, Cassidy, et al. (2011) have conducted several studies of T-STEM Academies using regression and matching methods based on observable characteristics.

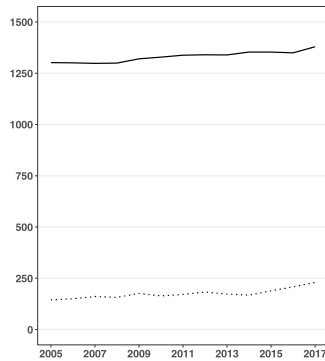
Table 1. Summary statistics for Texas high school teachers by CCRSM status, 2004–2005 to 2016–2017.

Characteristic	ECHS charter stand alone	ECHS non-charter stand alone	non-CCRSM Charter	T-STEM Charter Stand Alone	Traditional Comprehens.
Number of observations	1548	2693	42,560	5591	992,878
# of tch who leave sch	366 (24%)	500 (19%)	15,883 (37%)	1978 (35%)	196,499 (20%)
# of campuses	10 (2)	21 (8)	181 (25)	17 (6)	1337 (25)
# of school districts	8 (2)	19 (7)	90 (7)	9 (2)	904 (3)
Gender					
Female	962 (62%)	1661 (62%)	28,093 (66%)	3596 (64%)	578,483 (58%)
Male	586 (38%)	1032 (38%)	14,467 (34%)	1995 (36%)	414,395 (42%)
Race/Ethnicity					
White	845 (55%)	952 (35%)	22,100 (52%)	2671 (48%)	739,579 (74%)
Hispanic	392 (25%)	1326 (49%)	9626 (23%)	2126 (38%)	141,816 (14%)
Black	205 (13%)	328 (12%)	9021 (21%)	442 (7.9%)	87,884 (8.9%)
Asian	91 (5.9%)	53 (2.0%)	1257 (3.0%)	283 (5.1%)	13,942 (1.4%)
Other	15 (1.0%)	34 (1.3%)	556 (1.3%)	69 (1.2%)	9657 (1.0%)
Experience	9.7 (9.19)	9.6 (8.23)	5.2 (7.11)	3.1 (4.33)	12.2 (9.92)
Degree					
Bachelor	689 (45%)	1234 (46%)	32,313 (76%)	4352 (78%)	698,683 (70%)
Master	760 (49%)	1365 (51%)	8076 (19%)	1126 (20%)	268,943 (27%)
No Degree	* (<1%)	32 (1.2%)	1665 (3.9%)	48 (0.9%)	14,520 (1.5%)
Doctorate	* (6%)	62 (2.3%)	506 (1.2%)	65 (1.2%)	10,732 (1.1%)
Certificate					
Others	871 (56%)	1664 (62%)	15,899 (37%)	2007 (36%)	672,904 (68%)
No Certificate	100 (6.5%)	91 (3.4%)	21,227 (50%)	2815 (50%)	59,667 (6.0%)
Science	196 (13%)	350 (13%)	1823 (4.3%)	265 (4.7%)	75,049 (7.6%)
Math	195 (13%)	346 (13%)	1800 (4.2%)	369 (6.6%)	71,449 (7.2%)
Math & Others	119 (7.7%)	88 (3.3%)	768 (1.8%)	56 (1.0%)	50,013 (5.0%)
Others & Science	46 (3.0%)	83 (3.1%)	772 (1.8%)	48 (0.9%)	49,448 (5.0%)
Math & Science	* (1%)	38 (1.4%)	139 (0.3%)	20 (0.4%)	9877 (1.0%)
Math & Others & Sci	* (<1%)	33 (1.2%)	132 (0.3%)	11 (0.2%)	4471 (0.5%)
Annual salary (in \$)	48,457 (10,667)	51,369 (8483)	41,314 (11,733)	44,662 (7665)	48,387 (10,070)
Urbanicity					
Large Central Metro	721 (47%)	1082 (40%)	29,126 (68%)	1966 (35%)	382,756 (39%)
Large Fringe Metro	* (9%)	* (2%)	2805 (6.6%)	* (<1%)	215,760 (22%)
Medium Metro	314 (20%)	1416 (53%)	5589 (13%)	2057 (37%)	112,026 (11%)
Non-core	* (<1%)	* (<1%)	455 (1.1%)	* (<1%)	114,650 (12%)
Micropolitan	199 (13%)	137 (5.1%)	2663 (6.3%)	* (2%)	85,109 (8.6%)
Small Metro	165 (11%)	21 (0.8%)	1922 (4.5%)	1442 (26%)	82,577 (8.3%)
Enrollment size	337 (118)	353 (121)	550 (457)	713 (243)	1680 (1092)
School's oper. years					
0 years	67 (4.3%)	261 (9.7%)	3838 (9.0%)	948 (17%)	8538 (0.9%)
1 year	130 (8.4%)	336 (12%)	4007 (9.4%)	946 (17%)	10,677 (1.1%)
2 years	168 (11%)	347 (13%)	3654 (8.6%)	899 (16%)	12,916 (1.3%)
3 years	173 (11%)	290 (11%)	3408 (8.0%)	659 (12%)	13,908 (1.4%)
4 years	171 (11%)	301 (11%)	3162 (7.4%)	524 (9.4%)	15,052 (1.5%)
5 years and up	839 (54%)	1158 (43%)	24,491 (58%)	1615 (29%)	931,787 (94%)
Oper. exp. per pupil	6075 (1525)	6892 (2779)	8259 (3531)	8092 (1221)	7803 (10,965)
Proportion of stu.					
Econ. disadvantaged	0.61 (0.20)	0.69 (0.14)	0.68 (0.28)	0.65 (0.19)	0.46 (0.23)
Multi-lang. learner	0.02 (0.02)	0.03 (0.04)	0.12 (0.14)	0.15 (0.10)	0.06 (0.07)

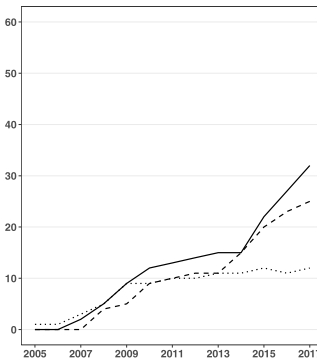
Note: CCRSM = college and career readiness school model. + implies rounded due to small cell size.

Their results show T-STEM Academies are associated with higher attendance rates and greater high school graduation rates.

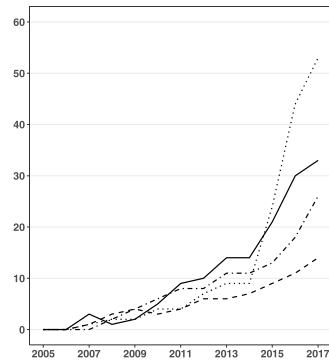
While these studies provide some evidence of the positive effects of CCRSM high schools in Texas, limited work explores the underlying mechanisms of those impacts. This study is the first to examine trends in teacher turnover in ECHS and T-STEM Academies. We pose the following two questions:

A. Non-CCRSM high schools

— Traditional comprehensive
 Non-CCRSM charter

B. Newly opened CCRSM

— ECHS non-charter standalone
 ECHS charter standalone
 --- T-STEM charter standalone
 -.-.- T-STEM non-charter standalone

C. School conversion CCRSM

— ECHS non-charter standalone
 ECHS non-charter school-within-school
 --- T-STEM non-charter standalone
 -.-.- T-STEM non-charter school-within-school

Figure 1. Number of College and Career Ready School Model high schools in Texas, by charter status, 2004–2005 to 2016–2017.

Note: ECHS = Early College High Schools; T-STEM = Texas Science, Technology, Engineering, and Math Academics. Panel A shows comparison group schools which include all non-CCRSM high schools (traditional public high schools and charter high schools). Newly opened CCRSM (Panel B) refers to high schools that initially open as a Career Ready School Model high school. School conversion CCRSM (Panel C) refers to high schools that initially opened as a non-CCRSM traditional high school or a non-CCRSM charter high school, and then converted to a CCRSM high school.

Research question 1: To what extent do CCRSM schools maintain greater teacher retention compared to traditional high schools serving similar student populations?

Research question 2: How do effects vary between charter and non-charter CCRSM schools, between provisional and designated schools, and for different types of teachers?

In the following subsection, we provide further motivation for these questions, drawing on extant literature on teacher turnover.

1.3. Teacher turnover and a theory of action

We use research on teacher retention and effective teaching and learning environments to establish a theory of action and describe our hypotheses. A stable learning environment is key to high school reforms aimed at promoting postsecondary educational success (Hansen 2014; Knight and Duncheon 2020; Martínez et al. 2024). High teacher attrition disrupts student-teacher relationships and damages school climate (Kraft and Papay 2014; Loeb, Kalogrides, and Horng 2010). Teacher turnover rates vary widely across schools; high-poverty schools and charter schools disproportionately experience chronic turnover (e.g. above 30 percent, Goldhaber and Theobald 2021; Hanushek, Kain, and Rivkin 2004; Knight et al. 2024; Malloy and Wohlstetter 2003; Stuit and Smith 2012). Meanwhile, school contexts, including those offering greater administrative support, professional development, and teacher autonomy – elements described in the Texas Education Agency’s CCRSM blueprint documents – are associated with higher teacher retention (Duncheon and DeMatthews 2018; Geiger and Pivovarova 2018; Ingersoll 2001; Johnson and Birkeland 2003; Knight 2019; 2020).

We thus hypothesize that CCRSM schools maintain lower teacher turnover compared to traditional public high schools. We further hypothesize that charter school versions of CCRSMs have higher turnover than non-charter versions of these schools, but maintain lower turnover compared to non-CCRSM charter high schools. Finally, as these schools are relatively new, we hypothesize that teacher turnover declines over the first few years, as the school establishes organizational routines after its initial opening.

2. Data and analytic approach

2.1. Data

We draw on longitudinal statewide student- and teacher-level data available through the University of Texas at Austin Education Research Center. To identify CCRSM schools, we first obtained a current list of CCRSM schools from the Texas Education Agency (TEA) that lists each school identification number and name, CCRSM status, and year of opening. By design, this list excludes CCRSM schools that closed or lost status, and surprisingly, TEA does not keep historical records of CCRSM schools for every year.² However, in addition to a current list, TEA has annual lists of CCRMS schools for many recent school years, but not for school years 2017–2018, 2015–2016, 2013–2014, or 2005–2006 to 2011–2012. We construct a longitudinal dataset of CCRSM schools using the current list of CCRSM schools and the opening date and use the annual lists to identify schools that closed or lost CCRSM status. In some cases, schools switched their names or their state-assigned identification number from one year to the next, and only maintained the same physical address. We identified these changes by matching addresses over time across various school lists. When we merged these lists to student level data, there were some cases in which a CCRSM school did not have any enrollment in its first year of operation but starts enrolling students in its second year. We include all CCRSM schools with at least one student in grade 9 and 1 student in grade 10 the following year. We define years of operation based on the years in which the school is approved and included in our analytic sample. The final sample includes information on 1,097,969 teacher-year observations from 2004–2005 to 2016–2017. We use 2017–2018 data to measure teacher turnover in 2016–2017, the final year of our analytic dataset. Our available data extend back to school year 1999–2000, and we use these first five years of data to identify year-of-opening for traditional public schools (most traditional public schools in our dataset are already open in the first year of data).

As described further below, our analysis proceeds in two parts. The first part, our primary analysis, focuses on high schools that never convert or change CCRSM types from their initial status. Three CCRSM school types fit this category and all three use the stand-alone model. These include: (a) ECHS charters; (b) ECHS non-charters; and (c) T-STEM charters.³ We use traditional high schools as the comparison group for these schools, but also draw comparisons with non-CCRSM charters that have similar student and teacher characteristics. By focusing non-converting schools, the treatment contrast is between teachers in CCRSM schools in a given year and similar teachers in similar non-CCRMS schools the same year (for models that exclude teacher fixed effects). The second part of our analysis focuses on schools that convert from traditional to one of the following CCRSM types: (a) ECHS non-charters stand-alone; (b) ECHS non-charter school-within-school; or (c) T-STEM non-charter school-within-school.⁴

Table 1 shows summary statistics for the school types in our primary analysis (non-converting schools), for all available years of our sample, and Table 2 shows the same information for 2016–2017, the last year of our analytic dataset. Row 1 of Table 1 shows the number of school-year observations and Row 2 shows the teacher attrition rate by CCRSM type, our focal outcome variable. Traditional charter schools (non-CCRSM charters) have the highest attrition rate at 37%, while the attrition rate in T-STEM charter schools is 36%. Compared to other charter schools, ECHS models that are charter schools have significantly lower attrition at 22%. The teacher attrition rate in traditional high schools is 20%, while ECHS non-charter models have the lowest attrition rate among all different types of high schools in Texas, at 18%. Figure 2 shows the distribution of teacher attrition among different CCRSM school types for all years of our data.

