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Absent and Afraid? Immigration Enforcement and Student Attendance in the Second Trump Administration

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Intensified immigration enforcement activity under the second Trump administration has increased anxiety for immigrants in the United States, including many families with school-age children. This study provides early evidence on the effects of the second Trump presidency on the attendance of students who may be from immigrant families. Using a difference-in-differences design, I estimate the effects of the second Trump presidency on the attendance of English learners (ELs) relative to non-ELs in samples of schools in Rhode Island and Connecticut. I find negative effects in both settings. In Connecticut, I find small decreases in average attendance for EL students and larger increases in chronic absenteeism of 0.83 percentage points (2.8%). In Rhode Island, I find that attendance for EL students fell by 1.97 percentage points (2.3%). Together with other recent work, my results suggest that immigration enforcement under the second Trump presidency is already impacting students and schools in a variety of settings nationwide.

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Absent and Afraid? Immigration Enforcement and Student Attendance in the Second Trump Administration

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Abstract

Intensified immigration enforcement activity under the second Trump administration has increased anxiety for immigrants in the United States, including many families with school-age children. This study provides early evidence on the effects of the second Trump presidency on the attendance of students who may be from immigrant families. Using a difference-in-differences design, I estimate the effects of the second Trump presidency on the attendance of English learners (ELs) relative to non-ELs in samples of schools in Rhode Island and Connecticut. I find negative effects in both settings. In Connecticut, I find small decreases in average attendance for EL students and larger increases in chronic absenteeism of 0.83 percentage points (2.8%). In Rhode Island, I find that attendance for EL students fell by 1.97 percentage points (2.3%). Together with other recent work, my results suggest that immigration enforcement under the second Trump presidency is already impacting students and schools in a variety of settings nationwide.

1 Introduction

On January 20, 2025 – the first day of his second term – President Donald Trump signed three executive orders intensifying federal immigration enforcement, taking steps to realize his campaign promise to lead the largest mass deportation of unauthorized immigrants in U.S. history. In the months since taking office, President Trump has taken unprecedented steps to increase the scope and severity of immigration enforcement in the United States, heightening anxiety for documented and undocumented immigrants alike.

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Given the youthful distribution of immigrant households in the United States, these tactics are likely to disproportionately impact families with school-age children. A quarter of all children in the country are immigrants or the children of immigrants (Urban Institute, 2019). This includes 5.3 million children who live with at least one undocumented parent, the vast majority of whom are U.S. citizens by birth (Capps et al., 2015). Prior research has shown that enforcement activity can have destabilizing impacts for immigrant households, increasing stress and anxiety, causing financial hardship, and leading to changes in living arrangements (Barajas-Gonzalez et al., 2022; Gelatt et al., 2019; Amuedo-Dorantes & Arenas-Arroyo, 2019). Enforcement activity has also been linked to negative effects on educational outcomes, including declines in test scores and increases in disciplinary outcomes, grade repetition, and drop out (Amuedo-Dorantes & Lopez, 2015; Kirksey et al., 2020; Heinrich et al., 2023).

One educational outcome of particular concern in the current enforcement environment is school attendance. Studies from earlier eras have found negative effects of immigration enforcement on school attendance for children in immigrant families (Kirksey & Sattin-Bajaj, 2021; Bellows, 2019; Kirksey, 2020). Immigration enforcement can impact school attendance if families fear that leaving home or sending their child to school increases their risk of detention or family separation. These concerns have become much more salient since President Trump overturned the long-running policy of U.S. Immigration and Customs Enforcement (I.C.E.) of limiting immigration-related arrests near sensitive sites such as churches or schools.

Disruptions to student attendance are concerning for both affected students and their peers. At the individual level, school attendance is a precursor to other important educational outcomes (including student test scores) and is strongly related to life outcomes such as educational attainment, economic well-being, and crime (Aucejo & Romano, 2016; Liu et al., 2021; Jacob & Lefgren, 2003; Ansari et al., 2020; Goodman, 2014). At the school level, research has found that increases in absences have negative spillover effects on the absent student's classmates (Goodman, 2014), meaning that increased absences for children from immigrant families are expected to negatively impact the learning of their non-immigrant peers.

