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Spread Too Thin: The Effects of Teacher Specialization on Student Achievement

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Although the majority of elementary school teachers are in self-contained classrooms and teach all major subjects, a growing number of teachers specialize in teaching fewer subjects to higher numbers of students. We use administrative data from Indiana to estimate the effect of teacher specialization on teacher and school effectiveness in elementary schools. We find that teacher specialization leads to lower teaching effectiveness in math and reading, and the negative effects are larger when teaching students who are more likely to experience difficulties in school. Moreover, we find no evidence that increasing the proportion of teacher specialists at the school level generates improvements in indicators of school quality.

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Spread Too Thin:

The Effect of Teacher Specialization on Student Achievement[1]

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Abstract

Although the majority of elementary school teachers are in self-contained classrooms and teach all major subjects, a growing number of teachers specialize in teaching fewer subjects to higher numbers of students. We use administrative data from Indiana to estimate the effect of teacher specialization on teacher and school effectiveness in elementary schools. We find that teacher specialization leads to lower teaching effectiveness in math and reading, and the negative effects are larger when teaching students who are more likely to experience difficulties in school. Moreover, we find no evidence that increasing the proportion of teacher specialists at the school level generates improvements in indicators of school quality.

Keywords: teacher specialization, student-teacher relationship, teaching effectiveness

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1. Introduction

The majority of U.S. elementary school students learn in self-contained classrooms where one teacher covers all major subjects, whereas secondary school students learn from subject-area specialists who cover fewer subjects. Yet, elementary school teachers typically have expertise in some subjects over others (Cohen et al., 2018; Goldhaber et al, 2013), and a teacher's content knowledge in a particular area predicts higher student achievement (Ball et al., 2008; Campbell et al., 2014). Thus, subject-area specialization has the potential to increase teacher and school effectiveness by leveraging and developing a teacher's subject expertise (Condie et al, 2011; Jacob & Rockoff, 2011).

Although subject-area specialization in elementary schools is conceptually appealing along some dimensions, it does not come without tradeoffs. From the perspective of teacher effectiveness, one potential negative consequence is increased student/teacher ratios and the corresponding weaking of student-teacher relationships. Unlike self-contained classrooms that enable teachers to cultivate strong relationships by focusing on fewer students and spending more time with them, subject-area specialization spreads teachers across more students (Bastian & Fortner, 2020). Because strong student-teacher relationships are an important ingredient in positive student growth (Hegde & Cassiday, 2004), the benefits of specialization may not outweigh the advantages of learning from a general classroom teacher.

Educators and policymakers have weighed the benefits and drawbacks of teacher specialization in elementary schools for a century (Ackerlund, 1959; Lobdell & Van Ness, 1963; Parker et al., 2017), yet there remains little empirical evidence on this understudied topic. While evidence of differential effectiveness across subjects supports subject area teacher specialization (Condie et al, 2011; Jacob & Rockoff, 2011) recent research suggests that specialization can lead to lower teaching effectiveness (Fryer, 2018; Bastian & Fortner, 2018).

Our study brings new evidence to the thin body of literature and provides important policy implications. Using longitudinal administrative data from the Indiana Department of Education (IDOE) covering the 2010-11 to 2016-17 school years, we begin by documenting school and teacher characteristics that are associated with teachers becoming specialists. Next, because we observe the same teachers at different points in time in both general and specialized roles, we test whether subject area teacher specialization (i.e., teaching only one or two subjects in a given year) increases or decreases math and reading teaching effectiveness. We complement this investigation by considering if the effectiveness of specialists is heterogenous across different student populations. Finally, because specialization could improve total school outcomes independent of the impact of specialization on an individual teacher's average effectiveness, we explore the net effect of teacher specialization on school improvement across a range of student outcomes, including student achievement, absences, and disciplinary infractions.

We find few differences across schools with higher or lower rates of teacher specialization. Counterintuitively, teachers with low value-added scores and teachers considered not highly qualified by Indiana's Department of Education are more likely to become specialists. For individual teachers, we find clear evidence that they perform worse in specialized teaching roles relative to general roles as measured by their impacts on student achievement in math and reading. Moreover, reductions in teaching effectiveness are greater for students who are more likely to face difficulties in school (i.e., low-achieving students, students who are eligible for free or reduced-price lunch, English language learners, and students who are enrolled in special education). From the perspective of total school performance, we find no evidence that schools that increase the proportion of teachers working as specialists experience improvement in student achievement, absences, or disciplinary infractions.

2. Background on Teacher Specialization

Discussion regarding the potential benefits of elementary school teacher specialization dates back for more than a century. Though the percent of elementary schools that implement teacher specialization has varied widely over time (Lobdell & Van Ness, 1963; Hood, 2010), an increasing number of elementary schools assign teachers to fewer subjects and a greater number of students (Gewertz, 2014; Hood, 2010; Parker et al., 2017). In the mid-1990s, only 5% of elementary schools implemented teacher specialization, but that number rose to 20% by the end of the 2000s across U.S. school districts (Hood, 2010).

This growing interest in elementary school teacher specialization is closely linked with demand for quality teachers. A large body of studies confirm that teacher quality plays a critical role in student learning and development (e.g., Chetty, Friedman, & Rockoff, 2014; Jennings & Greenberg, 2009), yet the quality and supply of teachers in the U.S. workforce has been a concern over the past several decades (Corcoran et al., 2004; Hanushek & Pace, 1995).

Two lines of emerging literature provide compelling evidence that supports the advantages of teacher specialization. One line of research demonstrates that a teacher's effectiveness varies across subjects. Although a highly effective teacher in one subject tends to be also highly effective in other subjects, teachers are more effective in some subjects than others (Condie et al., 2011; Cohen et al., 2018). This suggests that assigning teachers to subjects based on their comparative advantages may enhance student learning.

