Peer Effects or Native Flight? A Study of English Language Learners in California

Abstract

Using ten years of test score and student demographic data from the universe of California public schools, I investigate how the proportion of English Learners (ELs) in a cohort affects average test scores of native-speaker students in that grade. My empirical strategy, which relies on within-school variation over time, reveals a small but statistically significant negative relationship between EL proportions and average native-speaker scores. This effect is concentrated among lower-quality schools and cannot be entirely attributed to negative peer effects. Importantly, I also find evidence for "native flight" – students moving schools in response to higher EL proportions – substantial enough to explain a large fraction of the negative EL coefficient under reasonable assumptions.

JEL Codes: I21, J15, R23

Keywords: peer effects, native flight, English Learners

1 Introduction

The rise of international immigration over the past few decades has brought a large influx of immigrant students, who typically have limited fluency in the destination country language, into the schools of migrant destination countries across the globe. This study investigates how this has affected the schooling experiences of native-speaker students in California, where students with limited English proficiency make up over 20% of the public school population.

The most direct channel through which immigrants might affect native students' education outcomes is through their interactions (with each other and with teachers) in the classroom. The extensive peer effects literature has repeatedly shown that characteristics of one's peers can affect individual academic performance (Black et al., 2013; Hanushek et al., 2009; Hoxby, 2000; Stinebrickner and Stinebrickner, 2006; Zimmerman, 2003), and there are several characteristics that set immigrant students apart from their native peers. This paper focuses on the defining characteristic of ELs: their limited English proficiency.

Peer effects are not the only way for ELs to affect the schooling experiences of their non-EL peers. Another potential channel relates to the "native flight" phenomenon, which, in this context, refers to native-speaker students switching out of schools in response to increasing proportions of non-natives.[1] Several studies have provided evidence of native flight from public schools in various forms – shifts to private school in the United States (Betts and Fairlie, 2003; Cascio and Lewis, 2012; Murray, 2016), Denmark (Gerdes, 2013; Rangvid, 2009), and across countries (Mavisakalyan, 2011), as well as migration away from districts with growing EL proportions in California (Cascio and Lewis, 2012). When thinking about how non-native speakers affect native-speaker schooling experiences as a whole, it is important to also con-

[1] Although it is the students who are switching from school to school, the decision to switch is most likely being made entirely or partially by parents. For brevity, I will often refer to this phenomenon as students moving schools, without referencing the parental decision that determines it.

sider how non-native proportions might change native students' school choices.

In this paper, I use aggregated standardized test score data from all California public schools to investigate how average cohort test performance among native-speakers is affected by EL proportions, in a context where average proportions of non-native speakers far exceed those that have been studied in the past. Using data from 2001 to 2013, I run grade-specific regressions that control for school fixed effects, year fixed effects, fractions of economically disadvantaged students, and school-specific achievement trends. It is important to note that the estimate I obtain from this specification represents the overall effect of EL proportions on average native-speaker test scores (at the cohort level), which includes: (1) any direct peer effects that ELs may have on their non-EL classmates, and (2) any compositional changes in the non-EL population driven by native flight. Therefore, a negative coefficient could be the result of either negative peer effects, the exit of non-ELs who are disproportionately high-achieving, or a combination of both.

This analysis yields three main results. First, the estimated effect of EL proportions on average non-EL test scores is negative and statistically significant, though small in magnitude. Secondly, I find evidence of native flight – specifically, that native-speakers appear to be shifting out of schools (to other schools in the district) in response to increasing EL proportions. Although I unable to quantify how much of the overall negative coefficient is explained by peer effects and native flight separately, the magnitudes of the native flight estimates are large enough to explain large proportions of the (small) coefficient under some reasonable assumptions about which types of students are leaving. Finally, regardless of whether it is due to peer effects or native flight, the negative coefficient on EL proportions is almost entirely driven by schools on the lower end of the quality distribution – those located in poor districts and those that typically perform poorly on these standardized tests.

These findings contribute to the large and growing economic literature on peer effects in education.[2] Most studies on peer effects in education have focused on characteristics such as race (Hanushek et al., 2009; Hoxby, 2000), gender (Black et al., 2013; Hoxby, 2000), socioeconomic background (Stinebrickner and Stinebrickner, 2006), or academic achievement (Zimmerman, 2003). Some recent studies, however, focus more specifically on qualities related to immigrant status and language ability. Contini (2013) analyzes immigrant background peer effects in Italy and finds a weak negative effect of immigrant proportions on learning outcomes overall but no effect for native Italian-speakers of high socioeconomic status. Gould et al. (2009) also find negative impacts of immigrants on high school outcomes in Israel. On the other hand, two other recent papers find that accounting for selection into schools by including school fixed effects completely eliminates the negative correlation between native student performance and the proportion of non-native or immigrant students in England (Geay et al., 2013) and the Netherlands (Ohinata and van Ours, 2013).

Even within the United States, evidence is mixed. For instance, Cho (2012) finds that having an EL classmate during kindergarten and first grade significantly decreases test score gains for native speakers in reading but not in math. Using the same data, Gottfried (2014) finds that higher EL proportions are associated with improved socioemotional measures for their English-speaking classmates. For 4th to 8th graders in North Carolina, larger EL proportions negatively impact test scores of certain subgroups but not others (Diette and Oyelere, 2014, 2017). Conger (2015) finds no evidence of negative EL peer effects for Florida high school students.[3] Given the mixed nature of these results, it is clear that the existing literature cannot be used to draw conclusions about California, for which no estimates of EL peer effects currently exist, despite it having the largest proportion and number of ELs in the entire coun-

[2]See Sacerdote (2011) for a comprehensive review.

[3]Hunt (2017) finds that higher shares of immigrants – at the state-level – leads to higher educational attainment for natives, which is argued to be due labor market factors rather than classroom peer effects.

try. In line with the absence of a firm consensus in the existing literature, I find no evidence of systematic and large negative peer effects; any negative peer effects that do exist are small in magnitude and concentrated in struggling schools.