This paper provides early evidence on the effects of the heightened immigration enforcement environment under the second Trump administration on the attendance of students who are likely to be from immigrant families. Using data from public-facing school attendance dashboards for samples of schools in Rhode Island and Connecticut, I identify the effect of the intensified enforcement activity on attendance using a difference-in-differences design that compares the outcomes of English learners (ELs) and non-English learners (non-ELs). I find negative effects on attendance in both states. In Connecticut, I find that the attendance of EL students fell by 0.37 percentage points, or 0.4% relative to the EL sample mean, while chronic absenteeism increased by 0.83 percentage points, or 2.8% relative to the EL sample mean. An alternative strategy comparing Hispanic/Latino and white students generates similar results. In Rhode Island, I find that average attendance for EL students fell by 1.97 percentage points, or nearly 2.3% relative to the EL sample mean. I also show that anxiety/awareness of immigration enforcement activity, which I measure using data from google searches, is related to increases in absences in Rhode Island, consistent with the hypothesis that enforcement concerns are driving these effects.

This paper is most closely related to recent work by Dee (2025), who analyzes changes in attendance in five high-immigrant school districts in the Central Valley of California after the start of the second Trump presidency. Using an event-study design, Dee finds that absences increased by 22% in January and February 2025. My paper differs from Dee's both methodologically and geographically. First, while Dee's design relies on an assumption of common trends across years, my difference-in-differences design uses a control group to account for secular variation in attendance over time (e.g., due to weather, sickness, or school calendars). Second, while Dee's paper uses data from an agricultural region with a large undocumented workforce in a border state, my paper considers effects in two dense Northeastern states with large urban areas. That both papers find substantial negative effects on attendance despite these differences in settings and methodologies suggests that recent enforcement activities are having broad effects on students and schools across the country. This is further underscored by a recent working paper by Figlio and Özek 2025, which finds negative effects of the second Trump presidency on student test scores for Spanish-speaking students in a large urban district in Florida.[1]

This paper also contributes to the literature on immigration enforcement and student outcomes from earlier periods (Gándara & Ee, 2022; Dee & Murphy, 2020; Amuedo-Dorantes & Arenas-Arroyo, 2019). This includes several papers that have found negative effects of immigration enforcement related activities on student attendance (Kirksey, 2020; Bellows, 2019; Meadows, 2023). While my findings – like those of the other recent studies focused on the second Trump presidency – are largely consistent with findings from studies on earlier periods, my contemporary results speak to the urgency of this issue, the speed at which detectable effects are materializing, and the way this new era of enforcement is impacting communities not usually targeted by enforcement actions.

2 Context

Connecticut and Rhode Island are neighboring states in the Northeast with large, long-standing, and diverse immigrant populations. Immigrants make up about 16.2% of the population in Connecticut and 14.6% in Rhode Island, slightly above the national rate (14.3%) (American Immigration Council, 2025a,b). Latin Americans make up a growing share of immigrants in both states and undocumented immigrants constitute about 20% of the foreign-born populations (Ibid). In Rhode Island, substantial immigrant populations are found in the cities of Providence – where over 38% of all students are classified

[1] Figlio & Özek (2025) do not find effects on absences using annual student-level absence data. The authors note that since they only have access to annual absence data they may be unable to detect increases in absences that occurred in the spring of 2025.

as English learners, more than twice the rate in New York City – and Central Falls (Rhode Island Department of Elementary and Secondary Education, 2025; New York City Department of Education, 2024). Bridgeport and Hartford are home to large immigrant populations in Connecticut. Both Rhode Island and Connecticut are blue states with relatively welcoming immigration policies, including allowing undocumented immigrants to get driver's licenses and qualify for in-state tuition at public colleges and universities.