Another hypothesized advantage of specialization is that it should reduce teacher preparation and training burdens. Scholars also show that teaching the same grade repeatedly helps teachers develop their expertise faster (Ost, 2014; Blazar, 2015), whereas teaching multiple grades and managing wider ranges of content preparation hampers their effectiveness (Bastian & Janda, 2018). Because teacher specialization enables teachers to spend more time on a narrower range of content, teacher specialization can also expedite teachers' preparation and professional development by allowing teachers to devote their time to a smaller number of subjects. Teachers report that preparing and teaching fewer subjects reduces stress and increases their job satisfaction (Strohl et al., 2014).

Despite theory and evidence suggesting teacher specialization is a promising strategy to increase teacher effectiveness, assigning teachers to fewer subjects may come with unintended consequences. Teachers are responsible for teaching more students, making it more difficult for them to learn each individual students' strengths and weaknesses, special circumstances, and needs (Ackerlund, 1959; Culyer, 1984; Vidergor & Gordon, 2015). This lack of student-teacher familiarity likely provides challenging environments for students to build attachment with teachers and develop a sense of school belonging (Allen et al., 2018; Bouchard & Berg, 2017). Research consistently shows that establishing strong relationship with teachers play an important role in student development by increasing school engagement and connectiveness, particularly in early stages of schooling (Curby et al., 2009; O'Connor & McCartney, 2007; Wu et al., 2010) For parents, not having a single teacher may make it more difficult to communicate regarding the progress of their child's development and learning.

Given these considerations, teacher specialization may have more adverse effects on students from vulnerable populations. Although relationships with teachers influence the learning of all students, the opportunities to build relationships with teachers can play a greater role for students who face more challenges in schools (Hamre & Pianta, 2005; Meehan et al., 2003). For example, if students from low-income families have relatively fewer educational resources and support at home, strong bindings with teachers may help offset these disadvantages (Liew et al., 2010; Murray & Malmgren, 2005). Similarly, academically struggling students likely face greater difficulties if they study with teachers who do not spend enough time with them to know their learning styles and tailor instruction to their particular needs (Liew et al., 2010).

Although discussions regarding the pros and cons of teacher specialization are far from new, rigorous and systematic empirical evidence on the effects of teacher effectiveness and school improvement is rare. Two recent studies suggest the costs of teacher specialization outweigh the benefits. Research from a randomized control trial involving 46 schools in Houston Independent School District (HISD), where students are predominantly from racial/ethnic minority and low-income families, finds that teacher specialization has adverse effects on average academic achievement and behavioral outcomes (Fryer, 2018). Specifically, students in treatment schools encouraged to adopt specialization experienced a 0.11 SD decrease in a combined index of math and reading test scores, and were more likely to be suspended and accrue absences.

Related research examining data from North Carolina's elementary schools also found discouraging results (Bastian & Fortner, 2018). Though they found that more effective teachers (i.e., as measured by value-added scores and principal evaluations) were more likely to be specialists, teachers were less effective in math (-0.04 SD) and reading (-0.01 SD) when they taught one or two subjects than when they taught more subjects. Moreover, the North Carolina study found no evidence that increased levels of specialization and school effectiveness.

Using data covering the universe of public elementary schools in Indiana across seven years, we contribute to this growing literature in several important ways. First, we identify factors that predict which school and teacher characteristics predict teacher specialization. Next, we employ teacher fixed effects models to reveal the effect of teacher specialization on teaching effectiveness overall and across student subgroups. Finally, we examine the net effect of teacher specialization on school-level student achievement, absences, and discipline rates, and explore potential heterogeneous effects across different levels of student achievement, student poverty, and minority student rates.

3. Data and Sample

We use administrative data from the Indiana Department of Education (IDOE) from 2010-11 through 2016-17 school years. These data include student characteristics (e.g., gender, race/ethnicity, enrollment in free or reduced-priced program, and enrollment in special education) and teacher characteristics (e.g., gender, race/ethnicity, education level, subjects taught). The data also include student math and reading test scores from grades 3 through 5 on the Indiana Statewide Testing for Educational Progress Plus (ISTEP+). We use ISTEP+ test scores as our main outcome of interest to assess whether teacher effectiveness increases or decreases when teachers specialize in fewer subjects.

Our primary analytic sample includes 15,895 unique math teachers and 17,101 unique reading teachers. We link 591,311 unique students to these teachers. We exclude the 10 percent of teachers in our sample who co-teach in the classroom (i.e., two teachers teach in one class at the same time) because identifying each teacher's contribution to the student outcomes is difficult. Table 1 presents descriptive statistics for the teachers and students in our analytic sample, which we restrict to teachers in 4^{th} and 5^{th} grade due to the inclusion of lagged student achievement in our analytic models. Following Bastian and Fortner (2018), we define specialists as teachers who teach one or two subjects out of the four major subjects (i.e., math, reading, social science, and science). When teachers teach three or four subjects, we define them as generalists. About 22 percent of ever-specialists teach math, and 25 percent of ever-specialists teach reading. We present more detailed information, including details about the number of subjects taught by teachers in a given year, in Appendix Table 1.

Teachers in our data are mostly female and White, which reflects U.S. teacher demographic characteristics (U.S. Department of Education, 2017). On average, Indiana teachers in our sample have roughly 12 years of experience, and slightly fewer than half have a graduate degree. The students in our sample are more racially/ethnically diverse than the teachers; Black, Hispanic, and other race/ethnicity students make up about 30 percent of students. Half of the students are eligible for free or reduced-price lunch, and 7 percent are English language learners. About 14 percent of students receive special education services.

4. Analytic Models

4.1 Subject-area specialization and teaching effectiveness

Our primary goal is to estimate the causal effect of subject-area specialization on teaching effectiveness and school improvement. An ideal strategy would compare outcomes for teachers or schools randomly assigned to incorporate specialization to teachers or schools that are not. Such a strategy would rule out the possibility that the timing of assignment to specialization is related to other unobserved factors, or that teachers or schools adopting teacher specialization are a select group with different characteristics than teachers or schools that do not.