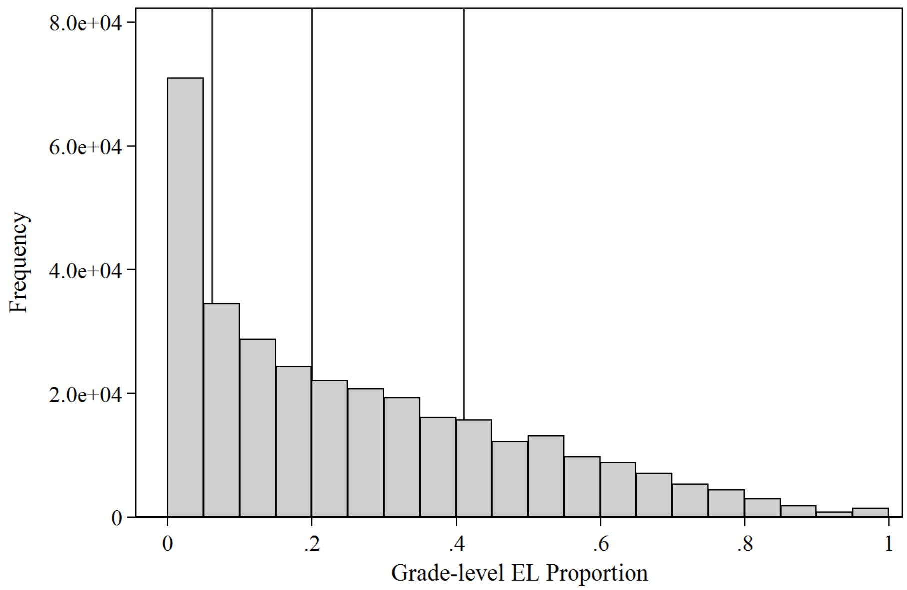
This paper also contributes to the aforementioned literature on native flight from public schools. Unlike existing work, which has documented native flight at the level of the district (or even larger geographic areas), I find evidence of native flight at the school-level: specifically, fluent English speakers moving out of schools in response to increasing EL proportions, and into other schools within the same district. The native flight I document here also occurs over a much shorter time frame than is documented in existing studies, which tend to utilize changes across decades rather than the year-to-year variation I use in this study. These findings shed light on a type of native flight that differs from what has been considered in previous work.

2 Background

2.1 ELs in California

In the 2012-2013 academic year, ELs accounted for approximately 23% of California's K-12 public school population, the highest proportion (and raw number) across all states (National Center for Education Statistics, 2015). The high percentages of ELs pose an extra challenge to California public schools, as these students often require specialized resources and thus higher per capita spending (Carroll et al., 2005). Figure 1 illustrates the distribution of grade-level EL proportions across all California public schools during the academic years starting in 2001 to 2012. There is substantial variation in EL proportions across schools, grades, and years: although 25% of the observations have EL proportions lower than 10%, the top quartile of the sample have proportions exceeding 40%.

Figure 1 Distribution of Grade-Level EL Proportions



Notes: Vertical lines depict the 25th, 50th, and 75th percentiles of the distribution. Sample includes grades 2-6 of all California public schools from academic years 2001-2002 to 2012-2013.

Currently, schools support the English language development of ELs through one of the following settings: (1) Structured English Immersion (SEI), where students who have not reached a certain level of fluency (as determined by the district) are taught a curriculum separate from that of their English-speaking peers, but primarily in English. (2) English Language Mainstream (ELM), where students who have reached a higher level of fluency join their English-speaking peers in the classroom (with some additional support), or (3) Alternative Programs, where students may be taught in a language other than English. Parents must submit special requests for their child's placement in Alternative Programs, which are not available at all schools.[4]

[4]These requests are not common. In the 2010-11 school year, no waivers were submitted in 90% of the schools.

In practice, there is considerable variation across schools in the programs actually provided to ELs. According to data from 2010-11, the most recent year for which EL program data is available, 14% of schools with EL students reported that all of their ELs were enrolled in SEI. On the other hand, over twice this amount (29%) reported that none of their students were in SEI (and therefore most likely in ELM, as alternative programs are much less common).[5] In short, the majority of schools either only offer ELM or some combination of SEI and ELM, which means that most public school classrooms in California are likely to have a mix of ELs and native speakers. An obvious consideration for determining the optimal program for EL development, which is outside the scope of this paper, is how quickly ELs can achieve fluency under the various alternatives and how segregation and integration differentially affect their educational and social development. Another important concern, which is what I deal with in this paper, is how the presence of ELs in classrooms affect the academic performance and school choice decisions of their English-speaking peers. Recently, there has been some interesting work done on the intersection of these two topics: Chin et al. (2013) investigate how the provision of bilingual education programs to ELs affects the academic performance of both ELs and non-ELs, and find no significant effects on the former but significant spillover benefits for the latter.

2.2 Potential Channels for Peer Effects

There are a number of channels through which EL presence might directly affect their non-EL classmates' learning. Depending on their background and training, teachers may slow down to cater to ELs, thus covering less material than they would have otherwise. Some qualitative studies have reported that teachers indeed have a hard time balancing the needs of ELs against

[5] Unfortunately, because this data on student participation in various EL programs is not available at the grade-level, I cannot use this in my primary analysis.

the needs of others (Haworth, 2009; Karabenick and Noda, 2004), a struggle which could potentially lead to a decline in the quality of teaching when ELs are present.

On the other hand, one could also imagine the existence of positive EL peer effects if non-EL students benefit from cultural diversity or learn the material more thoroughly by teaching or helping EL classmates. In addition, classes that have students with unique needs often are provided with extra resources (Lipsky and Gartner, 1995), which could benefit native-speakers who would not have otherwise received this additional support.

2.3 Reasons for Native Flight

Why might EL proportions affect school choice decisions of non-ELs? Existing literature has proposed a number of possible reasons, though no single mechanism has been pinned down. As described in Betts and Fairlie (2003) , earlier studies of "white flight" (which preceded the coining of the term and investigation into "native flight") speculate that white families might move in response to increased minority presence, because of irrational prejudice (Conlon and Kimenyi, 1991), or because they use minority proportions as a negative signal of school quality when other measures are not easily observed. Betts and Fairlie (2003) also point out that native flight, specifically, could be driven by parental concerns about ELs putting a strain on school and teacher resources or changing teaching methods in ways that would not be beneficial to their children. Though I do not explore these alternative hypotheses in this paper, all of these reasons are certainly relevant to the context of this study.

3 Data

3.1 Enrollment Data

To calculate EL proportions by grade, year, and school, I use the publicly available enrollment and EL data from the California Department of Education (CDE). The enrollment files provide total counts and the EL files provide EL student numbers for all public schools in California, separately for each grade and year. I restrict to academic years 2001-2002 to 2012-2013 because of the availability of consistently reported test score data, described in more detail below.