Tables 1 and 2 highlight important differences between both types of ECHS and other schools in our data. For example, there is a higher proportion of teachers with a master's degree for both charter and non-charter ECHS compared to other schools, which aligns with requirements for teaching dual-credit coursework (Duncheon and Muñoz 2019). Both types of ECHS have higher average

Table 2. Summary statistics for Texas high school teachers by CCRSM status, 2016–2017.

Characteristic	ECHS charter stand alone	ECHS non-charter stand alone	Non-CCRSM charter	T-STEM charter stand alone	Traditional comprehen.
Number of observations	186	570	5433	1057	84,162
# of tch who leave campus	35 (19%)	100 (18%)	1834 (34%)	347 (33%)	17,860 (21%)
# of campuses	12	32	230	25	1383
# of school districts	10	28	87	12	906
Gender					
Female	115 (62%)	354 (62%)	3679 (68%)	664 (63%)	48,583 (58%)
Male	71 (38%)	216 (38%)	1754 (32%)	393 (37%)	35,579 (42%)
Race/Ethnicity					
White	89 (48%)	220 (39%)	2757 (51%)	547 (52%)	59,102 (70%)
Hispanic	56 (30%)	266 (47%)	1396 (26%)	321 (30%)	14,318 (17%)
Black	30 (16%)	64 (11%)	989 (18%)	106 (10%)	8128 (9.7%)
Asian	* (6%)	15 (2.6%)	169 (3.1%)	64 (6.1%)	1465 (1.7%)
Other	* (<1%)	5 (0.9%)	122 (2.2%)	19 (1.8%)	1149 (1.4%)
Experience	9.5 (8.76)	10.4 (8.51)	5.0 (6.85)	4.4 (5.05)	11.8 (9.64)
Degree					
Bachelor	91 (49%)	274 (48%)	3980 (73%)	762 (72%)	57,314 (68%)
Master	88 (47%)	278 (49%)	1242 (23%)	268 (25%)	24,254 (29%)
No Degree	* (<1%)	9 (1.6%)	133 (2.4%)	14 (1.3%)	1605 (1.9%)
Doctorate	*(3%)	9 (1.6%)	78 (1.4%)	13 (1.2%)	989 (1.2%)
Certificate					
Others	93 (50%)	328 (58%)	1747 (32%)	296 (28%)	52,585 (62%)
No Certificate	27 (15%)	70 (12%)	3135 (58%)	632 (60%)	11,388 (14%)
Science	23 (12%)	59 (10%)	184 (3.4%)	42 (4.0%)	6165 (7.3%)
Math	24 (13%)	67 (12%)	188 (3.5%)	57 (5.4%)	6058 (7.2%)
Math & Others	*(2%)	17 (3.0%)	81 (1.5%)	10 (0.9%)	3537 (4.2%)
Others & Science	11 (5.9%)	15 (2.6%)	74 (1.4%)	13 (1.2%)	3523 (4.2%)
Math & Science	*(2%)	9 (1.6%)	10 (0.2%)	* (1%)	590 (0.7%)
Math & Others & Science	* (<1%)	5 (0.9%)	14 (0.3%)	* (<1%)	316 (0.4%)
Annual salary (in \$)	49,172 (13,306)	53,754 (8329)	46,205 (11,943)	49,492 (7431)	53,084 (9925)
Urbanicity					
Large Central Metro	83 (45%)	246 (43%)	3446 (63%)	333 (32%)	34,815 (41%)
Large Fringe Metro	* (9%)	23 (4.0%)	459 (8.4%)	* (<1%)	17,804 (21%)
Medium Metro	36 (19%)	243 (43%)	867 (16%)	283 (27%)	10,570 (13%)
Non-core	* (<1%)	* (<1%)	36 (0.7%)	* (<1%)	8661 (10%)
Micropolitan	19 (10%)	* (4%)	340 (6.3%)	392 (37%)	6461 (7.7%)
Small Metro	30 (16%)	37 (6.5%)	285 (5.2%)	* (5%)	5851 (7.0%)
Enrollment size	381 (111)	394 (147)	726 (567)	721 (257)	1806 (1155)
School's operating years					
0 years	* (<1%)	86 (15%)	375 (6.9%)	* (5%)	498 (0.6%)
1 year	* (<1%)	74 (13%)	871 (16%)	131 (12%)	826 (1.0%)
2 years	11 (5.9%)	94 (16%)	538 (9.9%)	204 (19%)	443 (0.5%)
3 years	* (<1%)	* (<1%)	540 (9.9%)	131 (12%)	813 (1.0%)
4 years	* (5%)	* (3%)	349 (6.4%)	* (<1%)	721 (0.9%)
5 years and up	165 (89%)	298 (52%)	2760 (51%)	540 (51%)	80,861 (96%)
Oper. exp. per pupil	6110 (1,504)	7200 (2307)	8564 (2901)	8740 (1250)	8465 (12,845)
Proportion of students					
Econ. disadvantaged	0.62 (0.21)	0.65 (0.15)	0.66 (0.29)	0.62 (0.22)	0.49 (0.23)
Multi-lang. learner	0.03 (0.02)	0.04 (0.05)	0.17 (0.16)	0.20 (0.12)	0.07 (0.08)

Note: CCRSM = college and career readiness school model.

teacher experience compared to T-STEM charter and non-CCRSM charter schools, but experience levels are generally similar to traditional high schools (see [Figure 3](#)). We also find a meaningful difference in enrollment size between ECHS, T-STEM and traditional schools. Both types of ECHS enroll, on average, about 350 students, T-STEM Academies and non-CCRSM charter schools are slightly larger on average, and traditional schools on average enroll an even larger number of students, around

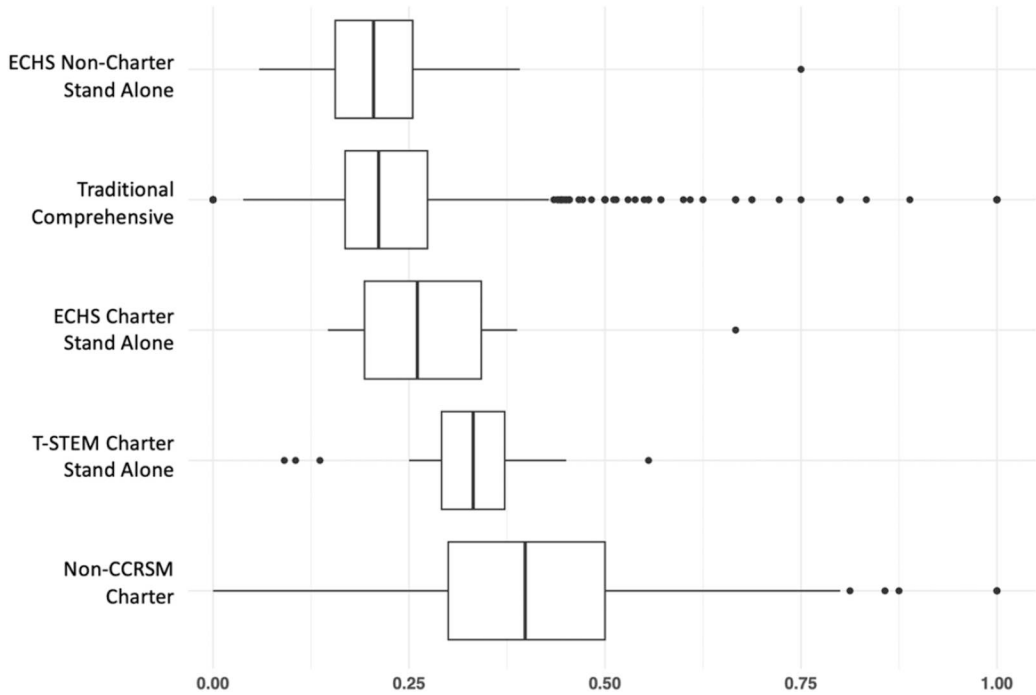


Figure 2. Distribution of teacher attrition by CCRSM school type for all available school years, 2004–2005 to 2016–2017.

Note: ECHS = Early College High Schools; T-STEM = Texas Science, Technology, Engineering, and Math Academics. Boxes represent the interquartile range and lines within boxes represent median turnover rates. Perpendicular lines represent the 95th percentiles and dots represent outliers of teacher turnover outside the 95th percentile. Graphs show only our final analytic sample of schools, which excludes school-within-school models and schools that do not change their CCRSM school type.

1700. **Figure 4** shows the distribution of enrollment size by school type. Most traditional high schools range in size from 1500 to 2500 students, but the distribution is bimodal, with a large number of traditional high schools enrolling approximately 500 students. These schools tend to be in smaller districts or in rural areas but are otherwise similar to larger comprehensive high schools in terms of student and teacher characteristics. Lastly, **Figure 5** shows the distribution of years of operating for each type of school. While most school-year observations in our data are from the fifth or greater year of operation, the data include many school-year observations of schools in their first five years of operations, particularly for CCRSM schools and for charter schools.

2.2. Analytic approach

In the first part of our analysis, we focus on schools that never convert CCRSM status. In the second part, we study schools that convert from traditional to one of several CCRSM models.

2.2.1. Part 1: analysis of ‘non-converting’ CCRSM schools

For schools that maintain the same CCRSM school type from their initial opening throughout our window of observation (‘non-converting’ schools), we use ordinary least squares regression and, in some models, include teacher and county fixed effects. We fit linear probability models of the likelihood a teacher exits their school at the end of a school year, estimating variations of [equation 1](#):

$$Exit_{ist} = \beta_0 + \beta_1 CCRSM_{st} + \beta_2 STU_{st} + \beta_3 TCH_{ist} + \beta_4 SCH_{st} + \theta_t + \varepsilon_{ist}, \quad (1)$$

where $Exit_{ist}$ is an indicator variable for whether teacher i exits their current school s , based on their school assignment in the next school year. Our key variables of interest are dummy indicators for the

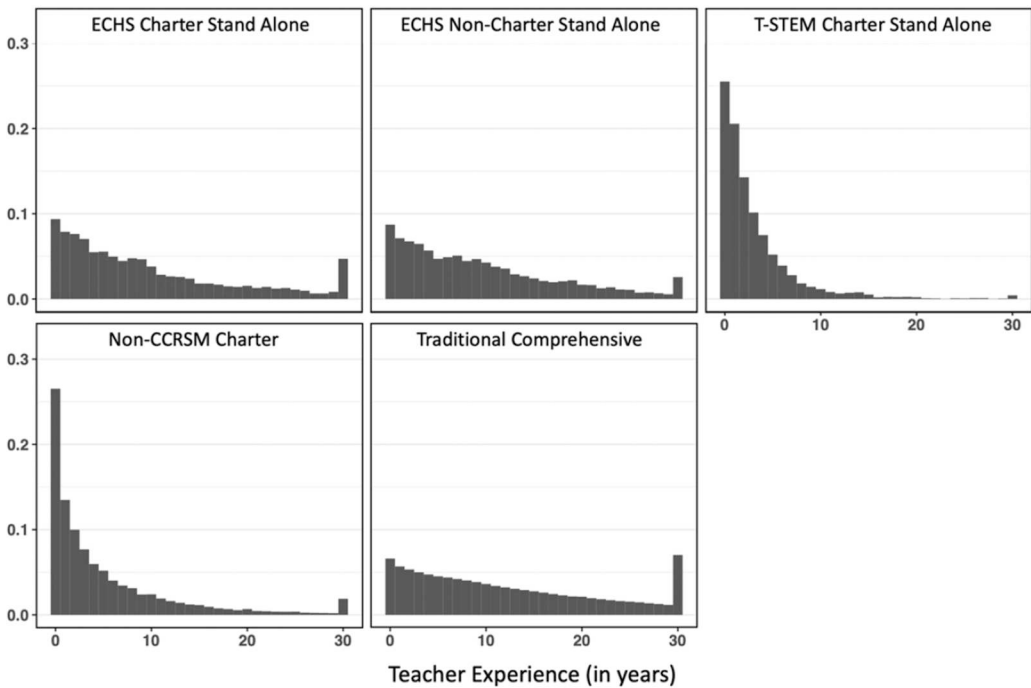


Figure 3. Distribution of average teacher experience by school type, 2004–2005 to 2016–2017.