Because we do not have random-assignment, we leverage quasi-experimental panel data methods to recover estimates that—under the identifying assumptions of our models—carry a causal interpretation. Specifically, we use multi-layer fixed effects models, with the key layer being fixed effects for individual teachers themselves. The teacher fixed effects isolate identifying variation to occur within teachers only—i.e., we identify the effect of specialization by comparing the effectiveness of the same teachers in years when they do and do not specialize. Our identification hinges on the assumption that factors that lead to changes in a teacher's specialization status are unrelated to time-varying changes in their own performance or the expected performance of the students assigned to them, conditional on observed student controls. Our primary specification is as follows:

$$Y_{ijgst} = \beta_1 Specialist_{jst} + \beta_2 \boldsymbol{Student}_{ijst} + \beta_3 \boldsymbol{Teacher}_{jst} + \beta_4 \boldsymbol{School}_{st} + \delta_j + \theta_g + \rho_t + \epsilon_{ijgst} \quad (1)$$

Y_{ijgt} represents the standardized math or reading score for student *i* with teacher *j* in grade g and school *s* at time *t*. $Specialist_{jst}$ is the treatment variable of interest and indicates whether a teacher is a specialist in a given school year in school *s* at time *t*. $\boldsymbol{Student}_{jst}$ includes student characteristics including prior year test scores in math or reading, gender, race/ethnicity, eligibility for free or reduced-priced lunch (FRL), enrollment in special education services, English language learner status (ELL), and class size. $\boldsymbol{Teacher}_{jst}$ includes whether a teacher has a graduate degree and whether a teacher is a new to school. $\boldsymbol{School}_{st}$ includes school size, the percent of Black and Hispanic students, and the percent of students who are eligible for free or reduced-priced lunch. δ_j is a teacher fixed effect, θ_g is a grade fixed effect, π_s is a school fixed effect, and ρ_t is a year fixed effect. ϵ_{ijgst} is the error term, which we cluster at the school level.

To examine whether the effects of specialization vary by time, we also run models where we include a set of indicators for one, two, or three or more years since becoming specialist. These models allow us to test whether the effects of specialization change as teachers accumulate experience in that role. To examine whether teacher specialization and effectiveness vary across student subgroups, we add interaction terms to our models to examine if effects are different for students from certain subgroups, including students who are eligible for FRL, enrolled in special education services, ELL, and lower-achieving students. We also present models run separately for each subgroup in Appendix Tables 2 and 3 the results are qualitatively similar.

4.2 Teacher specialization and school improvement

While our teacher fixed effects models estimate the effectiveness of individual teachers, it could still be the case that schools are effectively assigning teachers in ways that improve average school outcomes. For example, though assigning a teacher to a specialist role may lower an individual teacher's average effectiveness, students may still be better off if that teacher is better at a particular subject than the other generalists in the school. We use longitudinal school-grade data and school fixed effects to test whether the percentage of teachers who are specialists in a given year has an effect on school improvement in achievement, unexcused absences, and percent of students receiving disciplinary infractions. The following equation presents our school fixed effects specification:

$$Y_{sgt} = \beta_1 SpecializationRate_{sgt} + \beta_2 \boldsymbol{School}_{st} + \delta_s + \theta_g + \rho_t + \epsilon_{sgt} \quad (2)$$

Y_{sgt} represents one of the school-grade level outcomes (math achievement, reading achievement, absences, or disciplinary incidents) for school *s* in grade g at time *t*. We measure math and reading achievement by aggregating ISTEP+ math and reading scores at school-grade level, respectively. Absences indicate average unexcused days absent at school-grade level, and disciplinary incidents indicate percent ever-disciplined students at school-grade level. $SpecializationRate_{sgt}$ indicates the percentage of students taught by a specialist in math or reading in a school-grade, by year. When examining non-test score outcomes, we use the percentage of students taught by either math or reading specialists. $School_{st}$ indicates time varying school-grade level characteristics, including the percentage of teachers who have a graduate degree, the percentage of teachers who are new to the school, school size, the percentage of students who are Black and Hispanic, and the percentage of students who are eligible for free or reduced-lunch prices. δ_s is a school fixed effect that controls for time-invariant school characteristics. θ_g is a grade fixed effect, and ϵ_{sgt} is an error term. To examine potential heterogenous effects of teacher specialization, we also include interaction terms between the percentage of students who study with specialists and school characteristics, including poverty level, the percentage of racial/ethnic minority student rates, and prior-year student achievement. As a robustness check, we present results using school-year level instead of school-grade level in Appendix Tables 4 and 5, and the results are consistent.

5. Results

5.1 **Descriptive characteristics**

We first examine school characteristics and how they relate to the prevalence of teacher specialization (i.e., quartiles of percent of students with subject area specialists). Overall, we find few differences across schools with more or less teacher specialization (Table 2). Schools with high and low specialization are similar in terms of percent Black, percent Hispanic, percent FRL, prior achievement, and school size. Additionally, teacher specialization does not vary much by school urbanicity.

Next, we investigate teacher characteristics that predict specialization in math or reading. Perhaps counterintuitively, Table 3 shows that teachers with lower lagged value-added scores and those categorized by the Indiana Department of Education as not highly qualified are more likely to become subject-area specialists, compared with generalist teachers within a school during the same school years. Column 1 in Table 3 shows that one SD increase in lagged math value-added score is associated with a 4.8 percentage point decrease in the probability of becoming a math specialist. In addition, being designated a highly qualified teacher is associated with 10.7 percentage point decrease in the probability of becoming a math specialist. Hispanic teachers and more experienced teachers are also less likely to become math specialists. Column 2 shows results from the models that predict becoming reading specialists, and the findings are substantively similar.

5.2 Teacher specialization and teaching effectiveness

Our primary results regarding the impacts on teaching effectiveness of subject-area specialization are shown in Table 4. Column 1 in shows that when a teacher specializes in fewer subjects, their teaching effectiveness in math is 0.04 SD lower compared with when that same teacher is a generalist. Column 2 shows that the first year of specialization generates the largest negative impact, at -0.045 SD, while the second, and subsequent years of specialization lead to -0.028 SD, and -0.032 SD decreases in math teaching effectiveness, respectively. Though the estimates are less pronounced in reading, the patterns are similar. On average, when a teacher teaches fewer subjects to more students, their average effectiveness in reading is 0.015 SD lower. This is largely driven by a -0.020 SD effect in the first year of specialization. Effects in reading effectiveness in subsequent years are not practically significant.