3.2 STAR Test Data

Under the Standardized Achievement Reporting (STAR) Program, initiated in 1997 and terminated in 2013, all California public school students in grades 2 to 11 are tested in reading, language arts, and mathematics every year. Students are only exempt through participation in a special education program or by parental request. Over 90% of enrolled students take the test every year, with participation rates close to 100% for elementary school students. No individual test scores are publicly available, but average scores and number of test-takers are broken down into various subgroups, including racial categories and EL status. Counts and average scores (by subgroup) are reported separately for every grade in every school in every year.

The test scores reported in the STAR data represent the arithmetic mean across all students in a given category (defined by race, gender, EL status, socioeconomic status, etc). The scores are scaled to adjust for any discrepancies in difficulty across years due to added or altered questions. STAR data users are advised not to compare scores across grades but are reassured that scaling makes the test scores comparable across years. The scaled scores range from 150 to 600. For every grade and subject area, scores below 300 represent "below basic" performance, scores from 301-350 are considered "basic," while scores above 350 are considered "proficient." The main goal is to have all students performing at the proficient level: basic scores show only a limited grasp of the material, while below basic scores are indicative of a serious lack of knowledge.

3.3 Variables and Summary Statistics

My main independent variable of interest, cohort-level EL proportions, are obtained from the CDE enrollment data described above. From the STAR data, which reports the proportion of test-takers in various subgroups, I use the fraction of test-takers labeled as "Economically Disadvantaged," defined as those eligible for a free or reduced-price lunch or those whose parents have not graduated from high school.[6]

Table 1 reports average scores and proportions for different sub-groups. Although the scores reported in Table 1 show scaled scores, I standardize scores in my analysis in order to simplify the interpretation of coefficients, using means and standard deviations calculated for a particular grade-year combination. The dependent variable used throughout the analysis is the standardized score among Fluent-English Proficient and English Only students (native speakers). I look at both language arts and math scores of the California Standards Test (CST), using test scores from the spring of 2002 (the first year in which scaled CST scores were reported for all of my subgroups of interest) to the spring of 2013 (the last year of STAR testing). I focus on elementary grades 2 to 6 because students in middle school and high

[6]EL proportions are also available in the STAR data, and are highly correlated with EL proportions from the CDE enrollment data, but I use the latter because it includes all enrolled students and not just those who took the STAR test. I use STAR data for the economically disadvantaged proportions because these are not available in the CDE enrollment or EL data.

school move away from the fixed classroom environment. On average, native-speakers fall on the lower end of proficiency in both subjects. Both ELs and economically disadvantaged students perform worse and are either not proficient or barely proficient on average.

Table 1 Average Test Scores and Proportions by Grade and Sub-Group

	(1)	(2)	(3)	(4)	(5)	(6)	(8)	(9)
	Native-Speakers		English Learners			Economically Disadvantaged		
Grade	English Score	Math Score	Proportion	English Score	Math Score	Proportion	English Score	Math Score
2	359.0	383.5	0.37	322.3	346.2	0.60	327.3	348.6
3	349.3	389.3	0.33	302.2	343.5	0.60	314.3	352.2
4	370.8	382.0	0.29	320.5	337.4	0.59	337.3	350.1
5	361.0	377.8	0.24	308.6	318.1	0.58	330.3	340.0
6	356.5	359.8	0.21	301.0	303.4	0.57	326.8	327.0

Notes: Student-population-weighted statewide averages and proportions are reported. Sample includes grades 2-6 of all California public schools from academic years 2001-2002 to 2012-2013.

One disadvantage of the STAR data is that scores are not reported for individual classes. The grade-level fraction of ELs may not represent the English proficiency composition of each *classroom*, which is the unit likely to be most relevant for peer effects (though it is not clear which would be most relevant for native flight). However, this is only problematic if the true effect of ELs is highly nonlinear and if there are drastic differences in EL proportions across classrooms within a grade.

4 Estimation

4.1 Empirical Strategy

Because I do not have individual-level scores, my data consists of information for each school-year-grade combination. I begin with the following simple specification, estimated separately for each grade g.[7]

$$\bar{Y}_{sgy} = \alpha_0 + \alpha_1 \bar{X}_{sgy} + \eta_y + \bar{\epsilon}_{sgy}, \tag{1}$$

where $\bar{Y}_{sgy}$ is the grade-level average standardized test score for native English-speakers in school s, grade g, and year y. $\bar{X}_{sgy}$ is the fraction of EL students in school s, grade g, and year y. Year fixed effects (η_y) control non-linearly for time trends that are identical across all schools.

In this specification, $\bar{X}_{sgy}$ is unlikely to be exogenous because EL proportions are not randomly assigned. ELs tend to come from lower income households living in poorer districts that likely have lower quality schools than districts with lower immigrant and EL proportions. This would suggest a negative correlation between $\bar{X}_{sgy}$ and $\bar{\epsilon}_{sgy}$ which could lead to biased estimates of EL peer effects. In order to deal with this selection, I add school fixed effects (μ_s), which results in a model that relies on within-school variation over time to identify α_1. The extent of this variation is explored in Table 2. In the first three columns, I report the standard deviation, minimum, and maximum of the raw EL proportion variable for each grade. In the remaining columns, I report these statistics for the residuals of this variable, calculated after regressing EL proportions on year and school fixed effects, by grade. Though the school and year fixed effects do eliminate much of the variation in this variable, the residuals still demonstrate substantial within-school variation.

The school fixed effects specification is as follows:

[7] This implies all coefficients are grade-specific, but I omit grade superscripts on the coefficients for simplicity.

Table 2 Overall and Residual Variation in EL Proportions by Grade

	(1)	(2)	(3)	(4)	(5)	(6)
	Raw proportions			Residuals		
Grade	Standard deviation	Min	Max	Standard deviation	Min	Max
2	0.25	0.00	1.00	0.07	-0.79	0.89
3	0.24	0.00	1.00	0.08	-0.74	0.92
4	0.22	0.00	1.00	0.07	-0.67	0.93
5	0.20	0.00	1.00	0.07	-0.72	0.93
6	0.17	0.00	1.00	0.06	-0.81	0.92

Notes: Residuals are calculated from by-grade regressions of EL proportions on year and school fixed effects. Standard deviation calculations are weighted using student populations (consistent with the statewide averages reported in Table 1).

$$\bar{Y}_{sgy} = \alpha_0 + \alpha_1 \bar{X}_{sgy} + \mu_s + \eta_y + \bar{\epsilon}_{sgy}. \tag{2}$$

μ_s controls for any time-invariant school characteristics that could be affecting test scores as well as EL proportions, while η_y captures non-linear time trends identical across schools.