Note: The experience variable is capped at 30 or more years. ECHS = Early College High School; T-STEM = Texas Science, Technology Engineering and Math Academy.

school type, labeled $CCRSM_{st}$. Models control for student characteristics at the school level, STU_{st} (percent of students who are classified as low-income, who identify with various racial/ethnic categories, and who score proficient on state reading and math tests), individual teacher characteristics, TCH_{ist} (race/ethnicity, gender, years of experience, educational attainment, and credential area), and school characteristics, SCH_{st} (urbanicity, enrollment size, years since the school opened, and grades served). We include year fixed effects, θ_t , in all models and add county and teacher fixed effects in subsequent specifications.

Potential omitted variables in the model described above prevents causal inference. These include unobserved regional differences, teacher characteristics, and school working conditions. County fixed effects provide controls for unobserved regional differences between treatment and comparison group schools. Some counties have an especially high number of CCRSM schools, and county fixed effects allow us to draw comparisons between these CCRSM schools and traditional non-CCRSM schools in the same county. Teacher fixed effects models control for unobserved differences in the types of teachers who work in CCRSM schools. These models compare the likelihood a teacher leaves a CCRSM school to the likelihood that same teacher leaves a traditional non-CCRSM school, for teachers who work in both CCRSM and non-CCRSM schools during our observation window (roughly 2% of all teachers and only 11% of all treatment teachers, see Table 4). About 89% of treatment teachers are observed only in a single treatment school type during the 13-year observation window and thus do not contribute to estimates for teacher fixed effects, which draw on variation in treatment within teachers. Limited mixing of individual teachers between treatment and comparison group schools reduces the power and generalizability of teacher fixed effects models. While we report teacher fixed effects models, our preferred specification omits teacher fixed effects and includes year and county fixed effects, as well as student, teacher, and school covariates.

While student and school covariates adjust for differences in working environments, we do not rule out the possibility that some schools that open as CCRSM are unique in ways not included in

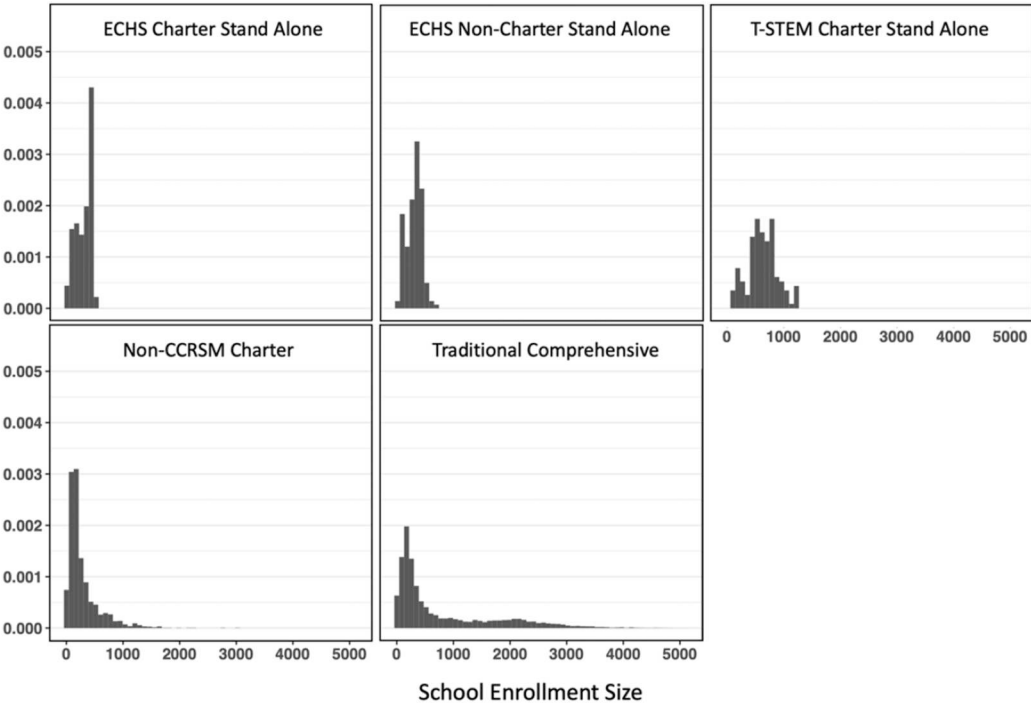


Figure 4. Distribution of school enrollment size by school type, 2004–2005 to 2016–2017.
Note: Distributions show density plots (epanechnikov kernel) with each school given equal weight. ECHS = Early College High School; T-STEM = Texas Science, Technology Engineering and Math Academy.

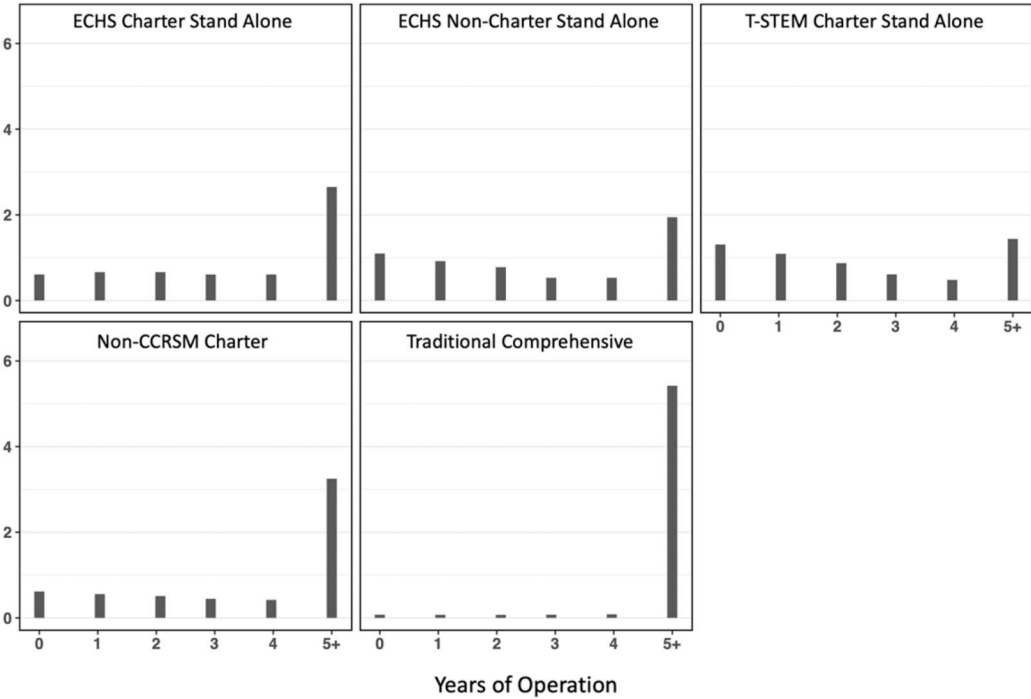


Figure 5. Distribution of school's years of operation by school type, 2004–2005 to 2016–2017.
Note: ECHS = Early College High School; T-STEM = Texas Science, Technology Engineering and Math Academy.

the CCRSM blueprint. Both the ECHS and T-STEM blueprints include extra student supports and teacher professional development, which are core elements of the intervention we are testing, and we would not want to control for these school factors. But administrators in these schools might also be more engaged or otherwise effective at supporting learning environments, which is not explicitly part of the blueprint. Estimates of the effects of CCRSM on teacher attrition might be downward bias since we do not account for these unobserved school factors. Similarly, if district leaders choose to open new schools as CCRSM when there are unique challenges facing the school, estimates would be upward bias. We do not use school fixed effects in Part 1 because non-converting schools, by definition, are only observed in the treatment on comparison group, so school fixed effects would drop treatment effects from the model. In Part 2 of our analysis, we use school fixed effects to control for these unobserved factors.

2.2.2. Part 2: analysis of CCRSM school conversions

In our second analytical approach, we consider an event-study design in which we restrict our sample to only schools that convert from a traditional high school to a CCRSM (no schools convert the other direction, from CCRSM to non-CCRSM). This event-study design can broadly be considered as a difference-in-differences model, where we take advantage of changes in school types to estimate the effect on teacher attrition. In the canonical difference-in-differences setup, there are two groups (treated and control units) and two time periods: in the first period no unit is treated while in the second period only treated units receive treatments. The main identification strategy assumes that in the absence of treatment, the average outcome for the treatment and control group would have followed parallel paths over time. When there are more than two time periods with varying treatment timing across units, researchers often implement a two-way fixed effects regression model (controlling for both time and group fixed effects). However, recent literature has shown that in the presence of heterogeneous treatment effects, interpretation of the two-way fixed effects model coefficient is tenuous (e.g. Callaway and Sant'Anna 2021; de Chaisemartin and D'Haultfoeuille 2020; Goodman-Bacon 2021; Sun and Abraham 2021). In particular, this coefficient identifies a weighted average of treatment effect where some weights may be negative.

We follow the methodology proposed by Callaway and Sant'Anna (2021), hereafter CS. They use a nonparametric approach to estimate what they call 'group-time average treatment effects.' This estimate then acts as a building block of the methodology. CS proposed various ways to aggregate group-time average treatment effects into more easily interpretable parameters. In what follows we briefly introduce the CS methodology and how we apply it for our study. For the analysis described in this section, we collapse our data at the school level, comparing average teacher retention rates across high schools.

Assume there are T periods, $t = 1, \dots, T$. Moreover, assume that no unit is treated in the first period and all treated units remain treated once they receive treatment at $t = 2, \dots, T$.⁵ Define $G_{i,g}$ to be a binary variable equal to one if school i is first treated in period g (using this notation, groups are defined by the time of their treatment) and define C as a binary variable for schools that never receive treatment. Then denote the generalized propensity score as $p_g(X) = P(G_g = 1 | X, G_g + C = 1)$, which is the probability that a school is first treated in period g conditional on covariates and either being a member of group g or never-treated group. Next, using the potential outcome framework (Rubin 2005), let $Y_{it}(0)$ and $Y_{it}(g)$ denote school i 's potential outcomes at time t with no treatment and if they receive treatment in period g , respectively. Therefore, the observed outcome for never-treated schools is $Y_{it} = Y_{it}(0)$ while for schools in our treatment groups we observe $Y_{it} = 1\{G_{ig} > t\}Y_{it}(0) + 1\{G_{ig} \leq t\}Y_{it}(g)$. To identify and estimate causal effects, CS considers a generalization of the average treatment effect on the treated (ATT). This estimand is called the group-time average treatment effect and is denoted by:

$$ATT(g, t) = E[Y_t(g) - Y_t(0) | G_g = 1],$$

where $ATT(g, t)$ is the average causal effect of receiving treatment for units in group g at time t . For example, in our case $ATT(2009, 2010)$ is the average effect of treatment on teacher retention in 2010 for those schools that switched to a CCRSM from a traditional school in 2009. By fixing g and varying t , one can study how average treatment effects for group 2009 evolve over time. In addition to the irreversibility of treatment assumption, CS impose random sampling, limited treatment anticipation, and overlap, which ensures the generalized propensity score is bounded away from one. CS also impose an extension of the parallel trends assumption:

$$E[Y_t(0) - Y_{t-1}(0) | X, G_g = 1] = E[Y_t(0) - Y_{t-1}(0) | X, C = 1],$$

which states that conditioning on covariates (held constant at pre-treatment levels) and in the absence of treatment, average untreated outcomes for group g and for the never-treated group would have followed parallel paths for all $t \geq g$.

Finally, CS show that under these assumptions the group-time average treatment effects, $ATT(g, t)$, is nonparametrically identified as:

$$ATT(g, t) = E \left[\left(\frac{G_g}{E[G_g]} - \frac{\frac{p_g(X)C}{1 - p_g(X)C}}{E \left[\frac{p_g(X)C}{1 - p_g(X)C} \right]} \right) (Y_t - Y_{g-1}) \right]. \quad (2)$$

Intuitively, this is simply a weighted average of the outcome variable, where weights depend on propensity score. Equation 2 compares observations from treatment group g and control group, while assigning more weight to those observations from the control group that are similar to observations from group g , and less weight to those observations that are less similar to the treatment group. We use a doubly robust estimand to estimate $ATT(g, t)$. We note the covariates we include (enrollment size and operating expenditures per pupil) are restricted to their pre-treatment values (see Sant'Anna and Zhao 2020).⁶

CS suggests several ways to summarize the information contained in the estimated $ATT(g, t)$ by aggregating group-time average treatment effects. For our model, we use two of their proposed aggregating schemes. First, we use a dynamic aggregation which resembles an event-study-type analysis, where the resulting parameter is the average effects across different lengths of exposure to the treatment. In the second method, the aggregation is taken across groups, which assesses the average effect of participating in the treatment for each group. We can further aggregate average effect for each group to calculate an overall ATT , which CS recommend using to assess the overall effect of participation in treatment. The CS approach allows for anticipation of treatment, but we do not include this adjustment in our models.