We next test whether the effects vary across student subgroups by including interaction effects between specialization and subgroup indicators (Table 5). Because we use teacher fixed effect, our estimations indicate whether the within-teacher change in teaching effectiveness has a greater impact for certain groups of students, conditional on average teacher performance. The reduction in teaching effectiveness is greater for students at a higher risk of experiencing difficulties in school. For math, non-FRL students with specialists experience a 0.034 SD decrease in test scores, while FRL students experience a 0.046 SD decrease compared with when the same teacher was a generalist. Similarly, ELL students with specialists experience a 0.051 SD decrease in test scores, compared with a 0.039 decrease for non-ELL students. The negative impact is even greater for students enrolled in special education services (-0.060 SD). In column 4, we show that specialization tends to have larger negative effects for students who were lower-achieving in the previous year.

Columns 5 through 8 also show that the negative effects of specialization in reading tend to be greater for students who may face more challenges in school. For example, while non-FRL students with specialists experience a 0.008 SD decrease in reading scores, FRL students exhibit a 0.014 SD decrease. Similarly, while being a reading specialist generates a 0.012 SD decrease in test scores for students not enrolled in special education, those enrolled in special education services experience a 0.031 SD decrease in reading scores. Students who were lower performing in the prior year also experience larger negative effects. Finally, the negative impact of specialization on reading is greater for non-ELL students than ELL students. One possible explanation is that ELL students may have unique reading-instruction needs such that they may benefit from a specialist mode of instruction.

5.3 Teacher Specialization and School Improvement

Finally, we examine the role of teacher specialization at the school level. Table 6 shows whether the percent of subject-area teacher specialization affects grade-level math or reading achievement. Columns 1 and 5 indicate that math teacher specialization is not associated with school level math or reading achievement. Columns 2 through 4 show the results from models with interactions between math teacher specialization and school characteristics indicating proportions of students in poverty, minority students, and prior achievement levels. We find no evidence of heterogenous effects between math specialization across these school characteristics. In terms of school level reading performance, the results show that specialization effects do not vary by proportions of students in poverty and minority students (Columns 6 and 7). We find some suggestive evidence that reading specialization negatively affects reading achievement at more high-achieving schools, though the effect is small.

We also test whether teacher specialization affects school level absences or school disciplinary outcomes (Table 7). We find no evidence that the percent of a school's teacher specialization affects these behavioral student outcomes. In addition, there are no heterogenous effects across different school characteristics, including school percent FRL, percent of Black and Hispanic students, and prior school level achievement.

6. Discussion and Conclusion

We use seven years of administrative data on elementary school students and teachers to investigate whether and the extent to which subject-area specialization affects teaching effectiveness and school performance. Although specialization is conceptually alluring because it can capitalize on teachers' comparative advantages and streamlines their preparation and training, it does not seem to benefit students. Our teacher fixed effect models show that teaching effectiveness in math and reading decreases when teachers teach fewer subjects to more students. We further show that the negative effects have a greater impact for students who tend to experience more challenges in school, including low-achieving students, FRL eligible students, English language learners, and students receiving special education services. This is consistent with related evidence showing that relationships are especially important for vulnerable students (Al-Yagon & Mikulincer, 2004; Baker, 1999; O'Connor & McCartney, 2007; Wu et al., 2010). At the school level, the relative concentration of teacher specialization does not translate into increased school level outcomes, including average achievement, absences, or school disciplinary incidents.

It is possible that specialization fails to live up to its promise is because school leaders are not able to effectively determine which teachers should specialize in which subjects. We show that teachers who exhibit lower value-added scores and are not designated as highly qualified tend to become specialists in Indiana. Yet, related work in North Carolina found higher-quality teachers (based on value-added score and principal evaluation) tend to become specialists, but otherwise had similar findings to ours (Bastian & Fortner, 2018). In both cases, subject area specialization reduced teaching effectiveness, and there is no evidence that increasing the number of specialists improves school performance.

One mechanism that may explain our findings is that specialization weakens student-teacher relationships. To explore this theory further, we e investigate whether the negative effects of specialization are reduced if students are assigned to the same specialist for two consecutive years (i.e., repeating student-teacher matching). We find that the negative effects of specialization in math achievement are significantly lower when students are taught by the same specialist in a consecutive year (Appendix Table 6). Although the results are suggestive, they show that finding strategies to increase student-teacher familiarity with specialists may improve their effectiveness (Hill & Jones, 2018).

This study contributes to our understanding of elementary school teacher specialization, but it has limitations. First, because our identification strategy relies on teacher fixed effects, we are not able to estimate teacher effectiveness for teachers who are either specialists or generalists all the time during the study period. While teacher fixed effects remove time-invariant characteristics and provide a reliable method to identify the effect on switchers, teachers who are always specialists and generalists do not contribute to our estimations. In addition, our school-level models cannot fully capture the complexity of decision-making that goes into assigning teachers to specialists' roles. Though the net effect of increased specialization appears to be null, we don't directly observe a counterfactual scenario where a school opts not to specialize with every other aspect within the school held constant. It is possible for example, that schools increase specialization as a strategy to deal with a shortage of qualified teachers, and without increased specialization school performance may actually decrease.

Despite these limitations, our findings provide useful insight into elementary school teacher specialization and echo the findings of related research (Bastian & Fortner, 2018; Fryer, 2018). Indeed, teacher surveys administered in the only randomized controlled trial evaluation of teacher specialization found that teachers in treatment schools were less likely to report providing tailored instruction for their students and demonstrated a negative impact on self-reported job performance (Fryer, 2018). Our findings underscore the importance of opportunities for teachers to know how their students learn and develop relationships (Grant, 1996; Hill &

Jones, 2018). Future research should further explore these mechanisms to determine optimal ways to harness the potential gains of specialization without the unintended consequences that teacher specialization seems to generate.