In equation 2, any time-varying school or district characteristics remain a threat to identification. I therefore consider three sets of additional controls to deal with some important concerns. First of all, immigrant populations tend to be of lower socioeconomic status than native-speaker households, which means that EL proportions are highly correlated with proportions of economically disadvantaged students, even after controlling for school fixed effects. I therefore control for the fraction of economically disadvantaged students ($\bar{Z}_{sgy}$), to ensure that α_1 is not capturing the effect of the socioeconomic characteristics of EL students and is instead isolating the effect of their limited English proficiency. This also ensures that I am not incorrectly attributing grade-level socioeconomic characteristics to the EL effect, which would happen if EL proportions and average income at the school level were negatively correlated for reasons other than the direct relationship described above.[8]

Secondly, changes in school EL proportions over time could be a reflection of district-level population changes that could have separate effects on school quality. To address this possibility, I control for a vector of observable, time-varying district characteristics (W_{dgy}), including enrollment, average daily attendance, expenditures per daily attendance, revenues per daily attendance, average teacher salary, minority proportion, number of full time equivalents, proportion of teachers with less than 2 years of experience, and pupil-teacher ratio.[9]

Even after controlling for these observables, any school-specific unobservables that drive both EL proportions and non-EL student performance are a concern. If there are any trends in school-specific student quality that are correlated with EL proportions in ways that are not accounted for adequately, these could also load onto α_1. In order to control for these trends, I use information from other grades in the same school to proxy for overall quality of the school's fluent English population.[10] Specifically, I average the test scores of non-ELs across all other grades in the same school for each year and include this variable as a control. My most robust specification, therefore, is the following:

$$\bar{Y}_{sdgy} = \alpha_0 + \alpha_1 \bar{X}_{sdgy} + \alpha_2 \bar{Z}_{sdgy} + \alpha_3 \bar{Y}_{sdg-1y} + \beta' W_{dgy} + \mu_s + \eta_y + \bar{\epsilon}_{sdgy}, \tag{3}$$

[8] For instance, if parents respond to declining school quality by moving to different schools or districts, and if richer, non-EL households (with higher-performing children) are the ones more likely to do this, this would lead to a spurious negative correlation between EL proportions and test scores even after controlling for μ_s and η_y.

[9] Data on revenues and expenditures are not available for test year 2002. In order to avoid dropping observations or variables, I impute missing values by fitting a quadratic trend for each district and predicting a value for 2002. Less than 5% of districts are missing variables in years other than 2002, and I impute these in the same way. For districts that have no data for a particular variable (less than 1% of the sample), I use the county mean for each missing year. For one district and one variable (average teacher salary) where this is still missing after these imputations, I use the statewide mean in each year. Results are robust to other methods of imputation.

[10] An alternative way to deal with this would be to include school-specific linear or quadratic trends, but this approach demands quite a bit from the data given that there are over 6,000 schools per grade in my sample and does not utilize the available, potentially useful information from other grades.

where g_{-1} represents the average taken over all other grades except grade g. Standard errors are clustered at the district level.[11]

4.2 Exploring Native Flight

Although specification 3 isolates the effect of EL proportions on average English-speaking student test scores, accounting for selection across schools and various coincident trends, it is important to note that α_1 cannot be interpreted as an unbiased estimate of EL peer effects, the direct effect of ELs on non-EL learning and achievement. This is because EL proportions might be changing average non-EL test scores by changing the composition of non-ELs, if students are indeed responding to increasing EL proportions by moving to other schools. Because controlling for disadvantaged proportions ($\bar{Z}_{sdgy}$) takes into account any changes in composition captured by this variable, I am only concerned about native flight that changes student composition in a way that this variable does not control for.

In order to investigate whether this kind of native flight is actually taking place, I check to see whether school native populations are responding to EL proportions, using a strategy similar to that of Cascio and Lewis (2012). Instead of analysis at the district-level, however, I continue to utilize the school-level variation I use in my previous analysis. Specifically, for each grade I calculate the total number of non-EL students in a district, and calculate the share of this district total that is attending each school. This non-EL school share is what I use as my dependent variable in a regression that is otherwise identical to equation 3. A negative coefficient on the EL proportion variable in this regression would be an indication that native-speakers are responding to higher EL proportions by shifting away from those schools (and into other schools in the district).

[11] There are approximately 900 school districts for each grade in this sample.

4.3 Exploring Heterogeneity

Finally, in order to explore heterogeneity in the overall EL effect (α_1), I also run equation 3, interacting $\bar{X}_{sgy}$ and $\bar{Z}_{sgy}$ with rough proxies for school quality. First, because eligibility for reduced-price lunch is determined based on household income (relative to household size), I use a dummy to identify districts with above-median proportions of children eligible for reduced-price lunch (after averaging these proportions across all years). District-level household income could affect school quality by affecting the composition of students (higher-income households have more resources available to help their children succeed academically) and by directly impacting the level of school funds (part of which comes from property taxes). Second, for each school, I calculate the average standardized score across all grades and years, create a dummy for schools with below-median scores, and interact my coefficients of interest with this dummy, as shown below.

$$\begin{aligned}
\bar{Y}_{sdgy} \quad = \quad & \alpha_0 + \alpha_1 \bar{X}_{sdgy} + \alpha_2 \bar{Z}_{sdgy} + \alpha_3 \bar{X}_{sdgy} D_{sd} + \alpha_4 \bar{Z}_{sdgy} D_{sd} + \\
& \alpha_3 \bar{Y}_{sdg-1y} + \beta' W_{dgy} + \mu_s + \eta_y + \bar{\epsilon}_{sdgy},
\end{aligned} \tag{4}$$

Here, D_{sdc} represents a school-level or district-level indicator variable intended to proxy for school quality.