3. Results

We first present the results from Part 1 of our analysis, and then discuss extensions that examine effect heterogeneity. We then describe the results of Part 2 of the analysis.

3.1. Differences in teacher retention across ECHS, T-STEM and traditional high schools

Table 3 displays our results for Part 1 under different specifications of equation 1. The first column is simply the average of teacher retention across different school types controlling for year-fixed effects. Consistent with the literature, we find charter schools have higher teacher turnover. While traditional high schools experience teacher exit rates of about 20%, T-STEM charter and non-CCRSM charter schools have attrition rates 16 and 17 percentage points higher, while attrition rates in ECHS charters are 2.5 percentage points higher and non-charter ECHS have 1.9 percentage points lower teacher attrition compared to traditional high schools. When we control for student,

Table 3. Regression results for teacher attrition among Texas high schools, 2004–2005 to 2016–2017.

	(1)	(2)	(3)	(4)	(5)
School Type					
ECHS charter stand alone	0.0392*** (0.0120)	0.0290** (0.0117)	–0.0131 (0.0118)	–0.124*** (0.0277)	–0.131*** (0.0287)
ECHS non-charter stand alone	–0.0133 (0.00816)	–0.00266 (0.00808)	–0.0347*** (0.00825)	–0.145*** (0.0195)	–0.123*** (0.0207)
T-STEM charter stand alone	0.154*** (0.00689)	0.0907*** (0.00679)	0.0745*** (0.00706)	0.104*** (0.0251)	0.165*** (0.0253)
Non-CCRSM charter	0.175*** (0.00282)	0.0881*** (0.00292)	0.0687*** (0.00321)	0.110*** (0.00928)	0.124*** (0.00974)
Male		0.0166*** (0.000942)	0.0164*** (0.000938)		
Race/Ethnicity					
Black		0.00402** (0.00174)	0.00128 (0.00176)		
Hispanic		–0.0245*** (0.00138)	–0.0133*** (0.00150)		
Asian		–0.00739* (0.00381)	–0.00861** (0.00382)		
Other		–0.0213*** (0.00466)	–0.0206*** (0.00466)		
Experience		–0.0131*** (0.000175)	–0.0128*** (0.000175)	0.00315*** (0.000371)	0.00266*** (0.000373)
Exp-squared		0.000366*** (0.00001)	0.000359*** (0.00001)	–0.00001*** (0.00001)	–0.00001*** (0.00001)
Degree					
Doctorate		0.0379*** (0.00449)	0.0369*** (0.00448)	0.0532*** (0.0150)	0.0551*** (0.0149)
Master		0.0358*** (0.00106)	0.0370*** (0.00106)	0.0265*** (0.00271)	0.0273*** (0.00272)
No degree		0.0244*** (0.00410)	0.0271*** (0.00407)	–0.0382*** (0.00834)	–0.0357*** (0.00833)
Certification					
Mathematics		–0.0111*** (0.00173)	–0.0100*** (0.00172)	–0.0377*** (0.0133)	–0.0378*** (0.0133)
Mathematics & Others		0.0134*** (0.00216)	0.0129*** (0.00215)	0.0335** (0.0133)	0.0336** (0.0133)

(Continued)

Table 3. Continued.

	(1)	(2)	(3)	(4)	(5)
Mathematics & Others & Science		0.00689 (0.00750)	0.00434 (0.00753)	-0.0323 (0.0258)	-0.0295 (0.0259)
Mathematics & Science		-0.0163*** (0.00431)	-0.0171*** (0.00427)	-0.0469** (0.0229)	-0.0446* (0.0230)
No Certificate		0.0815*** (0.00205)	0.0791*** (0.00205)	-0.00329 (0.00601)	-0.00246 (0.00601)
Others & Science		0.0188*** (0.00225)	0.0180*** (0.00224)	0.0225* (0.0125)	0.0226* (0.0125)
Science		-0.0110*** (0.00171)	-0.0100*** (0.00171)	-0.0556*** (0.0127)	-0.0561*** (0.0127)
Log wage		-0.0623*** (0.00256)	-0.0597*** (0.00240)	-0.0560*** (0.00363)	-0.0595*** (0.00351)
School Location					
Large Fringe Metro		0.0217*** (0.00123)	0.0228*** (0.00451)	0.0278*** (0.00569)	0.0340*** (0.00574)
Medium Metro		-0.0108*** (0.00151)	0.0346** (0.0176)	0.0604*** (0.0217)	0.0606*** (0.0217)
Micropolitan		0.0109*** (0.00187)	0.0380*** (0.0147)	0.0493*** (0.0181)	0.0589*** (0.0181)
Non-core		0.0266*** (0.00182)	0.0406** (0.0158)	0.0596*** (0.0195)	0.0688*** (0.0195)
Small Metro		0.00679*** (0.00174)	0.0555*** (0.0175)	0.0887*** (0.0214)	0.0845*** (0.0215)
Log enrollment size			-0.0188*** (0.000853)		-0.0221*** (0.00213)
School's operating years					
0 years			-0.00788** (0.00379)		-0.199*** (0.00468)
1 year			-0.00834** (0.00341)		-0.130*** (0.00403)
2 year			0.00301 (0.00322)		-0.0882*** (0.00370)
3 year			-0.00204 (0.00312)		-0.0640*** (0.00344)
4 year			0.0132*** (0.00308)		-0.0278*** (0.00326)

Log oper. expend. per pupil	0.0132*** (0.00168)	-0.0145*** (0.00221)	-0.0140*** (0.00374)	-0.0266*** (0.00426)
Prop stud. econ. disadv.	0.0549*** (0.00307)	0.0610*** (0.00341)	0.181*** (0.00675)	0.174*** (0.00676)
Prop stud. at risk of dropout	0.0682*** (0.00349)	0.0485*** (0.00390)	0.0765*** (0.00650)	0.0592*** (0.00654)
Prop stud. Mult. Lang. Learn.	-0.106*** (0.00766)	-0.0439*** (0.00906)	0.0651*** (0.0200)	0.0819*** (0.0200)
Constant	0.198*** (0.000483)	1.084*** (0.0345)	0.721*** (0.0509)	1.042*** (0.0601)
Observations	1,045,935	1,045,245	1,002,015	1,002,015
R-squared	0.009	0.034	0.262	0.265
Year FE	Yes	Yes	Yes	Yes
County FE	No	Yes	Yes	Yes
Teacher FE	No	No	Yes	Yes
Enroll. & oper. yrs. covariates	No	Yes	No	Yes

Note: Robust standard errors in parentheses.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

teacher, and most school characteristics (other than enrollment size and year of operation) in column 2, the coefficients for both T-STEM charter and non-CCRSM charter decline to about 9 percentage points. The coefficients for both types of ECHS, charter and non-charter, become statistically insignificant, suggesting that charter ECHS achieve a turnover rate similar to traditional high schools, and far lower than similar charter schools. Other covariates in our model align with extant literature. Years of experience exhibit a U-shaped relationship, with turnover highest among early career teachers and those approaching retirement. Teachers who identify as Latinx, Asian/Pacific Islander, or other persons of color have lower attrition, except those who identify as Black have roughly similar turnover to White teachers. Teachers with doctoral or master's degrees have higher a probability of exit than those whose highest degree is a bachelors.

The third column adds county fixed effects and controls for enrollment size and the year of operation. As discussed earlier, CCRSM schools are somewhat clustered within counties and there are meaningful differences in enrollment size and years of operating between different types of schools (see [Figures 4 and 5](#)). Although not shown, adding just county fixed effects to the column 2 specification does not meaningfully change our main coefficients of interest.⁷ When we control for enrollment and year of operation, the coefficient for ECHS non-charters declines to negative 4.3 percentage points, suggesting that ECHSs lose teachers through attrition at a rate 21.5 percent lower than similar traditional high schools. The coefficient for charter ECHS remains insignificant and the coefficient for T-STEM charters and non-CCRSM both decline to about 7 percentage points. The negative coefficient on enrollment suggests larger schools have lower attrition on average, and conversely that smaller schools have higher attrition. Controlling for enrollment allows us to compare CCRSM high schools, which tend to be smaller, with similarly sized non-CCRSM traditional high schools (which tend to have higher turnover).

Columns 4 and 5 of [Table 3](#) replicate the previous two columns, this time adding teacher fixed effects. Coefficients for all four treatment high school types increase in magnitude relative to the column 3 specification, and they are all now statistically significant. We caution the reader against directly comparing models with and without teacher fixed effects. Identification of the teacher fixed effects model relies on within-teacher variation in treatment and as noted, only a small proportion of teachers are observed in both traditional high schools and CCRSM or charter schools. Most teachers in our data only teach in one type of school during the sample period. [Table 4](#) shows the number of teachers who move between different school types. Of the 261,973 unique teachers in our data, only 6178 (2.4%) are observed in more than one treatment school type, and many of those result from teachers switching between non-CCRSM charters and traditional public schools.⁸ While results for teacher fixed effects models in columns 4 and 5 are based on a smaller proportion of the variation in treatment, the direction of coefficients is similar to other models (and larger in magnitude), providing some assurance that the column 3 model is not subject to bias from unobserved teacher factors.

3.2. Individual heterogeneity in the effect of CCRSMs on teacher retention

In this subsection, we investigate whether there exists heterogeneity in the influence of CCRSM schools on teacher turnover. Given that CCRSM schools go through an initial five-year probationary

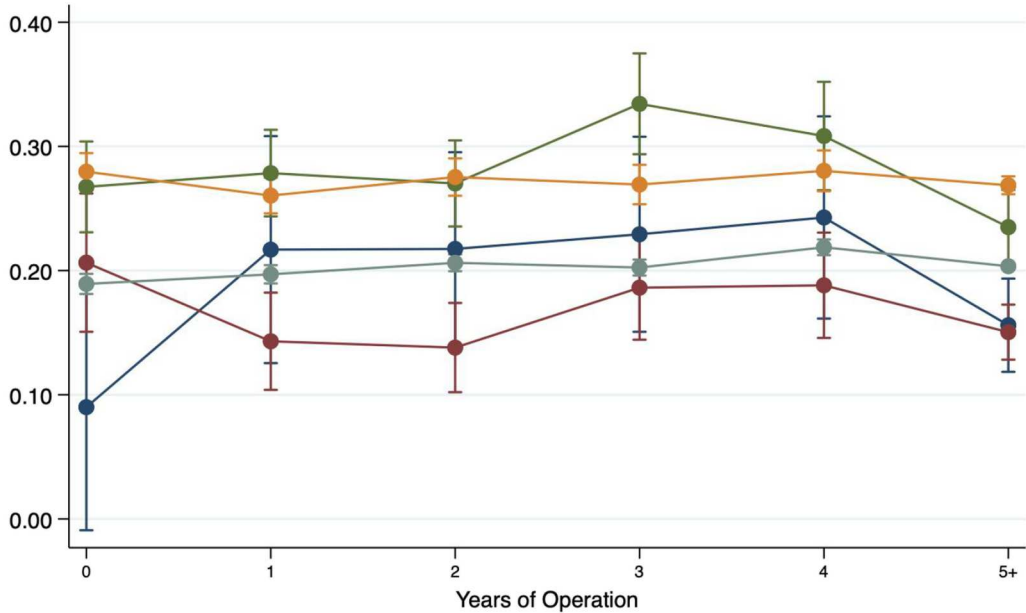
Table 4. Number of times teachers move to a different school type from their first reported school.