Reducing absenteeism has been a focus of both Rhode Island and Connecticut in the post-pandemic era. In 2023, Rhode Island Governor Daniel McKee launched the Attendance Matters initiative. As part of this effort, the state began publishing live, public-facing attendance dashboards for schools. Connecticut has addressed absenteeism through its Learner Engagement and Attendance Program (LEAP), which conducts outreach and home visits for chronically absent students. Both states have seen improvements in attendance over the past several years, though chronic absenteeism remains high for some students, including English learners (ELs). In Connecticut, EL students were 50% more likely to be chronically absent than non-ELs in school year (SY) 2024-25, while in Rhode Island EL's were 25% more likely to be chronically absent (Connecticut State Department of Education, 2025; Rhode Island Department of Education, n.d.).

3 Data and Sample

My school attendance data come from public-facing "live" attendance dashboards published by the state education agencies of Connecticut and Rhode Island.[2] In Rhode Island, these public attendance data were produced as part of the aforementioned "Attendance Matters" campaign. In Connecticut, attendance dashboards are published as part of the state's interactive public data portal (EdSight).

In Connecticut, my outcome measures are monthly school-by-student-group data on average attendance rates and the share of students who were chronically absent, which is defined as missing 10% or more of school days. Attendance rate data are reported beginning in September for the school year and chronic absenteeism data are reported beginning in October. I collect these data for SY's 2021-22 to 2024-25 for EL and non-EL students, students with and without disabilities, and by student race/ethnicity. In Rhode Island, my outcome measure is the daily count of absences for students by student group in a school. These data are available for SYs 2023-24 and 2024-25. I compile these data for EL and non-EL students and for students with and without disabilities. (Rhode Island data is not available broken down by student race/ethnicity). I convert daily absence data to attendance rates by in two steps. First, I calculate a daily absence rate, which I define as the number of absences for students in that group

[2]Attendance data for Connecticut come from: `https://public-edsight.ct.gov/students/attendance-dashboard?language=en_US`. Attendance data for Rhode Island come from: `https://www3.ride.ri.gov/attendance/public`.

divided by the number of students in that group per SY 2023-24 annual program membership reports. (SY 2024-25 data were not available). I then define the attendance rates for students in that group and school as 1 minus the absence rate. I multiply attendance rates by 100 for ease of interpretation.[3] I set to missing attendance rates of less than 50% out of concern about misreported data. In both states, I exclude observations from August and June to account for differences in school opening and closing dates. Appendix Figures A1 and A2 plot average attendance outcomes over time.

Outcome data are not available for all schools or dates in either state. Missing data appears to be due, for the most part, to suppression of data with small cell sizes. In Connecticut, absence data is not reported for any group with fewer than 20 students at the school. I limit my analysis to schools with at least 6 months of non-missing attendance data both for EL and non-EL students in a school year. I set to missing chronic absenteeism rates for schools with fewer than 5 observations for EL and non-EL students in a school year. My sample includes traditional public, regional, and technical/career education schools. This results in a final sample for Connecticut that includes 526 of 958 schools in the state, which represent about 87% of EL enrollment and 63% of all enrollment, as shown in Table 1.

[Table 1 about here]

In Rhode Island, daily absence data appear to be censored at 10 absences. This could lead to bias due to under-reporting of "low absence" days for EL students.[4] I do two things to address this. First, I limit my estimating sample to schools that have at least 100 non-missing school day absence observations for both ELs and non-ELs in the school year. This substantially reduces concerns about differential missingness. Second, I explore the sensitivity of my results to assumptions about missing data as robustness checks. My Rhode Island sample includes only 50 of 349 schools in the state, but these schools collectively enrolled over half (56%) of EL students and 24% of all students. My sample includes traditional public, alternative, and charter schools; 26 of the 50 schools are in Providence. In both states, schools in my sample skew toward larger schools with greater shares of non-white students.

I use search intensity data from Google Trends as a proxy for anxiety/awareness of enforcement activity, following prior work using Google Trends data (Bacher-Hicks et al., 2021, 2022). In this time of anticipation and uncertainty, Google Trends-based measures may be a better reflection of anxiety about enforcement activity than other indicators, such as immigration raids or arrests, though the two are correlated.[5] Google Trends data come from a random sample of searches

[3] I explore how sensitive my results are to using student membership data from SY 2023-24 to define attendance rates in SY 2024-25 as a robustness check.