Table 3 Effect of EL Proportion on Non-EL Language Arts Scores

	(1)	(2)	(3)	(4)	(5)
	Standardized Language Arts Scores				
	Grade 2	Grade 3	Grade 4	Grade 5	Grade 6
1. Year Fixed Effects					
EL proportion	-1.850***	-2.053***	-2.109***	-2.255***	-2.835***
	(0.109)	(0.126)	(0.148)	(0.162)	(0.195)
2. Year, School Fixed Effects					
EL proportion	-0.633***	-0.730***	-0.573***	-0.268	-0.251
	(0.166)	(0.0488)	(0.104)	(0.183)	(0.174)
3. Year, School Fixed Effects					
EL proportion	-0.446***	-0.552***	-0.370***	-0.0938	-0.0592
	(0.160)	(0.0525)	(0.0969)	(0.175)	(0.164)
Economically disadvantaged proportion	-0.669***	-0.695***	-0.793***	-0.771***	-0.824***
	(0.0732)	(0.0788)	(0.0642)	(0.0679)	(0.0695)
4. Year, School Fixed Effects, District Controls					
EL proportion	-0.273***	-0.497***	-0.416***	-0.226***	-0.187**
	(0.0866)	(0.0573)	(0.0551)	(0.0793)	(0.0788)
Economically disadvantaged proportion	-0.592***	-0.639***	-0.760***	-0.782***	-0.821***
	(0.0750)	(0.0786)	(0.0602)	(0.0608)	(0.0687)
Number of observations	61021	61337	61512	61639	42909
5. Year, School Fixed Effects, District Controls, Other Grades School Trend					
EL proportion	-0.280***	-0.405***	-0.244***	-0.0266	-0.0641
	(0.0768)	(0.0458)	(0.0454)	(0.0718)	(0.0455)
Economically disadvantaged proportion	-0.399***	-0.446***	-0.599***	-0.645***	-0.616***
	(0.0575)	(0.0583)	(0.0413)	(0.0467)	(0.0489)
Number of observations	60476	61336	61503	61620	42822

* p<0.1 ** p<0.05*** p<0.01. Standard errors (clustered at district level) in parentheses

District controls include: enrollment, average daily attendance, expenditures per daily attendance, revenues per daily attendance, average teacher salary, minority proportion, number of full time equivalents, proportion of teachers with less than 2 years of experience, and pupil-teacher ratio. "Other Grades School Trend" is the average of native-speaker z-scores across all other grades in that school in that year. Regressions are weighted by the total number of children enrolled in each school-grade-year.

5 Results

5.1 Overall EL Effect

Table 3 reports the estimated coefficients of interest (α_1 and, where relevant, α_2) in various specifications that use native-speaker language arts scores as the dependent variable. Each column represents a different grade level. Panel 1 reports results from equation 1, which includes no controls except for year fixed effects. The large and statistically significant coefficients show a strong negative association between EL proportions and native-speaker test scores across all grades. However, after I take school selection into account by adding school fixed effects, the coefficient magnitudes drop drastically, suggesting that the majority of the initial association can be attributed to students of lower ability sorting into schools with higher EL proportions. As an especially stark example, in grades 5 and 6, the coefficients in panel 2 are one-tenth the magnitude of the coefficients in panel 1.

Including the proportion of economically disadvantaged students as a control (in panel 3) results in an even further decline in the coefficients' magnitudes. Economically disadvantaged proportions are positively correlated with EL proportions because ELs tend to be of lower socioeconomic status and potentially also because location choices of families respond to school or district characteristics correlated with EL proportions. As a result, the omission of this variable results in a substantial overestimate of the magnitude of α_1. The magnitude of the economic disadvantage coefficient is larger than that of the EL coefficient across all grades, and this difference is significant in all but grades 2 and 3. Adding district controls reduces the coefficient magnitudes for some grades but increases the magnitudes for others: none of these differences are as drastic as those resulting from the inclusion of school fixed effects or economically disadvantaged proportions.

In the final panel, I control for school-specific trends in non-EL performance by including the average of non-EL scores across all other grades in the same school. The unobserved trends captured by this variable appear to be quite important, particularly for older grades, where the coefficient magnitudes drop almost to zero. In this final specification, the EL effect is not significantly different from zero in grades 5 and 6, and is small in magnitude across the board. The largest coefficient (from the third grade regression) implies that a percentage point increase in the EL proportion would lead to a 0.004 standard deviation decrease in native-speaker test scores.

Results for math scores are summarized in Table 4. As with the language arts results, the coefficients in the first panel fall by more than half (in some cases more than 80%) with the inclusion of school fixed effects and proportions of economically disadvantaged students. In the most rigorous specification (panel 5), the coefficients are negative, significant, and small in magnitude across all grades, especially grades 5 and 6. Again, the magnitude of the coefficient in the third grade regression is the largest, and it implies that a percentage-point increase in EL proportions would lead to a 0.005 standard deviation decrease in native-speaker test scores.

5.2 Native Flight

The negative coefficients reported above, though purged of any school sorting biases or coincident trends, are not necessarily unbiased estimates of a direct EL peer effect. These coefficients represent the total effect of ELs on average non-EL achievement, including any compositional effects that EL proportions might have on the non-EL population, particularly through native flight. If native flight is taking place, and if the native-speaker students most likely to leave are ones that perform better on these tests, this would produce negative EL coefficients even in absence of any negative peer effects. While the aggregate data I use does

Table 4 Effect of EL Proportion on Non-EL Math Scores

	(1)	(2)	(3)	(4)	(5)
	Standardized Math Scores				
	Grade 2	Grade 3	Grade 4	Grade 5	Grade 6
1. Year Fixed Effects					
EL proportion	-1.738***	-1.628***	-1.528***	-1.602***	-2.381***
	(0.0956)	(0.133)	(0.149)	(0.166)	(0.200)
2. Year, School Fixed Effects					
EL proportion	-0.688***	-0.919***	-0.778***	-0.610***	-0.473***
	(0.137)	(0.0964)	(0.0796)	(0.153)	(0.137)
3. Year, School Fixed Effects					
EL proportion	-0.508***	-0.755***	-0.601***	-0.458***	-0.305**
	(0.136)	(0.0998)	(0.0757)	(0.150)	(0.134)
Economically disadvantaged proportion	-0.649***	-0.638***	-0.689***	-0.671***	-0.723***
	(0.0787)	(0.0805)	(0.0743)	(0.0791)	(0.0785)
4. Year, School Fixed Effects, District Controls					
EL proportion	-0.424***	-0.649***	-0.616***	-0.523***	-0.309***
	(0.131)	(0.0961)	(0.0653)	(0.0762)	(0.111)
Economically disadvantaged proportion	-0.598***	-0.573***	-0.641***	-0.654***	-0.702***
	(0.0748)	(0.0766)	(0.0668)	(0.0758)	(0.0781)
Number of observations	61041	61351	61585	61649	42907
5. Year, School Fixed Effects, District Controls, Other Grades School Trend					
EL proportion	-0.390***	-0.525***	-0.378***	-0.211***	-0.135**
	(0.0981)	(0.0678)	(0.0466)	(0.0598)	(0.0627)
Economically disadvantaged proportion	-0.442***	-0.402***	-0.461***	-0.463***	-0.600***
	(0.0576)	(0.0563)	(0.0447)	(0.0533)	(0.0614)
Number of observations	60495	61350	61576	61629	42816

* p<0.1 ** p<0.05*** p<0.01. Standard errors (clustered at district level) in parentheses

District controls include: enrollment, average daily attendance, expenditures per daily attendance, revenues per daily attendance, average teacher salary, minority proportion, number of full time equivalents, proportion of teachers with less than 2 years of experience, and pupil-teacher ratio. "Other Grades School Trend" is the average of native-speaker z-scores across all other grades in that school in that year. Regressions are weighted by the total number of children enrolled in each school-grade-year.