	0	1	2	3	4
ECHS charter stand alone	224	37	–	–	–
ECHS non-charter stand alone	460	52	1	–	–
T-STEM charter stand alone	2099	180	12	–	–
Non-CCRSM charter	16,908	1985	102	15	1
Traditional	231,056	2600	711	30	5

Note: Table shows, for example that 224 teachers started their careers in an ECHS charter stand-alone high school and are never observed in any other CCRSM school type during our window of observation, from 2004–2005 to 2016–2017.

period, we first examine how turnover in CCRSM schools changes in the first few years of operation, compared to similar newly opened traditional high schools. Figure 6, Panel A depicts the predictive margins of school type and years of operation. Few clear patterns emerge. We find a decline in

Panel A. Predictive margins of attrition by years of operation



Panel B. Predictive margins of attrition by enrollment size

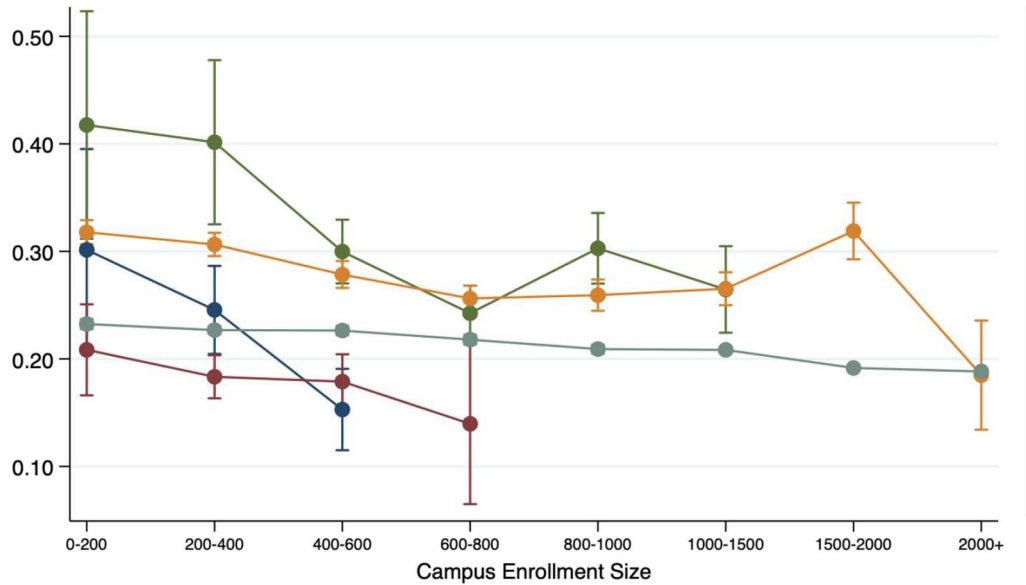


Figure 6. Predictive margins of attrition by school type and school's years of operation (Panel A), enrollment size (Panel B), and teacher experience (Panel C), with 95% confidence interval Panel A. Predictive margins of attrition by years of operation Panel B. Predictive margins of attrition by enrollment size Panel C. Predictive margins of attrition by teacher experience.

Note: CCRSM = college and career readiness school model. Figure 1 provides information about the number of new high schools opened each year across CCRSM types and Figure 5 shows the cell size for each CCRSM school type by years of operation. While almost all traditional comprehensive high school observations are in their fifth or greater year, about five to seven are opened each year, slightly more than CCRSM schools.

Panel C. Predictive margins of attrition by teacher experience

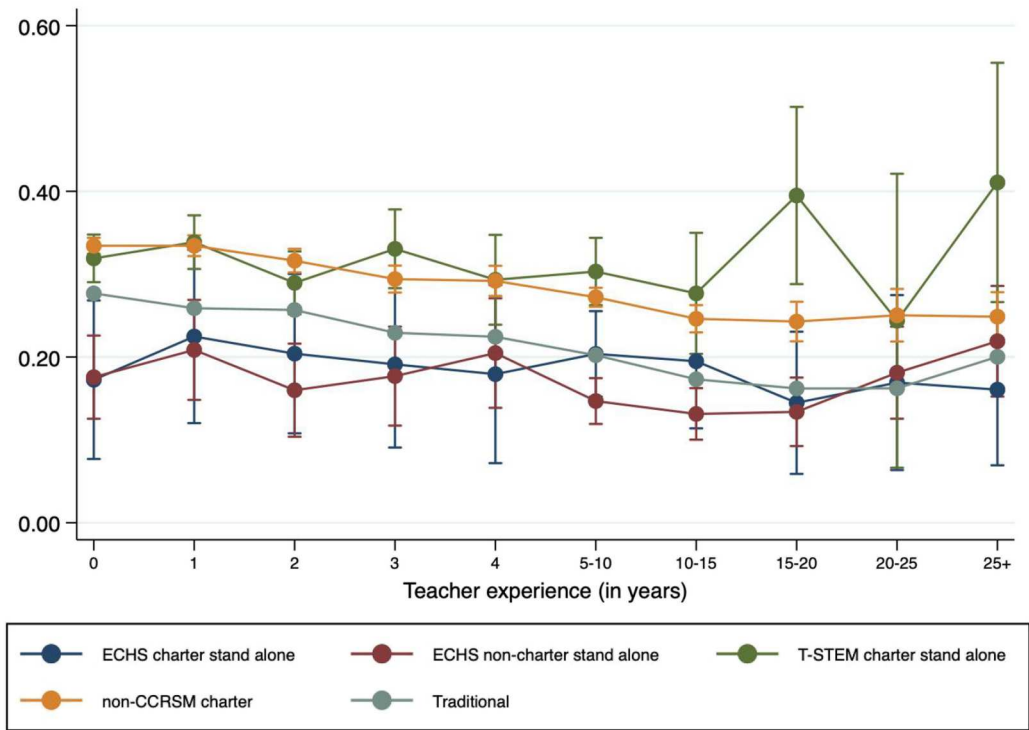


Figure 6. Continued.

turnover for stand-alone non-charter ECHSs after the first year of operation, and charter ECHSs and T-STEMs both have lower turnover in their sixth or greater year compared to earlier years of operation. But results in Panel A of Figure 6 show that most schools have relatively stable rates of teacher turnover in the first five years of operation.

Given that both T-STEM and ECHS are designed as smaller schools, but in practice have varying enrollment sizes, we next examine whether their influence on teacher retention is related to enrollment size. Panel B of Figure 6 shows the predictive margins. Non-charter ECHSs have consistently lower teacher turnover across various enrollment sizes, especially among larger campuses (those with 400–600 students and 600–800). While charter ECHSs have higher teacher turnover than traditional comprehensive high schools on average, turnover in charter ECHSs also generally decreases at larger enrollment levels, and the largest charter ECHSs (with 400–600 students) actually have lower teacher turnover than similar traditional comprehensive high schools. Conversely, for every level of enrollment size, T-STEM charter and non-CCRS charter schools have a higher probability of teacher exit.⁹ Across all school types, larger high schools generally have lower teacher turnover, especially for stand-alone charter ECHSs. Given that turnover is stable in the first five years of operation, and models control for other factors that may be related to size, such as urbanicity and county fixed effects, we suspect that lower turnover in larger high schools may relate to school positive contextual factors such as a positive work environment.¹⁰

Finally, we examine how CCRSM effects on teacher turnover differ by teacher experience. Panel C of Figure 6 shows the predictive margins of school type and teacher experience. Turnover generally declines over the first 15–20 years of experience, and then increases in later years, but we do not find strong evidence of differences in this trend across CCRSM types.

3.3. Dynamic treatment effects for schools converting to CCRSM

In the final subsection, we present results from our event-type analysis, in which we use school fixed effects to control for unobserved school factors beyond CCRSM type. As discussed in the methodology section, we follow Callaway and Sant'Anna (2021) framework to calculate group-time average treatment effects, then by aggregating these parameters by length of exposure to treatment, we can test whether there exist any dynamic treatment effects in our sample. We first collapse our data to a school-by-year level, so our outcome becomes teacher retention rate for a school in a given year.¹¹ We define treatment as a school converting its model from a traditional high school to a CCRSM type school. Table 5 shows the number of school conversions between different school types for our whole sample. Given small sample sizes, we focus on three kinds of conversions: (a) traditional schools that convert to a ECHS non-charter school-within-school model at some point during our sample period (59 schools); (b) traditional schools that convert to an ECHS non-charter stand-alone model (16 schools); and (c) traditional schools that convert to a T-STEM non-charter school-within-school model (25 schools). We do not examine the six traditional schools that convert to stand-alone T-STEMs, or any of the charter school conversions shown in Table 5. The comparison group is all not-yet-treated units.

3.3.1. Traditional schools converting to an ECHS non-charter school-within-school model

We observe 59 traditional high schools that converted to an ECHS non-charter school-within-school model at some point between 2001 and 2017. As noted, the school-within-school ECHS model differs from the stand-alone model in that only about one-quarter to a third of students and teachers in the school are specifically associated with the ECHS. Because we do not observe which teachers and students are enrolled in the school-within-school ECHS, we examine teacher turnover at the school, before and after the conversion. Figure 1 Panel C shows the timing for all conversions from traditional high schools to school-within-school non-charter ECHSs, and the number of our treatment units for each year. By following the CS methodology, under the parallel trends assumption and no anticipation, we can construct the group-time average treatment effects for periods when $t \geq g$ (for every year t greater than the treatment year g). We can also calculate the group-time average treatment effects for $t < g$ to assess pre-trends to validate the parallel trends assumption. Hence, we can construct eight group-time ATT effects for each year that a treatment happens.

As discussed in section 2, there are several ways to aggregate group-time ATT to more interpretable causal parameters. One way is to aggregate based on length of exposure to treatment (which is closest to an event-type study), to test whether there are any dynamic treatment effects. Figure 7, Panel A shows the results of this aggregating scheme. One potential issue with this aggregation is that the sample size for each event-time changes with different lengths of exposure to treatment.

Table 5. Number of school-year observations for CCRSM schools that converted from either a traditional high school or a non-CCRSM charter schools, 2004–2005 to 2016–2017.

	School type in previous year		
	Traditional	Non-CCRSM Charter	Other
ECHS non-charter SWS	53	–	–
ECHS non-charter stand alone	29	–	1
ECHS charter SWS	–	1	–
ECHS charter stand alone	–	1	3
ECHS / T-STEM non-charter SWS	3	–	–
T-STEM non-charter SWS	26	–	–
T-STEM non-charter stand alone	14	–	–
T-STEM charter SWS	–	3	2
T-STEM charter stand alone	–	9	–
Any CCRSM model (total)	125	14	6

Note: SWS = school-within-school. The third column shows that one ECHS non-charter stand-alone converted from T-STEM non-charter standalone, three ECHS charter stand-alone schools converted from ECHS non-charter stand-alone, and two T-STEM charter SWS was converted from T-STEM charter stand-alone.

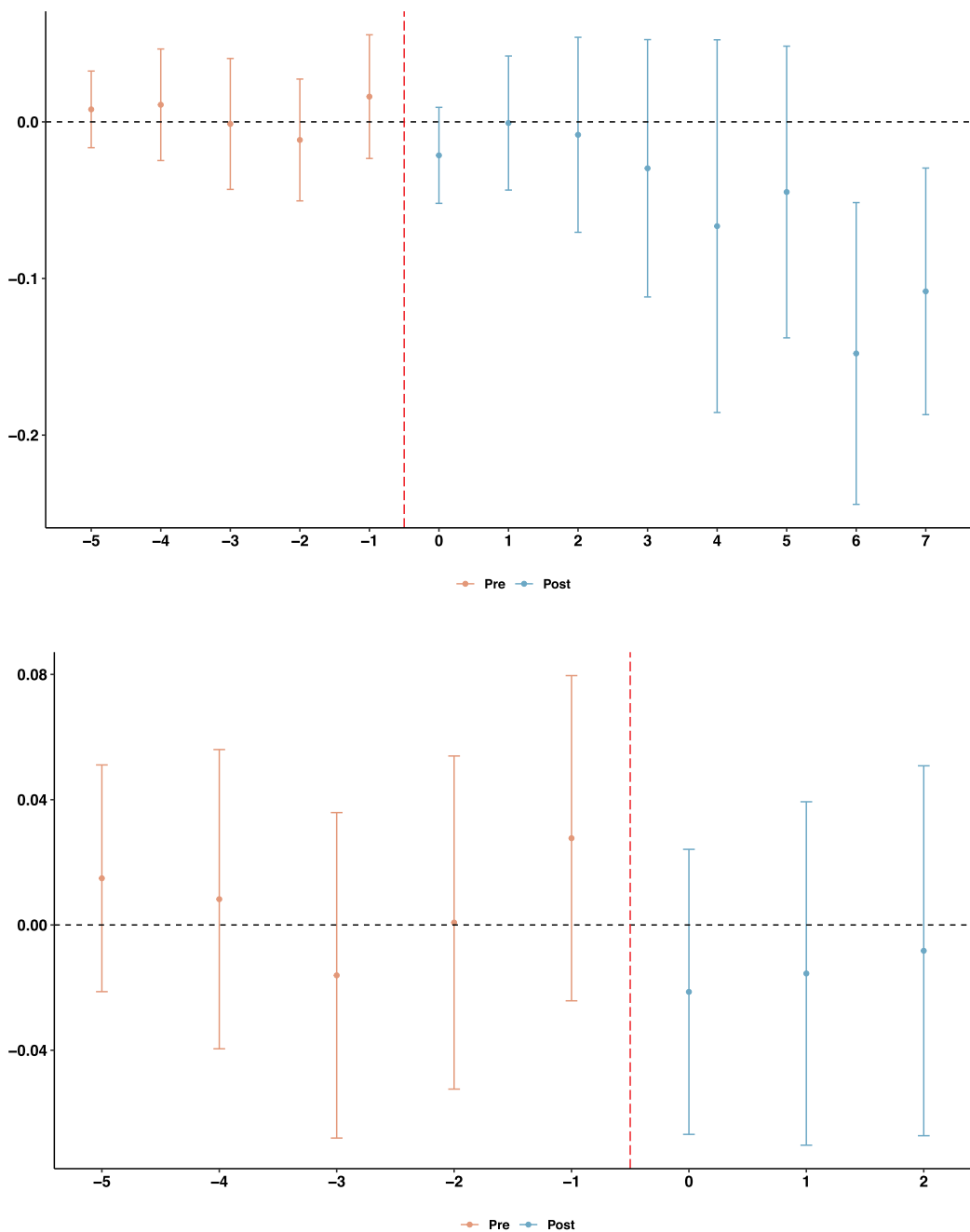


Figure 7. Average treatment effect by length of exposure for traditional schools that convert to ECHS non-charter school-within-school model.