[4] This might be a concern since in almost all cases there are fewer EL students than non-EL students in a school, meaning EL students would be more likely to report fewer than 10 absences on a day.

[5] Appendix Figure A3 plots my preferred measure of enforcement-related search intensity against ICE arrest data in Rhode Island. The correlation between immigration arrests and my search index is about 0.48.

in an area and are normalized to the time period and geography of the query and reported on a scale from 0 to 100. Google Trends data are available on a weekly basis. I collect weekly Google Trends data for Rhode Island from July 2023 through June 2025 for the google topic "United States Immigration and Customs Enforcement (Federal Agency)." Google topics are considered more reliable and expansive indicators of search intensity than specific search terms because they take into account acronyms, common misspellings, and searches in other languages (Google News Initiative, 2025). I standardize this measure to have a mean of 0 and a standard deviation of 1. Figure 1 plots my standardized measure of I.C.E. search intensity over time. Relative search intensity was very low prior to January 2025, peaked around the time of the second inauguration, and has remained high, with additional smaller peaks, since that time. As a robustness check, I consider results using an alternate index measure created from google trends measures for six enforcement-related search term/topics.

[Figure 1 about here: google search intensity]

Attendance patterns in schools are also significantly affected by two other factors: weather events and illness (Goodman, 2014; Azor-Martínez et al., 2014). To proxy for weather-related effects on absences, I collect Google Trends data for three weather related terms ("snow," "storm," and "school closings"). To proxy for illness-related effects on absences, I collect Google Trends data for six common childhood illnesses: covid-19; flu (influenza); hand, foot and mouth disease; gastroenteritis; strep throat (streptococcal pharyngitis), and pink eye (conjunctivitis). I standardize all google trends measures to have a mean of 0 and a standard deviation of 1, as before. Finally, I also collect data on three "placebo" measures of search activity, which I use as controls in models relating I.C.E. search activity to student outcomes. These are discussed in detail in the following section. Appendix B provides additional detail on the google trends-based measures used in this analysis.

4 Methods

My primary identification approach is a difference-in-differences design that compares outcomes for EL and non-EL students. EL students are not a perfect proxy for children in immigrant families. While most English learners are (presumably) first or second generation immigrants, many first and second generation immigrants will not be included in this group, either because they have been reclassified as English proficient or because they were never classified as ELs in the first place. This, combined with the possibility of spillover effects on non-EL attendance, means that estimates from the models described in this section are expected to be biased against detecting effects on EL attendance. For this reason, my estimates are best interpreted as lower bound estimates of true effects.

In Connecticut, my outcome data are available at the month-by-school-by-student group level. My preferred specification is as follows:

$$Attend_{smyg} = \beta_1 After_{my} + \beta_2 AfterxEL_{myg} + \mu_{mg} + \lambda_{yg} + \theta_s + \epsilon_{smyg}, \quad (1)$$

where s indexes the school, m indexes the month, y indexes the school year, and g indexes the student group (i.e., EL or non-EL). $Attend_{smyg}$ is the attendance measure for students at school s in group g for that month/year. $After_{my}$ is an indicator that is equal to 1 if the observation falls in or after January 2025.[6] I estimate this equation using a dataset that includes only observations for EL and non-EL students, such that β_2 can be interpreted as the difference in attendance for ELs relative to non-ELs. θ_s are school fixed effects. μ_{mg} are month-by-EL fixed effects. I include these to adjust for seasonal differences in attendance and to account for the fact that these seasonal patterns may differ for EL and non-ELs. λ_{yg} is a set of school-year-by EL-status fixed effects. I include these interactions to account for shifts in the EL/non-EL student populations over time – which could be relevant given changes in immigration in this period – and to flexibly adjust for differences in expected outcomes across cohorts. This is relevant because the years covered by my data immediately follow the pandemic, when EL attendance suffered disproportionately large setbacks (Gilreath, 2024), and we might expect EL and non-EL students to follow distinct recovery trajectories. (See Appendix Figure A1 for average outcomes). I cluster standard errors at the school level and weight observations by the number of students in the student group using analytic weights in Stata.[7]