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Table 1: Teacher and Student Characteristics

	Math	Reading
<u>Teacher</u>		
Ever Specialists (%)	22.7	24.8
Female (%)	85.0	86.0
Black (%)	4.2	4.3
White (%)	94.4	93.8
Hispanic (%)	1.1	1.2
Other race/ethnicity (%)	0.2	0.8
Teaching experience (Year)	11.9	11.9
Graduate degree (%)	43.5	43.3
N (Unique teacher observation)	15,895	17,101
<u>Student</u>		
Female (%)	49.1	
Black (%)	11.3	
White (%)	70.9	
Hispanic (%)	11.0	
Other race/ethnicity (%)	9.0	
Free or reduced-price lunch eligibility (%)	50.2	
English Language Learner (%)	6.7	
Enrollment in special education (%)	14.0	
N (Unique student observation)	591,311	

Note. This summary statistics are based on unique teacher, teacher, and school data from 2010-11 to 2016-17 academic year in Indiana for students in 4 and 5 grades.

Table 2: School Characteristics and Different Levels of Teacher Specialization

	Specialization Quartile 1 (< 3.6%)	Specialization Quartile 2 (3.6%~26.3%)	Specialization Quartile 3 (26.3~53.7%)	Specialization Quartile 4 (53.7%~100%)
% Black	7.2	4.5	5.7	7.7
% Hispanic	6.6	4.7	5.6	6.1
% FRL	27.0	25.2	27.0	30.8
School enrollment	404.0	416.8	413.8	458.5
Prior year school level achievement	-0.04	-0.01	-0.005	-0.05
Rural	0.28	0.39	0.34	0.32
City	0.39	0.19	0.29	0.33
Town	0.10	0.15	0.16	0.14
Suburb	0.22	0.27	0.21	0.20
N (school-year cases)	2170	2170	2170	2170

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. FRL= free or reduced-price lunch. Results are based on school-year level data from 2010-11 to 2016-17 academic year for students in grades 4 and 5. Standard errors in parentheses. Specialists indicate teachers who teach one or two subjects in a given school year.

Table 3: Characteristics of First-time Specialists

	First Time Math Specialist	First Time Reading Specialist
Prior value-added Score	-0.048*	-0.022
	(0.019)	(0.032)
Highly qualified designation	-0.107***	-0.036**
	(0.014)	(0.012)
Female teacher	0.008	0.011
	(0.008)	(0.008)
Black teacher	0.004	0.018
(ref. White teacher)	(0.015)	(0.023)
Hispanic teacher	-0.042**	0.028
	(0.016)	(0.033)
Other race/ethnicity teacher	0.092	0.031
	(0.102)	(0.037)
Years of teaching experience	-0.002***	-0.003***
	(0.000)	(0.000)
Graduate degree	0.000	0.006
	(0.007)	(0.008)
Constant	0.213***	0.220***
	(0.014)	(0.014)
School FE	X	X
Year FE	X	X
N (teacher-year cases)	33259	39560

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. These models include school and year fixed effects to estimate the probability of becoming specialist within a school and year. Because the starting year of data is 2011, we are not able to identify the first-time specialist in 2011. We thus exclude teacher data in 2011 in our analyses that predict first-time specialists. Highly qualified teacher designation in Indiana indicates teachers who are qualified in the subject via (1) passing PRAXIS/NTE, (2) 24 credits/degree in core academic, or (3) national board certification. Standard errors in parentheses

Table 4: Teacher Specialization and Teaching Effectiveness

	Math		Reading	
	Model 1	Model 2	Model 1	Model 2
Specialization	-0.040***		-0.015**	
	(0.006)		(0.004)	
First year of specialization		-0.046***		-0.020***
		(0.007)		(0.004)
Second year of specialization		-0.029***		-0.003
		(0.008)		(0.004)
Three years+ specialization		-0.032***		-0.008
		(0.009)		(0.005)
Constant	0.036*	0.036*	-0.006	-0.006
	(0.014)	(0.014)	(0.011)	(0.011)
Teacher Fixed Effects	X	X	X	X
N (student-year cases)	1789158	1789158	1783212	1783212

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.01$. All models include teacher, school, grade, and year fixed effects. In addition, we control for student level controls (i.e., prior achievement, gender, race/ethnicity, FRL, ELL, enrollment in special education, and class size), teacher level controls (i.e., graduate degree and new to school,), and school level controls (i.e., school-level achievement, % Black, % Hispanic, % FRL, and school enrollment). For ELA achievement outcome, we include ELA teacher specialization in the models. The data are based on teacher-year data from 2010-11 to 2016-17 academic year in Indiana for students in fourth and fifth grades. We cluster standard errors at the school level.

Table 5: Specialization and Student Achievement across Student Subgroups

	Math				Reading			
Teacher Specialization	-0.034***	-0.039***	-0.036***	0.023**	-0.008*	-0.016***	-0.012***	-0.015**
	(0.006)	(0.006)	(0.006)	(0.007)	(0.004)	(0.003)	(0.003)	(0.005)
FRL	-0.081***	-0.088***	-0.088***	-0.108***	-0.093***	-0.102***	-0.102***	-0.122***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)
ELL	-0.025***	-0.018***	-0.025***	-0.067***	-0.058***	-0.067***	-0.058***	-0.094***
	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.003)
Special education	-0.127***	-0.127***	-0.113***	-0.198***	-0.207***	-0.207***	-0.196***	-0.312***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)
Achievement Q1 (reference: Q4)				-1.762***				-1.682***
				(0.004)				(0.003)
Achievement Q2				-1.115***				-1.091***
				(0.003)				(0.003)
Achievement Q3				-0.643***				-0.604***
				(0.003)				(0.003)
Prior achievement (Math or ELA)	0.752***	0.752***	0.752***		0.704***	0.704***	0.704***	
	(0.001)	(0.001)	(0.001)		(0.001)	(0.001)	(0.001)	
Specialization * FRL	-0.012***				-0.014***			
	(0.002)				(0.002)			
Specialization * ELL		-0.012**				0.015***		
		(0.004)				(0.004)		
Specialization * Special education			-0.024***				-0.019***	
			(0.004)				(0.003)	
Specialization * Achievement Q1				-0.082***				0.000
				(0.006)				(0.004)
Specialization * Achievement Q2				-0.091***				0.004
				(0.005)				(0.004)
Specialization * Achievement Q3				-0.062***				-0.014***
				(0.005)				(0.004)
Constant	0.026*	0.029*	0.028*	0.949***	-0.011	-0.006	-0.008	0.855***
	(0.013)	(0.013)	(0.013)	(0.015)	(0.012)	(0.012)	(0.012)	(0.013)
Teacher Fixed Effects	X	X	X	X	X	X	X	X
N (student-year cases)	1789158	1789158	1789158	1789158	1783212	1783212	1783212	1783212