Note: Figure shows dynamic treatment effects are shown, with 95% confidence intervals. Balanced samples include only those groups that are exposed to treatment for at least two periods. The vertical red dashed line is the time of treatment; red dots are pre-treatment effects and blue dots are post-treatment. For the full sample, we set the smallest event time at -5 (allowing us to calculate dynamic treatment effects up to five years in the past) and the largest event time at 7 (allowing us to calculate the dynamic treatment effects up to seven years after the school switches to an ECHS non-charter school-within-school model).

For example, we can only identify the instant treatment effect for treatment group 2017, while for group 2015 we can identify up to two years in the future. To address this issue, we further balance the sample by restricting groups that are exposed to treatment for at least two periods and then calculate the dynamic effects for those time periods. This effectively drops observations from groups 2016 and 2017, which is almost 50% of our treatment sample size. Figure 7, Panel B shows the event study plot for this balanced sample, showing the instantaneous treatment effects, as well as the average treatment effects one and two years after switching the school type. Results from these two plots present a similar story. While post-treatment observations show a potential decline in turnover of between one and three percentage points, and up to eight percentage points in some later years (Panel A), we do not find evidence of a statistically significant effect on teacher retention for schools that convert from traditional to the ECHS non-charter school-within-school model. Importantly, the sample includes only 59 school conversions and only 11 before the 2014–2015 school year. Despite a potential downward trend in turnover following school conversion, a lack of precision in our estimates, resulting from small sample sizes, limits our ability to observe statistically significant results.

Finally, we can use another aggregating scheme to estimate average treatment effects across different groups, that is we can aggregate group-time ATT into group-specific average treatment effects and then calculate overall ATT by averaging the group-specific treatment effects across different groups. Panel A of Table 6 shows these results. Our overall ATT estimate is not statistically significant, but treatment effects for some of the groups (2005, 2008 and 2013) are significant, showing effects that range from 12.2 to 16.1 percentage point increase in turnover (for a given group-time set of schools) to negative 20.7 percentage points. Again, the small sample size associated with each individual group-time means these estimates are sensitive to changes in turnover for individual schools. The overall ATT for conversions to ECHS non-charter school-within-school of -0.018 , or about two percentage points, is more closely aligned with our preferred OLS specification from Table 3 for ECHS non-charter *stand-alone* schools of -0.043 , or about four percentage points.

3.3.2. Traditional schools converting to ECHS non-charter stand-alone model

Next, we consider traditional schools that switch to ECHS non-charter stand-alone model at some point during our sample. Again, Table 5 shows the number of schools that adopt this type of conversion, 16, and Figure 1 Panel C shows the timing of conversions. Recognizing the small sample size, we conduct the same analysis as before, and encourage readers to interpret results as imprecise. As before, we present dynamic treatment effects (in Figure 8, Panel A) and then show the same results for the balanced panel in Figure 8, Panel B. Similar to our results for schools converting to ECHS non-charter school-within-school, the findings in Figures 8 show a parallel trend in turnover per-treatment, and a potential slight post-treatment decline in turnover that is not statistically significant. Panel B of Table 6 shows group-specific point estimates and an overall ATT estimate of -0.028 , or about three percentage points.

3.3.3. Traditional schools converting to T-STEM non-charter school-within-school model

Lastly, we consider the 25 traditional schools that convert to a T-STEM non-charter school-within-school model. Figure 1 Panel C shows the timing and cumulative number of conversions and Figure 9 show dynamic treatment effects for all schools and for the balanced panel (for schools exposed to treatment for at least two years). As with the previous two cases, the estimated parameters are negative but statistically insignificant due to small sample size. Panel C of Table 6 shows the aggregation into group-specific average treatment effects. The overall ATT in this case is negative and statistically significant, suggesting that converting traditional high schools to a T-STEM school-within-school model leads to a reduction in teacher attrition of 2.5 percentage points.

Table 6. Average treatment effects across different groups for traditional schools that switch to ECHS non-charter school-within-school model (Panel A), ECHS non-charter stand-alone model (Panel B), and T-STEM non-charter school-within-school model (Panel C).

	ATT	SE		ATT	SE
A. Traditional to ECHS non-charter sch.-within-sch.			D. Trad. to T-STEM non-charter stand-alone		
2007	−0.0576*	0.0027	2007	−0.1399*	0.0064
2008	−0.2072*	0.0037	2008	−0.0158	0.008
2010	−0.0438	0.0286	2011	0.0881*	0.0027
2012	−0.0268*	0.0064	2012	0.0455*	0.0037
2013	−0.0551	0.0967	2014	−0.0726*	0.0033
2015	0.0132	0.0213	2015	0.0207	0.0375
2016	0.0102	0.0173	2016	0.0463*	0.0025
2017	−0.1067*	0.024	2017	0.0037	0.1411
Overall ATT	−0.0171	0.0138	Overall ATT	0.0004	0.0261
B. Traditional to ECHS non-charter stand-alone			E. Trad. to CCRSM non-charter (aggregate)		
2007	−0.1244*	0.0057	2007	−0.1054*	0.0242
2010	−0.0254	0.0127	2008	−0.0866	0.0434
2011	−0.1002	0.0544	2009	−0.0715*	0.0124
2013	0.0683	0.057	2010	−0.0248	0.0161
2015	0.0299	0.0408	2011	−0.0468	0.0479
2016	0.0103	0.0179	2012	−0.0021	0.0228
2017	−0.0201	0.0113	2013	−0.0168	0.0347
Overall ATT	−0.0062	0.0164	2014	−0.0724*	0.0032
C. Trad. to T-STEM non-charter school-within-sch.			2015	0.0199	0.0165
2008	−0.0553	0.034	2016	0.0107	0.0112
2009	−0.0713*	0.011	2017	−0.0452	0.025
2010	0.0119*	0.0049	Overall ATT	−0.014	0.009
2011	−0.0181	0.0138			
2013	−0.0496*	0.0043			
2015	0.0140*	0.0046			
2016	0.0054	0.0193			
2017	−0.0292	0.0366			
Overall ATT	−0.026*	0.013			

Note: Figure 1 shows the annual number of school conversions by type. Selected results are shown graphically for Panel A (see Figure 7), Panel B (see Figure 8), and Panel C (see Figure 9).

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4. Discussion

In recent years, policymakers and education leaders have zeroed in on high school contexts as a mechanism for improving students' transition to college and postsecondary success. Extra academic and socioemotional student support, rigorous coursework, college counseling, and stable learning environments are high school factors that prior studies link to positive postsecondary outcomes. Recent research shows students attending innovative high school models, such as ECHS and T-STEM Academies – which include these high school factors – have a greater likelihood of enrolling in and completing a two- or four-year degree. Yet few studies have examined the specific mechanisms within these high schools that are associated with positive learning outcomes. The current study is the first of which we are aware to examine teacher turnover in ECHS and T-STEM Academies.

We find that the ECHS model, whether implemented in charter or traditional public schools, exhibits greater teacher retention compared to similar traditional comprehensive public high schools. Conversely, we find that charter T-STEM Academies have turnover rates roughly similar to that of charter high schools, both of which have substantially higher teacher attrition than traditional public high schools. In short, the ECHS model is effective at reducing teacher turnover by about two to four percentage points, even within charter school settings, while the T-STEM model does not seem to have a strong enough influence to overcome high teacher turnover rates in charter school settings. Stand-alone T-STEM Academies in traditional public (non-charter) schools are less common and we don't include these schools in our OLS regression analyses. In our event study analysis, we show that converting existing high schools to these CCRSM school models may lead to slight reductions in teacher turnover. When traditional non-charter high schools convert to

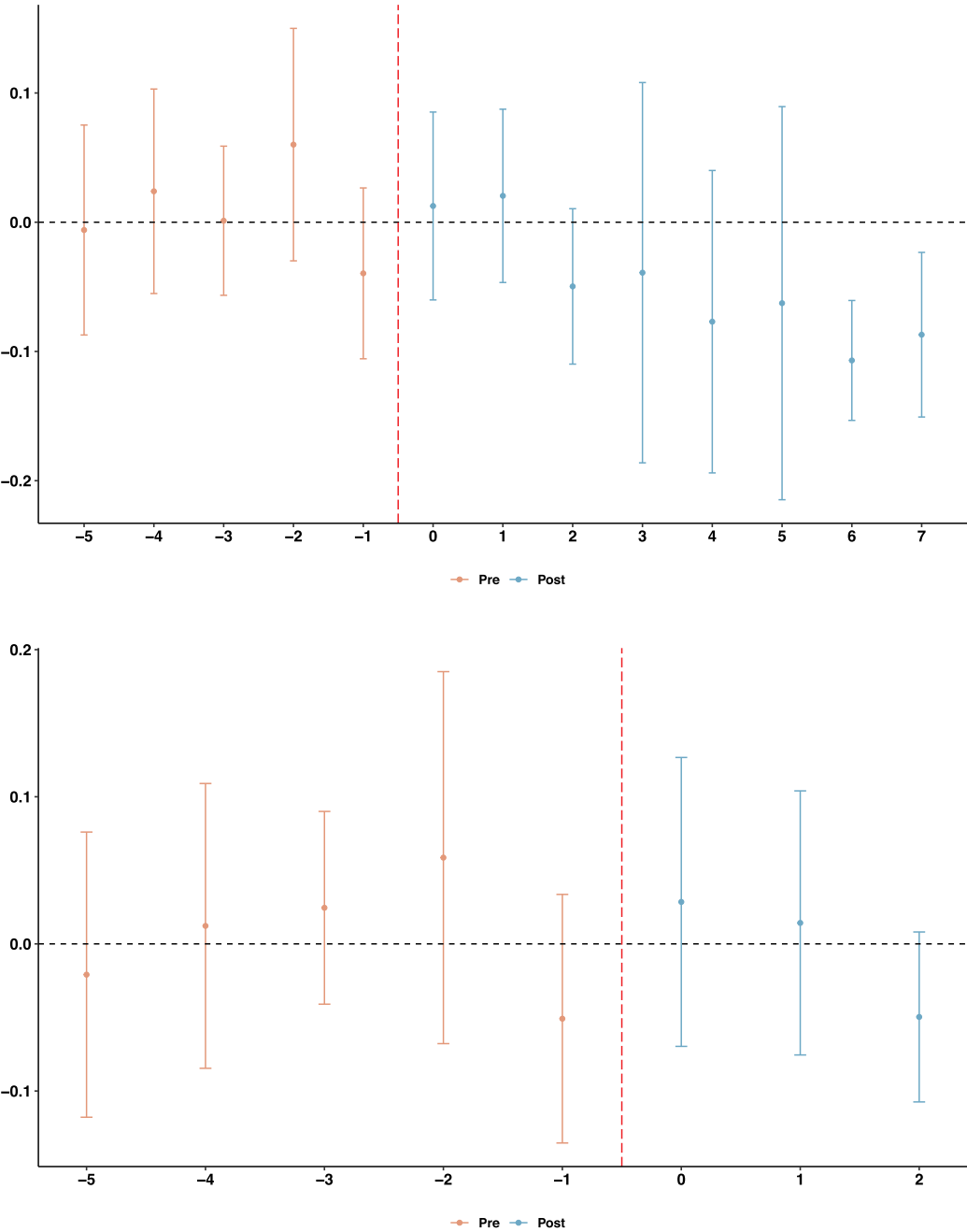


Figure 8. Average treatment effect by length of exposure for traditional schools that switch to ECHS non-charter stand-alone model.

Note: Figure shows dynamic treatment effects are shown, with 95% confidence intervals. Balanced samples include only those groups that are exposed to treatment for at least two periods. The vertical red dashed line is the time of treatment; red dots are pre-treatment effects and blue dots are post-treatment. For the full sample, we set the smallest event time at -5 (allowing us to calculate dynamic treatment effects up to five years in the past) and the largest event time at 7 (allowing us to calculate the dynamic treatment effects up to seven years after the school switches to an ECHS non-charter stand-alone model).