Table 5 Effect of EL Proportion on School Non-EL Population Share

	(1)	(2)	(3)	(4)	(5)
	School's share of district's total non-EL population				
	Grade 2	Grade 3	Grade 4	Grade 5	Grade 6
El proportion	-0.0848***	-0.0770***	-0.0714***	-0.0655***	-0.0727***
	(0.0139)	(0.0118)	(0.0130)	(0.0132)	(0.0154)
Economically disadvantaged proportion	-0.000341***	-0.000324***	-0.000337***	-0.000237*	-0.000572**
	(0.000119)	(0.000118)	(0.000125)	(0.000143)	(0.000264)
Number of Observations	60504	61359	61571	61638	42839
Mean of Dependent Variable	0.125	0.131	0.133	0.137	0.230

* p<0.1 ** p<0.05*** p<0.01. Standard errors (clustered at district level) in parentheses

All regressions include school fixed effects, year fixed effects, district controls, and other-grade school trends (averaging across math and language arts scores). Regressions are weighted by the total number of children enrolled in each school-grade-year.

not allow me to separate peer effects from selective native flight, I do try to pin down whether native flight is occurring at all, using the strategy described in section 4.2.

Table 5 reports the results of regressions identical to those discussed in the previous section (the last panel of Tables 3 and 4) but using a different dependent variable. I calculate, for each school (and grade), the share of the district's total non-EL student population attending that school and investigate whether this variable responds to EL proportions. Across all grades, I find a significant negative relationship between EL proportions and these non-EL school shares, indicating a shift out of schools in response to higher EL proportions. Unlike the previous literature on native flight, I rely here on a fixed effects specification (for consistency with my other results) and do not use an instrumental variables strategy, which could mean there are some remaining sources of endogeneity that are not dealt with here. It is worth noting, however, that previous work has found that OLS slightly attenuates estimates relative to IV, and maintains the same sign (Cascio and Lewis, 2012; Murray, 2016).

For the native flight documented in Table 5 to be solely responsible for the negative coefficients reported in Tables 3 and 4, it would need to be disproportionately practiced by high-achieving students. Unfortunately, without individual-level data, it is not possible to determine whether this is the case, though it certainly seems reasonable to assume that parents who decide to move their children in response to changing student populations are likely very involved in the academic lives of their children, in ways that may help them outperform their peers academically.

With this plausible assumption in mind, I calculate the number of native students that exit a school in response to a given percentage point increase in EL proportions and then calculate the average scores these native-speaking students would need to have in order for their exit to generate the negative coefficients reported in Tables 3 and 4. For this exercise, I use the grade 3 math coefficient, which was the largest in magnitude across all grades and both subjects. A 10 percentage-point increase in EL proportions is predicted to decrease standardized math scores by 0.05 of a standard deviation. In addition, the native flight coefficient of 0.08 implies that a ten-percentage point increase in EL proportions would decrease school non-EL shares by 0.8 percentage points. Given an average district native-speaker population of 366 students per grade, this implies a loss of approximately 3 non-EL students. Could the departure of 3 non-ELs be enough to generate a decline of 0.05 standard deviations? The average scores of these three students would have to be at least 1.4, which is just above the 90th percentile.

Another way to approach this issue is to ask how much of the 0.05 standard deviation decline (in response to a 10 percentage-point increase in EL proportions) would be explained by the departure of 3 native students with an arbitrarily chosen average score. If the departing students had an average score of 0.7 (around the 75th percentile) this would result in a drop in average native-speaker scores of 0.02, 40% of the 0.05 effect.

In short, native flight would have to be very positively selected for it to be completely responsible for the negative coefficients reported in Tables 3 and 4, but even moderate positive selection would be able to explain large proportions of the small negative overall EL effects. Students that move schools in response to EL effects would have to have parents that are fairly invested in their children's academic lives and capable of researching and acting on alternative school options. It is not difficult to imagine that these children would be among the highest scorers in these standardized tests.

5.3 Heterogeneity

Having established that the proportion of ELs has a small negative effect on native-speaker scores, the next set of results explores what types of schools are driving this effect. I generate two proxies for school quality: an indicator variable for poorer districts and an indicator variable for high-performing schools. In Tables 6 and 7, I report the results of equation 4, which interacts the two variables of interest with an indicator variable equal to one for schools located in poorer districts. Specifically, I calculate the average district-level proportion of students eligible for reduced price lunch (for which eligibility is determined by household income) across all years and assign those with above-median proportions a one and all others a zero. In both language arts and math, it is clear that the negative EL effects found above are being completely driven by schools in poor districts. Across all grades and for both types of tests, schools in non-poor districts exhibit no significant EL effects, while the interactions are negative (and statistically significant) for grades 2 through 4.

The second indicator variable I use is an indicator for schools with lower-than-median scores. This indicator is assigned based on each school's average test score across all grades and all years. Tables 8 and 9 show a similar pattern as above: the negative EL effect appears to be concentrated among low-performing schools. For both math and language arts scores,

Table 6 Effect of EL Proportion on Non-EL Language Arts Scores, by District Poverty Indicator

	(1)	(2)	(3)	(4)	(5)
	Standardized Language Arts Scores				
	Grade 2	Grade 3	Grade 4	Grade 5	Grade 6
El proportion	-0.0215	-0.0712	-0.0165	-0.0124	-0.0176
	(0.0787)	(0.0671)	(0.0754)	(0.0753)	(0.0943)
El proportion	-0.362***	-0.451***	-0.290***	-0.0123	-0.0370
x Poor district	(0.115)	(0.0851)	(0.102)	(0.120)	(0.107)
Economically disadvantaged proportion	-0.739***	-0.716***	-0.816***	-0.820***	-0.825***
	(0.0830)	(0.0847)	(0.0667)	(0.0801)	(0.0907)
Economically disadvantaged proportion	0.501***	0.385***	0.310***	0.264***	0.307***
x Poor district	(0.105)	(0.103)	(0.0842)	(0.0944)	(0.101)
Number of Observations	60143	60995	61155	61238	42347

* p<0.1 ** p<0.05*** p<0.01. Standard errors (clustered at district level) in parentheses

All regressions include school fixed effects, year fixed effects, district controls, and other-grade school trends. Poor District = 1 for schools in districts that have above-median proportions of students eligible for free or reduced-price lunch (averaged across all years). Regressions are weighted by the total number of children enrolled in each school-grade-year.