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.01$. FRL= free or reduced-price lunch eligibility. ELL= English language learners. All models include teacher, school, grade, and year fixed effects. In addition, we control for student level controls (i.e., prior achievement, gender, race/ethnicity, FRL, ELL, enrollment in special education, class size), teacher level controls (i.e., graduate degree and new to school), and school level controls (i.e., school-level achievement, % Black, % Hispanic, % FRL, and school enrollment). For ELA achievement outcome, we include ELA teacher specialization in the models. The data are based on teacher-year data from 2010-11 to 2016-17 academic year in Indiana for students in fourth and fifth grades. We cluster standard errors at the school level.

Table 6: Teacher Specialization and School Level Achievement across School Characteristics

	School level math achievement				School level reading achievement			
% Specialization	-0.013	-0.028	-0.024	0.010	-0.008	-0.013	-0.004	-0.001
	(0.013)	(0.029)	(0.015)	(0.014)	(0.010)	(0.018)	(0.011)	(0.011)
% Specialization * % FRL		0.000				0.000		
		(0.001)				(0.001)		
% Specialization * % Black and Hispanic			-0.000				-0.000	
			(0.000)				(0.000)	
% Specialization * prior year school achievement				-0.036				-0.0038*
				(0.028)				(0.018)
Constant	0.112**	0.119**	0.111**	0.155***	0.103***	0.100***	0.097***	0.103**
	(0.036)	(0.036)	(0.036)	(0.045)	(0.028)	(0.029)	(0.028)	(0.036)
N (school-grade cases)	16082	16082	16082	13829	16076	16076	16076	13824

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.01$. All models include school fixed effects. FRL= free or reduced-price lunch. All models control for % FRL, % Black and Hispanic students, school size, % teachers who are new to school, % teachers with graduate degree. We cluster standard errors at the school level.

Table 7: Teacher Specialization and School Level Absence and Discipline across School Characteristics

	School Absences				School Discipline			
% Specialization	0.086	-0.047	0.003	0.008	-0.003	-0.000	-0.000	-0.005
	(0.059)	(0.170)	(0.048)	(0.069)	(0.002)	(0.005)	(0.002)	(0.003)
% Specialization * % FRL		-0.001				-0.000		
		(0.007)				(0.000)		
% Specialization * % Black and Hispanic			-0.004				0.000	
			(0.003)				(0.000)	
% Specialization * Prior year school achievement				-0.154				-0.010
				(0.243)				(0.009)
Constant	1.173***	1.162***	1.145***	1.074**	0.043***	0.042***	0.043***	0.051*
	(0.283)	(0.289)	(0.287)	(0.386)	(0.011)	(0.011)	(0.011)	(0.014)
N (school-grade cases)	16076	16076	16076	13824	16076	16076	16076	13824

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.01$. FRL= free or reduced-price lunch. All models control for % FRL, % Black and Hispanic students, school size, % teachers who are new to school, % teachers with graduate degree. We cluster standard errors at the school level.

Appendix Table 1: Number of Subjects in a Given Year for Teachers

Subjects to teach	Percent
One subject	
Only math	2.53
Only reading	10.03
Two subjects	
Math and reading	10.21
Math and social studies	0.56
Math and science	1.68
Reading and social science	4.01
Reading and science	1.34
Three subjects	
Math, reading, science	4.12
Math, reading, and social studies	4.47
Reading, science, and social studies	4.63
Math, science, and social studies	2.03
All four main subjects	54.39
N (Teacher-year cases)	55,518

Note. The table is based on teacher-year data from 2010-11 to 2016-17 academic year for students in grades 4 and 5.

Appendix Table 2: Teacher Specialization and Student Achievement by Free-Reduced Lunch, English Language Learner, and Special Education Enrollment