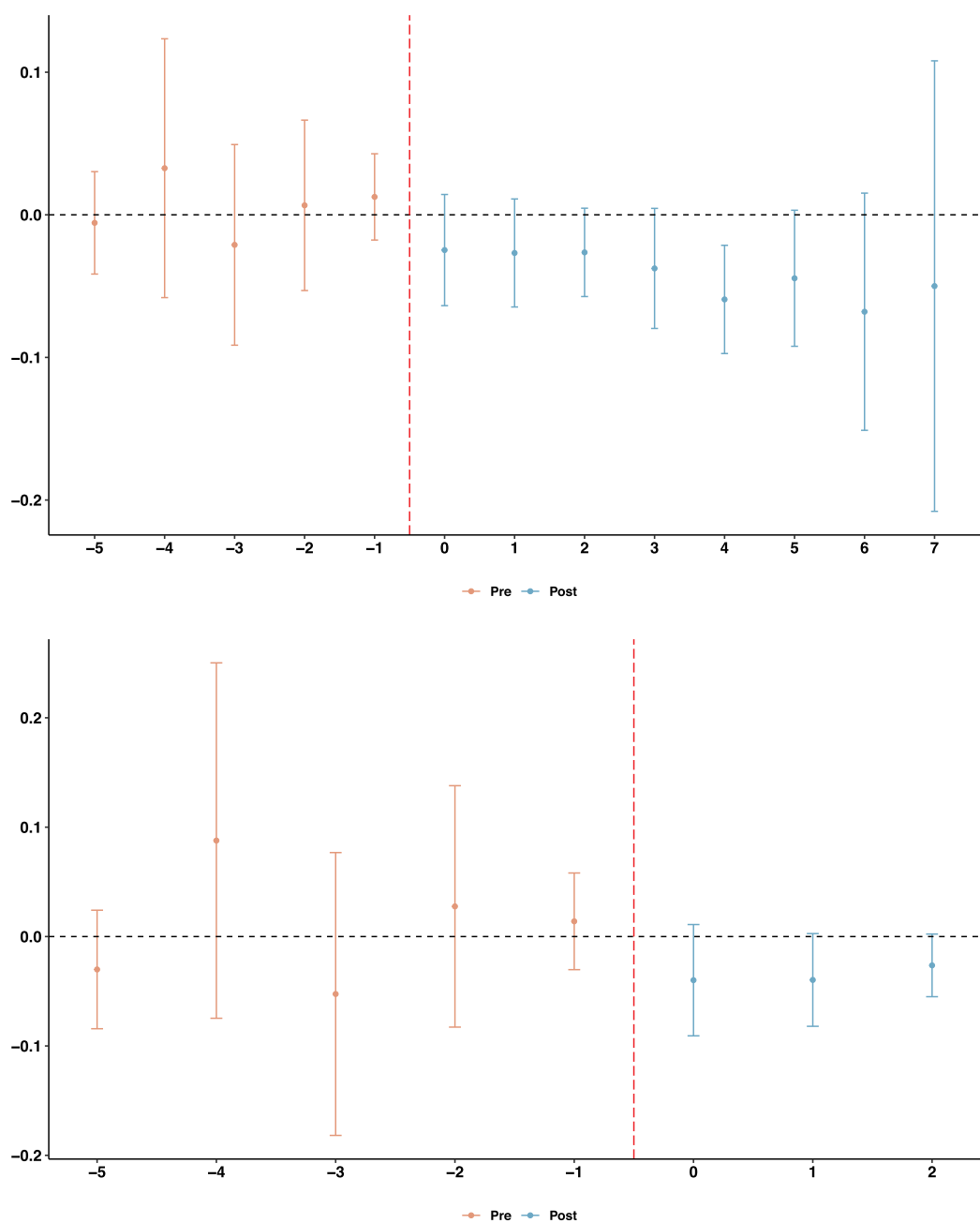


Figure 9. Average treatment effect by length of exposure for traditional schools that switch to T-STEM non-charter school-within-school model.

Note: Figure shows dynamic treatment effects are shown, with 95% confidence intervals. Balanced samples include only those groups that are exposed to treatment for at least two periods. The vertical red dashed line is the time of treatment; red dots are pre-treatment effects and blue dots are post-treatment. For the full sample, we set the smallest event time at -5 (allowing us to calculate dynamic treatment effects up to five years in the past) and the largest event time at 7 (allowing us to calculate the dynamic treatment effects up to seven years after the school switches to a T-STEM non-charter school-within-school model).

either a whole-school (stand-alone) ECHSs or a school-within-school models, we find overall ATT effects of between two and three percentage points, though these results are not statistically significant. When traditional non-charter high schools convert to school-within-school T-STEM Academies, teacher turnover declines by 2.5 percentage points.

4.1. The ECHS model and teacher retention

These results suggest that one mechanism through which ECHSs achieve positive outcomes is through creating a stable learning environment with lowered teacher turnover, which past research links to higher student test scores (see e.g. Ronfeldt, Loeb, and Wyckoff 2013). We view greater teacher retention in ECHSs as both an outcome of the structures embedded in the ECHS blueprint, and a mechanism that improves student learning experiences. As part of this blueprint, schools receive extra funding, which they can use for teacher professional and other teacher supports associated with greater retention (Ingersoll 2001; Johnson and Birkeland 2003). But other elements of the blueprint likely contribute to teacher retention, and some of these components could provide useful insights for traditional high schools. For example, ECHS students receive individualized instructional plans that support readiness and success (TEA 2022). For any student that does not pass the Texas Success Initiative assessment, a prerequisite for enrolling in Dual Credit coursework, educators leverage test data and other data artifacts to design and implement tailored interventions such as workshops, tutorials, and accelerated instruction. Several qualitative studies have shown teachers prefer work environments where they feel a sense of success with students, especially with students who have not historically had equitable learning opportunities in US. K-12 schools, such as low-income students and student of color (Johnson and Birkeland 2003). The ECHSs model requires an explicit focus on admitting students underrepresented in post-secondary institutions, and this focused mission could also contribute to teacher retention, although this particular element would be more difficult to scale.

4.2. School conversions as ‘rebranding’

School districts have flexibility for how to open CCRSM schools, including as either a whole school model or a school-within-school. While most CCRSM schools are recently opened, districts can also convert existing non-CCRSM schools to ECHS or T-STEM Academies, and in recent years, Texas added Pathways in Technology ECHSs or ‘P-TECH’ Academies. Prior research on ECHS focus almost exclusively on the stand-alone model, most of which are initially opened as ECHSs, rather than through a school conversion. In contrast, extant research on T-STEM Academies has explored both newly opened schools and conversions. Saw (2017; 2019) describes T-STEM conversions as ‘rebranding’ where school leaders emphasize reforms aimed at improving learning environments with special emphasis on math and science subjects. Rebranding (i.e. school conversion) is associated with slight increases in student test scores and graduation rates. These findings generally align with our results, which show that rebranding a CCRSM school may reduce turnover (and potentially lead to other positive outcomes). Point estimates for ECHS conversions are generally smaller than estimates for non-converting ECHSs, while conversions to T-STEM Academies lower turnover by 2.5 percentage points below prior trends.

Moving forward, we suggest further research into CCRSM schools, including analysis of principal hiring and turnover and other non-cognitive student outcomes. As schools continue to transition to a post-virtual learning environment, smaller high schools may provide an important space for students to develop closer relationships with peers and staff members. Research that further unpacks the benefits of CCRSM and related school models will improve these policy efforts.

Notes

1. The study uses two analytic samples, one with schools that are newly opened as CCRSM schools (‘non-converting’) and one with only schools that convert from a traditional public school to a CCRSM school.

2. Several TEA administrators who work on the College and Career Readiness School Models Team confirmed in personal correspondence via emails with CCRSM@tea.texas.gov that TEA does not keep historical records of CCRSM schools for every year.
3. Only a small number of 'non-converting' CCRSM schools are school-within-school models. We exclude these schools from our analysis as they are rare cases and have a small sample size.
4. While most charter CCRSM schools are non-converting in that they initially open as CCRSM schools, a few charter CCRSM converted after initially opening as non-CCRSM schools (these include ECHS charter stand alone, T-STEM charter school-within-school, T-STEM charter stand alone, see Table 5). We exclude these school types because they are rare cases and have a small sample size.
5. Our model satisfies this assumption: for our event-study framework we only look at school conversions, so for all treated units (schools that switch to CCRSM), we observe at least one period before receiving the treatment. Moreover, in our data, we do not observe any school that converts to a non-CCRSM model.
6. We use the did R package, which, as described in the last bullet under 'data requirements' in the package documentation, holds covariates constant at pre-treatment levels. This avoids introducing bias by allowing time-varying covariates that may be affected by treatment (Sant'Anna and Zhao 2020).
7. We also ran separate regressions adding just enrollment size and just years of operating to specification 2. For both models, especially the model that controls for enrollment size, the coefficients of interest are closer in magnitude and significance level to specification 3. We add all three covariates, county fixed effects and controls for both enrollment size and years of operating, to the specification 3 to facilitate comparisons with specification 5.
8. Of the 2271 teachers first observed in treatment schools, 240 (11%) are observed in another school type. Those observed in multiple school types are generally less experienced, have higher educational attainment, and are more likely to be male. Appendix Figures A1–A3 show the number of teacher-observations that move across CCRMS types.
9. This trend holds with one exception. Non-CCRSM charter high schools enrolling 2000 or more students have similar teacher retention to traditional high schools, about 20%. The largest T-STEM charter stand-alone campuses serve about 1500 students (see Figure 4) so we do not observe effects for T-STEM charters serving 2,000 or more students.
10. We also examined the triple interaction of CCRSM type, years of operating, and school size. These models show that the relationship between teacher turnover and school size generally holds during the first five years of operation for each CCRSM type, suggesting that the relationship between teacher turnover and school size is not dependent on years of operating (see Appendix Figure A4).
11. Retention rate is defined as the proportion of teachers at a given school who leave their teaching position at their current school, based on their school location and position for the next year.

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Appendix

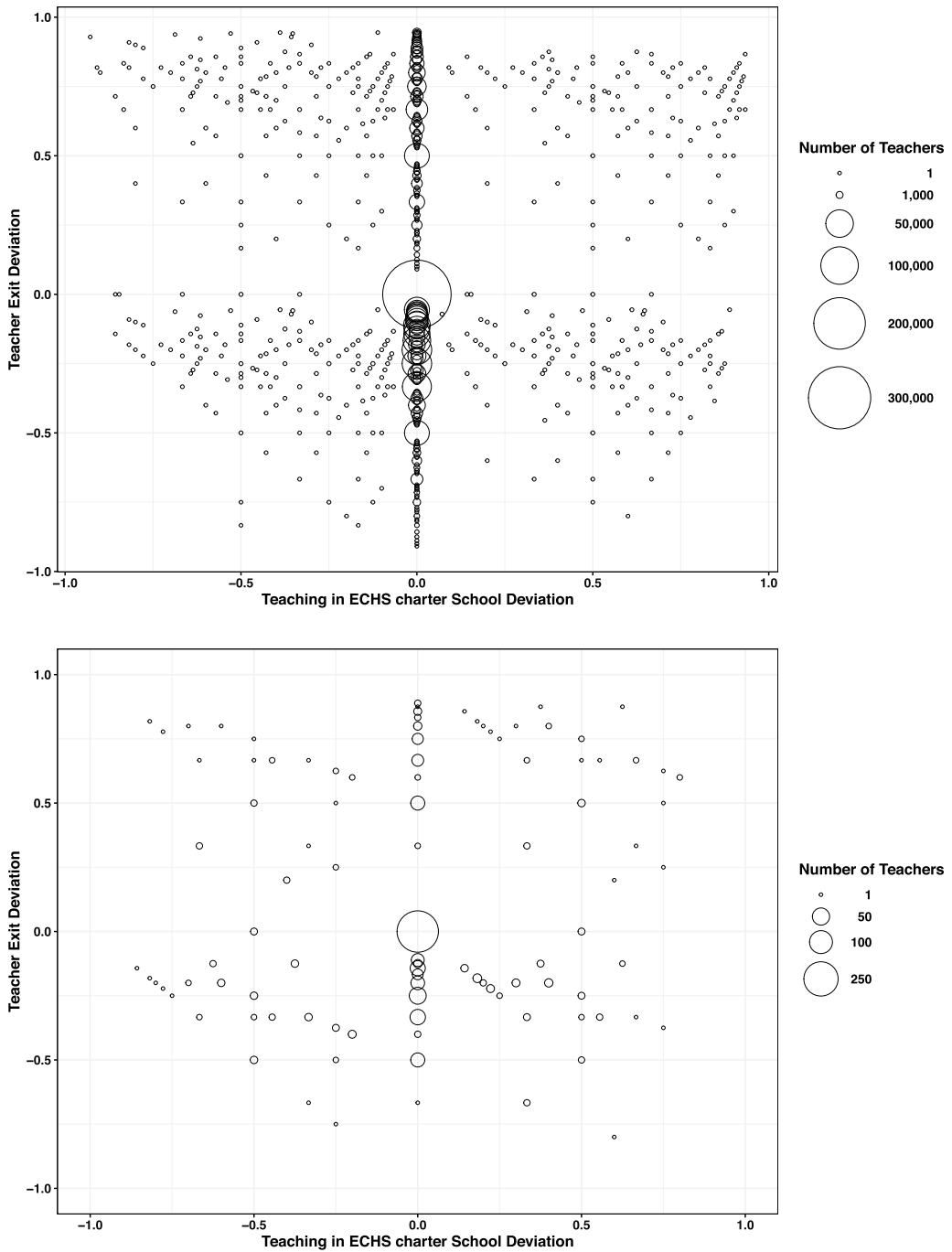


Figure A1. Within-teacher variation in treatment and turnover, ECHS charter stand-alone schools.