In Rhode Island, outcome data are available at the school-by-student group-by-day level for SYs 2023-24 and 2024-25. I adapt equation (1) to estimate effects on (constructed) attendance rates for EL students as follows:

$$Attend_{sdg} = \alpha_1 After_d + \alpha_2 AfterxEL_{dg} + \gamma X_{dg} + \omega_{mg} + \theta_s + \lambda_y + \epsilon_{sdg}, \quad (2)$$

Here, d indexes the calendar date (e.g., March 2, 2025) and all other indices are as before. $After$ is an indicator for observations that come after January 20, 2025. X_{dg} is a set of date-level controls that includes (1) indicators for days before and after recurring school breaks/holidays as specified in the statewide recommended calendar for school districts in Rhode Island (see Appendix Table A1 for a full list), (2) standardized google search measures for the six illness-related terms discussed in the previous section, and (3) standardized google search measures for the three weather-related terms and the interactions of these measures with an indicator for EL status (see Table 4 notes and "Data and Sample" section for details). I include interactions with EL status for my weather-related controls in light of Goodman (2014), who found larger negative effects of snowy

[6] Donald Trump's second inauguration took place on January 20, 2025. I chose a start date of January 2025 instead of February 2025 because other evidence, including Google Trends data, suggests anxiety about enforcement activity was high around the time Trump first took office.

[7] Attendance data for Connecticut report the number of students in that group by month. These are the data used as weights.

days on attendance for black/Hispanic students than white/Asian students in Massachusetts. I consider an alternative specification that drops these interacted terms as a robustness check. Like equation 1, equation 2 contains school fixed effects and also month-by-group fixed effects (ω_{mg}), which adjust for seasonal differences in attendance for EL and non-EL students. Unlike equation 1, my preferred specification of equation 2 includes only school year fixed effects (λ_y) instead of school year-by-group fixed effects. I do this because I have only two years of data for my Rhode Island sample – in Connecticut I have five years of data – and I am concerned that including both school year-by-EL and and month-by-EL fixed effects will lead to underestimating effects in my model because these month-by-EL and year-by-EL dummies will together capture variation I am seeking to isolate instead of merely seasonal/time trends. I consider alternative approaches as robustness checks. Standard errors are clustered by school and regressions are weighted by the number of students in the student group based on average daily membership counts for EL and non-EL students in the school based on 2023-24 membership reports, the same data used to calculate attendance rates, as previously discussed.

I also use daily attendance data from Rhode Island to assess whether changes in attendance relate to changes in anxiety/awareness of enforcement activity as measured by I.C.E. google search intensity. To do this, I adjust equation 2 as follows:

$$\begin{aligned} Attend_{sdg} = {} & \alpha_1 SearchICE_d + \alpha_2 SearchICExEL_{dg} + \gamma X_{dg} \\ & + \nu PlaceboSearches_d + \omega_{mg} + \kappa_y + \theta_s + \epsilon_{sdg}, \end{aligned} \tag{3}$$

where $SearchICE$ is the standardized measure of I.C.E. search intensity (which varies by week) and $SearchICExEL$ is the interaction of this measure with an indicator for EL observations. Equation 3 includes all controls in equation 2 and adds a set of three standardized search measures for "placebo" topics related to Donald Trump ("J.D. Vance", "tariff", "Department of Government Efficiency"). I include these to address concerns that searches about immigration enforcement might be correlated with general interest in the news and/or the Trump administration's actions. The coefficient of interest in this specification is α_2.