	Math						Reading					
	FRL	Non-FRL	ELL	Non-ELL	SPED	Non-SPED	FRL	Non-FRL	ELL	Non-ELL	SPED	Non-SPED
Specialization	-0.047***	-0.034***	-0.049*	-0.040***	-0.024*	-0.043***	-0.022***	-0.005	-0.019	-0.015***	-0.027***	-0.012**
	(0.007)	(0.007)	(0.020)	(0.006)	(0.011)	(0.006)	(0.004)	(0.005)	(0.010)	(0.004)	(0.007)	(0.004)
Prior Achievement	0.746***	0.755***	0.734***	0.752***	0.689***	0.760***	0.712***	0.695***	0.691***	0.703***	0.715***	0.699***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.004)	(0.002)	(0.003)	(0.002)
Female	0.006***	0.003*	0.011**	0.004***	-0.018***	0.007***	0.081***	0.091***	0.083***	0.086***	0.054***	0.091***
	(0.001)	(0.001)	(0.004)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.003)	(0.001)
Special education	-0.121***	-0.136***	-0.129***	-0.127***			-0.197***	-0.217***	-0.211***	-0.207***		
	(0.003)	(0.003)	(0.007)	(0.002)			(0.003)	(0.003)	(0.008)	(0.002)		
FRL			-0.041***	-0.089***	-0.080***	-0.088***			-0.042***	-0.103***	-0.081***	-0.104***
			(0.006)	(0.001)	(0.003)	(0.001)			(0.006)	(0.001)	(0.003)	(0.002)
ELL	-0.035***	-0.023***			-0.033***	-0.021***	-0.062***	-0.069***			-0.052***	-0.059***
	(0.003)	(0.005)			(0.008)	(0.003)	(0.004)	(0.005)			(0.008)	(0.003)
Black	-0.085***	-0.102***	-0.043***	-0.094***	-0.112***	-0.089***	-0.077***	-0.104***	-0.006	-0.092***	-0.078***	-0.090***
	(0.003)	(0.004)	(0.012)	(0.003)	(0.006)	(0.003)	(0.003)	(0.005)	(0.014)	(0.003)	(0.006)	(0.003)
Hispanic	-0.000	-0.040***	-0.078***	-0.011***	-0.020**	-0.017***	0.016***	-0.026***	-0.070***	0.004	0.010	-0.002
	(0.003)	(0.003)	(0.009)	(0.002)	(0.006)	(0.002)	(0.003)	(0.003)	(0.010)	(0.003)	(0.006)	(0.002)
Asian	0.180***	0.143***	0.132***	0.152***	0.147***	0.155***	0.174***	0.125***	0.094***	0.145***	0.122***	0.143***
	(0.007)	(0.005)	(0.019)	(0.005)	(0.017)	(0.005)	(0.007)	(0.006)	(0.020)	(0.005)	(0.016)	(0.005)
Other race	-0.024***	-0.021***	-0.023	-0.025***	-0.036***	-0.023***	-0.011***	-0.016***	-0.018	-0.017***	-0.011	-0.016***
	(0.002)	(0.003)	(0.020)	(0.002)	(0.006)	(0.002)	(0.003)	(0.003)	(0.020)	(0.002)	(0.006)	(0.002)
Graduate Degree	0.013	0.019*	-0.028	0.016*	0.016	0.015	-0.003	0.022**	-0.009	0.011	0.020	0.007
	(0.009)	(0.008)	(0.027)	(0.007)	(0.016)	(0.008)	(0.007)	(0.008)	(0.021)	(0.006)	(0.013)	(0.007)
New to school	-0.023***	-0.025***	-0.016	-0.024***	-0.012	-0.026***	-0.010*	-0.004	-0.011	-0.007	-0.014	-0.007
	(0.005)	(0.005)	(0.013)	(0.005)	(0.009)	(0.005)	(0.004)	(0.005)	(0.011)	(0.004)	(0.008)	(0.004)
Class size	0.001*	0.001**	-0.000	0.001**	0.002***	0.001*	0.001***	0.002***	0.001**	0.002***	0.002***	0.001***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
School level achievement	0.477***	0.505***	0.554***	0.478***	0.528***	0.476***	0.387***	0.436***	0.401***	0.404***	0.397***	0.406***
	(0.012)	(0.014)	(0.033)	(0.011)	(0.021)	(0.011)	(0.011)	(0.012)	(0.029)	(0.010)	(0.018)	(0.010)
% Black at school	0.002***	0.002***	0.002	0.002***	0.003***	0.002***	0.003***	0.002***	0.003***	0.002***	0.003***	0.002***
	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
% Hispanic at school	0.000	-0.000	-0.002	-0.000	-0.001	0.000	0.001	0.001	-0.000	0.000	-0.001	0.001

	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.001)	(0.000)
% of FRL at school	0.002***	0.003***	0.003***	0.003***	0.003***	0.003***	0.001**	0.003***	0.002*	0.002***	0.002***	0.002***
	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
School enrollment	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.011	-0.017	0.142***	0.024	-0.179***	0.033*	-0.050***	-0.064***	0.031	-0.010	-0.227***	-0.006
	(0.015)	(0.016)	(0.038)	(0.013)	(0.024)	(0.014)	(0.014)	(0.014)	(0.034)	(0.012)	(0.023)	(0.012)
N	840309	947485	105069	1681223	216276	1571031	835062	946458	102154	1677792	211133	1569743

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.01$. FRL= free or reduced-price lunch eligibility. ELL= English language learners. All models include teacher, school, grade, and year fixed effects. For ELA achievement outcome, we include ELA teacher specialization in the models. The data are based on teacher-year data from 2010-11 to 2016-17 academic year in Indiana for students in fourth and fifth grades. We cluster standard errors at the school level.

Appendix Table 3: Teacher Specialization and Student Achievement across Achievement Levels