Note: A value of zero on the x-axis implies a teacher is always or never observed in an ECHS charter stand-alone, 2004-05 to 2016-17. The figure shows that most teachers do not contribute to teacher fixed effect estimates, since very few teachers are observed in both ECHS charter schools and at least one type of comparison group high school.

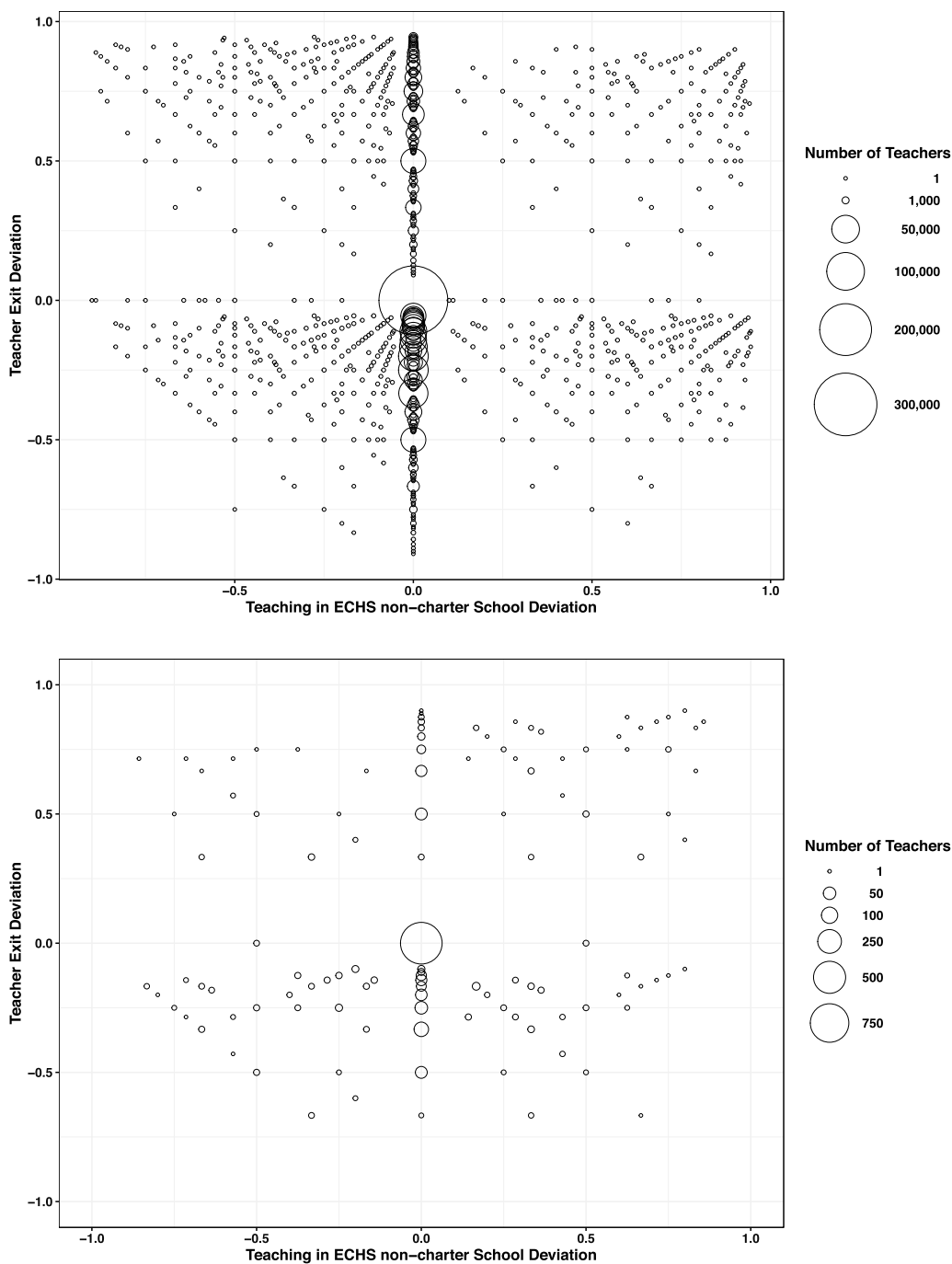


Figure A2. Within-teacher variation in treatment and turnover, ECHS non-charter stand-alone schools.

Note: A value of zero on the x-axis implies a teacher is always or never observed in an ECHS non-charter stand-alone, 2004-05 to 2016-17. The figure shows most teachers do not contribute to teacher fixed effect estimates, since very few teachers are observed in both ECHS non-charter schools and a comparison group high school.

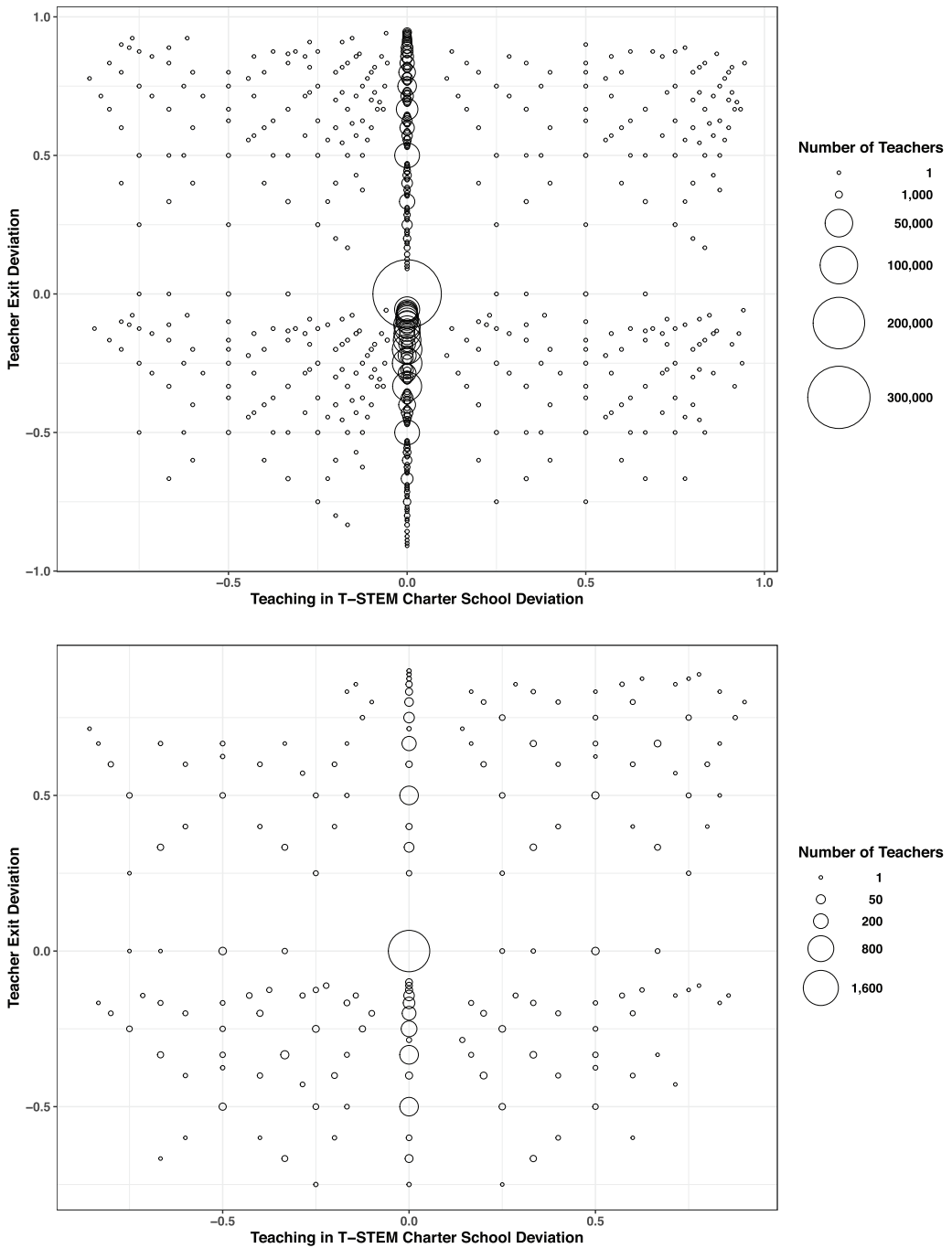


Figure A3. Within-teacher variation in treatment and turnover, T-STEM charter stand-alone schools.

Note: A value of zero on the x-axis implies a teacher is always or never observed in a T-STEM charter stand-alone, 2004-05 to 2016-17. The figure shows that most teachers do not contribute to teacher fixed effect estimates, since very few teachers are observed in both T-STEM charter stand-alone schools and a comparison group high school.

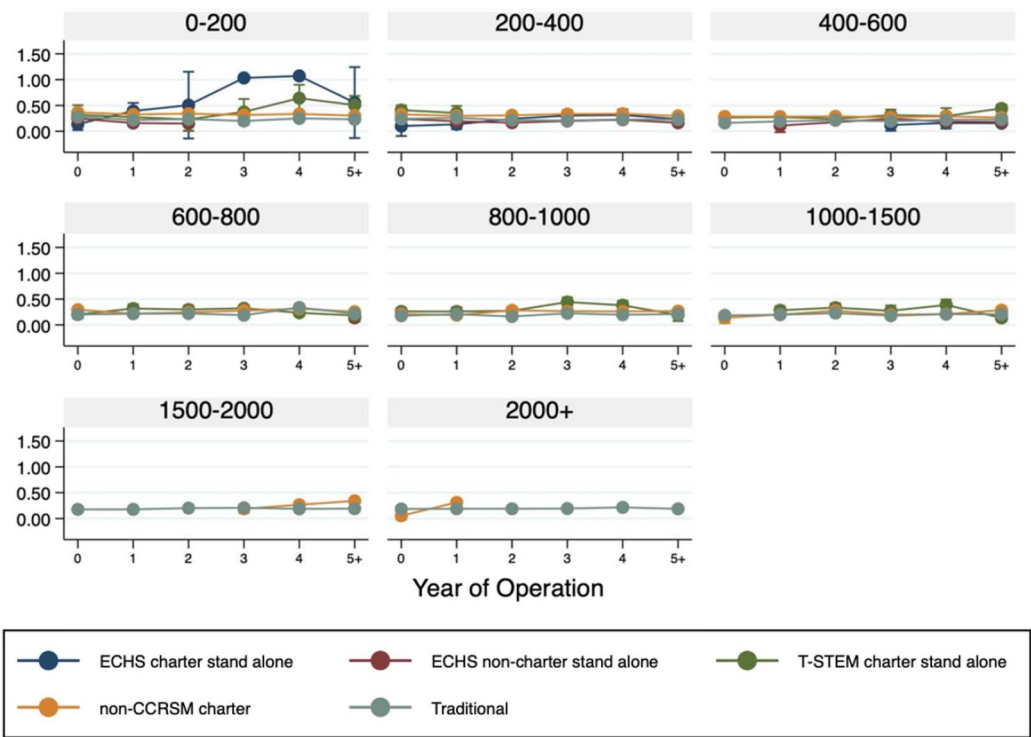


Figure A4. Predictive margins of school type, school's enrollment size and years of operation with 95% confidence interval.