Table 7 Effect of EL Proportion on Non-EL Math Scores, by District Poverty Indicator

	(1)	(2)	(3)	(4)	(5)
	Standardized Math Scores				
	Grade 2	Grade 3	Grade 4	Grade 5	Grade 6
El proportion	0.0171	-0.111	-0.102	-0.0397	-0.104
	(0.0849)	(0.0739)	(0.0946)	(0.105)	(0.136)
El proportion	-0.579***	-0.562***	-0.345***	-0.215	-0.0154
x Poor district	(0.125)	(0.0959)	(0.107)	(0.133)	(0.154)
Economically disadvantaged proportion	-0.736***	-0.651***	-0.743***	-0.635***	-0.907***
	(0.0890)	(0.0945)	(0.0738)	(0.102)	(0.112)
Economically disadvantaged proportion	0.423***	0.352***	0.412***	0.251**	0.454***
x Poor district	(0.113)	(0.120)	(0.0999)	(0.123)	(0.126)
Number of Observations	60159	61007	61226	61248	42345

* p<0.1 ** p<0.05*** p<0.01. Standard errors (clustered at district level) in parentheses

All regressions include school fixed effects, year fixed effects, district controls, and other-grade school trends. Poor District = 1 for schools in districts that have above-median proportions of students eligible for free or reduced-price lunch (averaged across all years). Regressions are weighted by the total number of children enrolled in each school-grade-year.

the interaction term (between EL proportion and the low-performance indicator) is negative and significant for grades 2 through 4.

Because EL proportions are higher on average in poorer districts and in low-performing schools, any non-linearity in the effect of EL proportions could be generating the results in Tables 10 and 11. In the Appendix, I show that this is not the case. Allowing for non-linearity in the effect of ELs does not alter these patterns of heterogeneity across schools.

This heterogeneity could be the result of peer effects being mitigated by school quality. If it is in fact teaching styles that are being affected by EL proportions and changing the learning experiences of native speakers (for instance, if teachers slow down the curriculum in order to cater to EL students), then there is likely substantial variation across teachers in the methods used to balance the needs of ELs and native speakers. In particular, teachers with better training or who are more experienced with ELs may be better at dealing with diverse linguistic ability in one classroom. Similarly, well-funded schools can afford resources that could facilitate the balancing of EL and non-EL needs: teaching aides or special EL classes separate from the mainstream classroom, for example.

Given that native flight is also an important factor here, it might also be the case that native flight is more common in lower quality schools, where parents have stronger incentives to transfer their children. Though there is still much to be done on parsing these EL effects into peer effects and compositional effects, these results demonstrate that both peer effects and native flight contribute to the negative overall EL effect, which is concentrated among schools on the lower end of the quality distribution.

Table 8 Effect of EL Proportion on Non-EL Language Arts Scores, by School Performance Indicator

	(1)	(2)	(3)	(4)	(5)
	Standardized Language Arts Scores				
	Grade 2	Grade 3	Grade 4	Grade 5	Grade 6
El proportion	-0.0938	-0.141**	-0.104**	-0.0612	-0.113
	(0.0766)	(0.0559)	(0.0516)	(0.0584)	(0.0873)
El proportion	-0.336**	-0.445***	-0.213***	0.0605	0.0768
x Low-performing school	(0.151)	(0.0667)	(0.0592)	(0.0759)	(0.101)
Economically disadvantaged proportion	-0.623***	-0.636***	-0.747***	-0.796***	-0.700***
	(0.0563)	(0.0587)	(0.0503)	(0.0588)	(0.0659)
Economically disadvantaged proportion	0.479***	0.408***	0.326***	0.351***	0.177**
x Low-performing school	(0.0886)	(0.0835)	(0.0707)	(0.0637)	(0.0782)
Number of Observations	60476	61336	61503	61620	42822

* p<0.1 ** p<0.05*** p<0.01. Standard errors (clustered at district level) in parentheses

All regressions include school fixed effects, year fixed effects, district controls, and other-grade school trends. Poor District = 1 for schools in districts that have above-median proportions of students eligible for free or reduced-price lunch (averaged across all years). Regressions are weighted by the total number of children enrolled in each school-grade-year.

Table 9 Effect of EL Proportion on Non-EL Math Scores, by School Performance Indicator

	(1)	(2)	(3)	(4)	(5)
	Standardized Math Scores				
	Grade 2	Grade 3	Grade 4	Grade 5	Grade 6
El proportion	-0.200**	-0.309***	-0.262***	-0.141*	-0.159
	(0.0960)	(0.0658)	(0.0584)	(0.0730)	(0.109)
El proportion	-0.389***	-0.419***	-0.202***	-0.108	0.0404
x Low-performing school	(0.131)	(0.0685)	(0.0617)	(0.0730)	(0.118)
Economically disadvantaged proportion	-0.633***	-0.553***	-0.610***	-0.609***	-0.737***
	(0.0636)	(0.0601)	(0.0526)	(0.0652)	(0.101)
Economically disadvantaged proportion	0.417***	0.332***	0.331***	0.322***	0.213*
x Low-performing school	(0.0848)	(0.0825)	(0.0798)	(0.0781)	(0.110)
Number of Observations	60495	61350	61576	61629	42816

* p<0.1 ** p<0.05*** p<0.01. Standard errors (clustered at district level) in parentheses

All regressions include school fixed effects, year fixed effects, district controls, and other-grade school trends. Poor District = 1 for schools in districts that have above-median proportions of students eligible for free or reduced-price lunch (averaged across all years). Regressions are weighted by the total number of children enrolled in each school-grade-year.

6 Conclusion

Consistent with the work of Geay et al. (2013) and Ohinata and van Ours (2013), I find that much of the observed negative correlation between native speaker test performance and non-native student proportions is explained by school selection. After accounting for selection across schools, along with various potential confounding trends, the estimated relationship between EL proportions and average non-EL test scores is negative, statistically significant, but small in magnitude. Importantly, I find evidence for the existence of native flight, which can explain a large proportion of this negative coefficient under reasonable assumptions about which students are leaving. Finally, it appears that most of the negative relationship is driven by lower-quality schools, which could be due to the exacerbation of negative peer effects in these schools or native flight being more likely in these schools. In short, any negative peer effects that do exist are small in magnitude and concentrated in low-performing, low-income schools. At the same time, there is evidence that the school choice decisions of non-ELs do respond to EL proportions: understanding the reasons for and consequences of this native flight are important questions for future research.