5 Results

5.1 Parallel Trends

I start by examining trends in outcomes for EL and non-EL students over time. Figure 2 plots the residualized values of average attendance and chronic absenteeism for EL and non-EL students in Connecticut over SY 2024-25 school year. I generate these residualized values in two steps. First, I regress the outcome on school fixed effects, school year-by-EL status fixed effects, and month-by-EL status fixed effects (the same controls included in equation 1), weighting the regression by the number of students in each group. I then calculate the residual for each school-by-month-by-EL group and take the average of these residuals, again weighting by the number of students in each group. I plot these average residuals in Figure 2, re-centering point estimates so that point estimates for EL and non-EL students are equal in December 2024. As Figure 2A shows, the residual variation in attendance for EL and non-EL students followed similar patterns prior to January 2025 but diverged beginning in February 2025, with EL students showing relative declines. The residual variation in chronic absenteeism shows the opposite trend: EL and non-EL students show similar trends in the beginning of the 2024-25 school year but ELs show sharp increases after January 2025.

[Figure 2 about here: residual trends CT]

I do the same to examine trends in daily absences for Rhode Island, generating predicted attendance values by regressing attendance rates on all controls and fixed effects included in equation 2 (excluding only the $AFTER$ and $AFTERxEL$ terms) and plotting the re-centered, weighted average residuals by school day in the 2024-25 school year in Figure 3. While patterns are a bit less clear in the daily data for Rhode Island, EL residuals show some downward spikes during the post-period. One notable dip in EL attendance corresponds to the February 3 "Day Without Immigrants" observation, when many students from immigrant families stayed home as part of a national protest against the Trump administration's enforcement efforts (Castillo et al., 2025). I re-estimate my model dropping this date as a robustness check.

[Figure 3 about here: residual trends RI]

5.2 Attendance/Chronic Absenteeism in Connecticut

Difference-in-differences estimates in Table 1 confirm the visual patterns shown in Figure 2 for my Connecticut sample. I find small but significant negative effects on EL attendance rates. My preferred estimates (column 3) indicate that attendance rates for EL students fell by 0.37 percentage points in the second Trump presidency, or roughly 0.4% relative to the EL sample mean. This finding is sensitive to the inclusion of school year-by-EL fixed effects as opposed to simply school year fixed effects, as shown by comparing columns (2) and (3). Estimates in column 6 indicate that chronic absenteeism increased for EL students by 0.83 percentage points after the Trump inauguration, or about 2.8% relative to the EL sample mean. The magnitude of this estimated effect is equal to about 11% of the statewide gap in chronic absenteeism rates for EL and non-EL students in SY 2024-25 (Connecticut State Department of Education, 2025).

[Table 2: CT DID Effects]

Estimates from an alternative difference-in-differences model that compares Hispanic/Latino and white, non-Hispanic/Latino are shown in Table 3. Estimate in column 3 of Table 3 show that average attendance for Hispanic/Latino students fell by a small amount (0.21 percentage points, or about 0.2% relative to the Hispanic/Latino sample mean). Consistent with findings from the EL/non-EL difference-in-differences estimates, effects on chronic absenteeism were relatively larger, with Hispanic/Latino chronic absenteeism increasing by 1.3 percentage points, or 4.6% relative to the Hispanic/Latino sample mean. Preferred estimates from this alternative approach are significant, same-signed, and of similar magnitude as estimates comparing EL and non-EL students. (See Appendix Figure A4 for a figure comparing pre-trends in residualized outcomes for Hispanic/Latino and white students).

[Table 3: CT DID Effects]

These results are robust to a number of alternative specifications, as shown in Appendix Table A2. Panel A of Appendix Table A2 shows robustness checks for the primary specification comparing EL and non-EL students. Dropping weights (columns 2 and 7) reduces the magnitude of estimated effects but effects remain same-signed and significant. Swapping in school-by-EL fixed effects for school fixed effects (columns 3 and 8) does not meaningfully change attendance effects but reduces the size of estimated effects on chronic absenteeism. In columns 4 and 9, I omit observations from SY 2020-21 and SY 2022-23 out of concerns that pandemic trends may be impacting results. Dropping two years of data reduces point estimates and they become insignificant at the $p < 0.05$ level, though estimates remain same-signed. (Results for the Hispanic/Latino and white comparison remain significant for chronic absenteeism). In columns 5 and 10, I re-estimate results omitting observations from February 2025 out of concern that unusually high absences on the February 3 "Day without Immigrants" may be impacting my results. Results are similar. Panel B of Appendix Table A2 presents robustness checks for my secondary specification comparing Hispanic/Latino and white students.