	Math				Reading			
	Lowest Quartile	2nd Quartile	3nd Quartile	Highest Quartile	Lowest Quartile	2nd Quartile	3nd Quartile	Highest Quartile
Specialization	-0.032***	-0.035***	-0.043***	-0.045***	-0.024***	-0.020***	-0.010	0.002
	(0.008)	(0.008)	(0.008)	(0.010)	(0.005)	(0.005)	(0.006)	(0.007)
Prior Achievement	0.564***	0.835***	0.871***	0.544***	0.585***	0.809***	0.812***	0.461***
	(0.003)	(0.004)	(0.004)	(0.003)	(0.003)	(0.005)	(0.005)	(0.003)
Female	0.011***	0.012***	0.011***	-0.009***	0.078***	0.075***	0.086***	0.118***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Special education	-0.141***	-0.124***	-0.107***	-0.086***	-0.253***	-0.176***	-0.128***	-0.085***
	(0.004)	(0.003)	(0.004)	(0.005)	(0.003)	(0.003)	(0.005)	(0.006)
FRL	-0.070***	-0.070***	-0.072***	-0.103***	-0.072***	-0.084***	-0.094***	-0.125***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
ELL	-0.044***	-0.008	-0.008	0.002	-0.079***	-0.040***	-0.024***	-0.007
	(0.005)	(0.004)	(0.005)	(0.007)	(0.005)	(0.005)	(0.006)	(0.007)
Black	-0.089***	-0.077***	-0.075***	-0.099***	-0.070***	-0.076***	-0.080***	-0.110***
	(0.004)	(0.004)	(0.004)	(0.006)	(0.004)	(0.004)	(0.005)	(0.007)
Hispanic	-0.007*	-0.009**	-0.016***	-0.026***	0.017***	0.016***	-0.004	-0.033***
	(0.004)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)
Asian	0.132***	0.131***	0.122***	0.172***	0.116***	0.130***	0.139***	0.146***
	(0.011)	(0.008)	(0.007)	(0.008)	(0.011)	(0.010)	(0.009)	(0.008)
Other race	-0.025***	-0.026***	-0.015***	-0.012*	-0.007	-0.010**	-0.020***	-0.011*
	(0.004)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)	(0.005)
Graduate Degree	0.012	0.018	0.014	0.007	0.016	0.002	0.011	0.017
	(0.012)	(0.010)	(0.009)	(0.013)	(0.009)	(0.009)	(0.008)	(0.012)
New to school	-0.023***	-0.023***	-0.014*	-0.030***	-0.008	-0.008	-0.012*	-0.004
	(0.006)	(0.006)	(0.006)	(0.008)	(0.005)	(0.005)	(0.006)	(0.007)
Class size	0.001*	0.001	0.001**	-0.000	0.001***	0.001***	0.002***	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
School level achievement	0.508***	0.456***	0.455***	0.507***	0.415***	0.397***	0.398***	0.422***
	(0.014)	(0.013)	(0.015)	(0.019)	(0.013)	(0.013)	(0.013)	(0.016)
% Black at school	0.002***	0.002***	0.002***	0.001	0.003***	0.002***	0.002***	0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
% Hispanic at school	0.000	0.000	-0.000	-0.001	-0.000	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)
% of FRL at school	0.002***	0.002***	0.003***	0.003***	0.001***	0.001***	0.002***	0.003***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
School enrollment	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-0.198***	0.005	-0.013	0.348***	-0.140***	0.006	-0.049**	0.262***
	(0.017)	(0.016)	(0.017)	(0.023)	(0.017)	(0.014)	(0.015)	(0.019)
N	438717	452959	453042	440195	435200	451140	449151	442833

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. FRL= free or reduced-price lunch eligibility. ELL= English language learners. All models include teacher, school, grade, and year fixed effects. For ELA achievement outcome, we include ELA teacher specialization in the models. The data are based on teacher-year data from 2010-11 to 2016-17 academic year in Indiana for students in fourth and fifth grades. We cluster standard errors at the school level.

Appendix Table 4: Teacher Specialization and School Level Achievement across School Characteristics

	School level math achievement				School level reading achievement			
% Specialization	-0.003	-0.028	0.000	0.014	-0.015	-0.008	-0.001	-0.000
	(0.015)	(0.029)	(0.019)	(0.016)	(0.011)	(0.022)	(0.013)	(0.014)
% Specialization * % FRL		0.001				-0.000		
		(0.001)				(0.001)		
% Specialization * % Black and Hispanic			-0.000				-0.001	
			(0.001)				(0.000)	
% Specialization * prior year school achievement				-0.063				-0.021
				(0.062)				(0.050)
Constant	0.112^{**}	0.119^{**}	0.111^{**}	0.155^{***}	0.103^{***}	0.100^{***}	0.097^{***}	0.103^{**}
	(0.036)	(0.036)	(0.036)	(0.045)	(0.028)	(0.029)	(0.028)	(0.036)
N	7527	7527	7527	5957	7527	7527	7527	5957

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.01$. The data are based on school-year data from 2010-11 to 2016-17 academic year in Indiana for students in fourth and fifth grades. We cluster standard errors at the school level. FRL= free or reduced-price lunch. All models control for % FRL, % Black and Hispanic students, school size, % teachers who are new to school, % teachers with graduate degree, and school fixed effects.

Appendix Table 5: Teacher Specialization and School Level Absence and Discipline across School Characteristics

	School Absences				School Discipline			
% Specialization	0.007	-0.013	0.007	0.006	-0.004	-0.003	-0.004	0.000
	(0.012)	(0.024)	(0.016)	(0.013)	(0.005)	(0.011)	(0.006)	(0.004)
% Specialization * % FRL		0.001				-0.000		
		(0.001)				(0.000)		
% Specialization * % Black and Hispanic			0.000				0.000	
			(0.000)				(0.000)	
% Specialization * Prior year school achievement				-0.037				-0.007
				(0.036)				(0.024)
Constant	0.404***	0.409***	0.404***	0.376***	0.063***	0.063***	0.063***	0.045*
	(0.032)	(0.033)	(0.032)	(0.047)	(0.017)	(0.017)	(0.018)	(0.022)
N	7526	7526	7526	5956	7526	7526	7526	5956

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.01$. The data are based on school-year data from 2010-11 to 2016-17 academic year in Indiana for students in fourth and fifth grades. We cluster standard errors at the school level. FRL= free or reduced-price lunch. All models control for % FRL, % Black and Hispanic students, school size, % teachers who are new to school, % teachers with graduate degree, and school fixed effects.

Appendix Table 6: Teacher Specialization and Student Achievement by Student-Teacher Repeated Matches

	Math	ELA
Specialization	-0.040***	-0.015***
	(0.006)	(0.003)
Repeating student-teacher matching	0.028***	0.027***
	(0.007)	(0.006)
Specialization * Repeating student-teacher matching	0.020*	-0.004
	(0.009)	(0.007)
Constant	0.030*	-0.009
	(0.013)	(0.012)
N (Student-year cases)	1787311	1781393

Note. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.01$. All models include teacher, school, grade, and year fixed effects. In addition, we control for student level controls (i.e., prior achievement, gender, race/ethnicity, FRL, ELL, enrollment in special education, class size), teacher level controls (i.e., graduate degree and new to school), and school level controls (i.e., school-level achievement, % Black, % Hispanic, % FRL, and school enrollment). For ELA achievement outcome, we include ELA teacher specialization in the models. The data are based on teacher-year data from 2010-11 to 2016-17 academic year in Indiana for students in fourth and fifth grades. We cluster standard errors at the school level.