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A Additional Tables

Appendix Tables 10 and 11 explore whether nonlinearities in the EL effect might be driving the pattern of heterogeneity documented in section 5. I repeat the exercise conducted in Tables 6 to 9, except I allow for the effect of EL proportions to be nonlinear. Specifically, I allow for a different slope for above-average EL proportions by including an interaction between the EL proportion variable and an above-average indicator. The pattern of results remains unchanged.

Table 10 Effect of EL Proportion on Non-EL Scores, by District Poverty Indicator, Allowing for Non-Linearities

Panel A. Language Arts Scores

	(1)	(2)	(3)	(4)	(5)
	Standardized Language Arts Scores				
	Grade 2	Grade 3	Grade 4	Grade 5	Grade 6
El proportion	0.0285	0.100	-0.00923	-0.107	-0.144
	(0.126)	(0.101)	(0.0939)	(0.0984)	(0.115)
El proportion	-0.346***	-0.429***	-0.345***	-0.198**	-0.142
x Poor district	(0.109)	(0.0927)	(0.0969)	(0.0958)	(0.112)
Economically disadvantaged proportion	-0.803***	-0.795***	-0.876***	-0.864***	-0.830***
	(0.0879)	(0.0884)	(0.0679)	(0.0827)	(0.0914)
Economically disadvantaged proportion	0.454***	0.326***	0.256***	0.220**	0.298***
x Poor district	(0.104)	(0.102)	(0.0848)	(0.0949)	(0.101)
Number of Observations	60143	60995	61155	61238	42347

* p<0.1 ** p<0.05*** p<0.01. Standard errors (clustered at district level) in parentheses

All regressions include school fixed effects, year fixed effects, district controls, other-grade school trends, and the interaction between EL proportions and an indicator for above-average EL proportions. Poor District = 1 for schools in districts that have above-median proportions of students eligible for free or reduced-price lunch (averaged across all years). Regressions are weighted by the total number of children enrolled in each school-grade-year.

Panel B. Math Scores

	(1)	(2)	(3)	(4)	(5)
	Standardized Math Scores				
	Grade 2	Grade 3	Grade 4	Grade 5	Grade 6
El proportion	0.157	0.103	-0.0581	-0.00898	-0.226
	(0.135)	(0.118)	(0.107)	(0.121)	(0.151)
El proportion	-0.530***	-0.514***	-0.380***	-0.354***	-0.156
x Poor district	(0.118)	(0.0904)	(0.118)	(0.126)	(0.153)
Economically disadvantaged proportion	-0.790***	-0.730***	-0.800***	-0.689***	-0.917***
	(0.0919)	(0.0957)	(0.0741)	(0.103)	(0.112)
Economically disadvantaged proportion	0.375***	0.289**	0.356***	0.193	0.438***
x Poor district	(0.113)	(0.119)	(0.101)	(0.124)	(0.124)
Number of Observations	60159	61007	61226	61248	42345

* p<0.1 ** p<0.05*** p<0.01. Standard errors (clustered at district level) in parentheses

All regressions include school fixed effects, year fixed effects, district controls, other-grade school trends, and the interaction between EL proportions and an indicator for above-average EL proportions. Poor District = 1 for schools in districts that have above-median proportions of students eligible for free or reduced-price lunch (averaged across all years). Regressions are weighted by the total number of children enrolled in each school-grade-year.

Table 11 Effect of EL Proportion on Non-EL Scores, by School Performance Indicator, Allowing for Non-Linearities

Panel A. Language Arts Scores

	(1)	(2)	(3)	(4)	(5)
	Standardized Language Arts Scores				
	Grade 2	Grade 3	Grade 4	Grade 5	Grade 6
El proportion	-0.0488	-0.0126	-0.131*	-0.186**	-0.229**
	(0.109)	(0.0894)	(0.0747)	(0.0764)	(0.111)
El proportion	-0.268*	-0.386***	-0.222***	-0.113	-0.0375
x Low-performing school	(0.143)	(0.0786)	(0.0630)	(0.0694)	(0.108)
Economically disadvantaged proportion	-0.678***	-0.702***	-0.790***	-0.820***	-0.703***
	(0.0624)	(0.0621)	(0.0509)	(0.0606)	(0.0669)
Economically disadvantaged proportion	0.430***	0.333***	0.240***	0.276***	0.164**
x Low-performing school	(0.0834)	(0.0805)	(0.0711)	(0.0613)	(0.0795)
Number of Observations	60476	61336	61503	61620	42822

* p<0.1 ** p<0.05*** p<0.01. Standard errors (clustered at district level) in parentheses
All regressions include school fixed effects, year fixed effects, district controls, other-grade school trends, and the interaction between EL proportions and an indicator for above-average EL proportions. Poor District = 1 for schools in districts that have above-median proportions of students eligible for free or reduced-price lunch (averaged across all years). Regressions are weighted by the total number of children enrolled in each school-grade-year.

Panel B. Math Scores

	(1)	(2)	(3)	(4)	(5)
	Standardized Math Scores				
	Grade 2	Grade 3	Grade 4	Grade 5	Grade 6
El proportion	0.0119	-0.0540	-0.205**	-0.157*	-0.297**
	(0.114)	(0.0976)	(0.0921)	(0.0927)	(0.125)
El proportion	-0.303**	-0.338***	-0.183***	-0.162**	-0.0876
x Low-performing school	(0.133)	(0.0706)	(0.0676)	(0.0809)	(0.130)
Economically disadvantaged proportion	-0.691***	-0.636***	-0.669***	-0.653***	-0.746***
	(0.0668)	(0.0620)	(0.0522)	(0.0674)	(0.101)
Economically disadvantaged proportion	0.389***	0.277***	0.266***	0.248***	0.188*
x Low-performing school	(0.0846)	(0.0823)	(0.0791)	(0.0792)	(0.111)
Number of Observations	60495	61350	61576	61629	42816

* p<0.1 ** p<0.05*** p<0.01. Standard errors (clustered at district level) in parentheses
All regressions include school fixed effects, year fixed effects, district controls, other-grade school trends, and the interaction between EL proportions and an indicator for above-average EL proportions. Poor District = 1 for schools in districts that have above-median proportions of students eligible for free or reduced-price lunch (averaged across all years). Regressions are weighted by the total number of children enrolled in each school-grade-year.