5.3 Attendance in Rhode Island

Effects on daily attendance rate are also negative, significant, and substantial in my Rhode Island sample. Columns 1-3 of Table 4 present estimated effects of the second Trump presidency on EL attendance rates. My preferred estimates (column 3) indicate that after Trump's inauguration attendance rates for ELs fell by 1.97 percentage points, or about 2.3% compared to the EL sample mean. These point estimates are substantially larger than estimated effects on monthly attendance from my Connecticut sample. Columns 4-6 relate EL attendance to my Google Trends-based measure of enforcement-related search activity. Estimates in column (6) indicate that a one standard-deviation increase in I.C.E.-related search activity is related to a 0.53 percentage point (0.6%) decrease in attendance for ELs. This is significant and substantial given the tremendous increase in search intensity associated with the start of the Trump presidency. In the week of January 21, 2024, my immigration enforcement search intensity index was -0.40 standard deviations (SDs). One year later, in the week of January 26,2025, my search intensity measure was 5.75 SDs.

[Table 4: RI DID Effects]

Estimates in Rhode Island are robust across many alternative specifications. Appendix Table A3 presents alternative estimates of the effect of the second Trump presidency on attendance (equation 2) and Appendix Table A4 presents alternative estimates of the relationship between enforcement search intensity and attendance (equation 3). Estimates are not dramatically changed by dropping analytic weights (column 2), swapping in schoolxEL fixed effects for school fixed effects (column 5), or excluding interacted terms in the weather controls (column 6). Dropping observations from the February 3 "Day without Immigrants" reduces the magnitude of point estimates (column 3). Swapping school year-by-EL fixed effects for school year fixed effects (column 4) substantially reduces the magnitude of estimates for both the "After" and "Search Intensity" models, though estimates remain negative and significant significant at the $p < 0.10$ level for the "After" specification. This is consistent with the concern that including school year interactions with group could lead to underestimation since there are only two school years of data available, as discussed.

My results are also robust to a number of sensitivity checks that address concerns about potential bias due to missing or incomplete data (columns 7-13 of Appendix Tables A3 and A4). In column 7, I redefine my attendance rates and weights assuming a 10% increase in the EL population at each school in my sample between SY 2023-24 and 2024-25. I do this to assess whether my results are impacted by using EL/non-EL enrollment statistics in 2023-24 to define the outcome and regressions weights.[8] Point estimates remain significant and same-signed, though magnitudes are reduced. I also consider specifications that impute high (75th or 99th percentile) attendance rates for EL students on days when non-EL absence data are reported but EL absence data are not (columns 9 and 10). This is to address concerns that EL data are more likely to be missing on days when EL students experienced relatively few absences due to data suppression rules. Point estimates are not substantially changed. Results are also similar if I limit my sample to days where both EL and non-EL absences are reported (column 11) or to schools with at least 100 students in membership in the group based on SY 2023-24 data (column 8).

Columns 12 and 13 present estimates from an alternative model that defines the outcome as the number of absences for students in a school/group – i.e, the raw outcome measure – instead of calculating attendance rates. For this outcome, including a schoolxEL group fixed effect in the model makes the most sense because it allows the intercept (expected absences) to differ by school and EL group, which is relevant given differences in the number of students in the EL/non-EL groups within a school. Estimates from the "After" model including this interaction (column 13) imply that absences for EL students rose by 7.3 after Trump's second inauguration. Estimates from the "Search Intensity" model imply that a one standard-deviation increase in I.C.E. search activity increased absences by 1.88 per day. Finally, column 14 of Appendix Table A4 presents

[8]If actual EL enrollment in SY 2023-24 was much lower than in SY 2024-25, calculated attendance rates for ELs would look artificially low in SY 2024-25.

estimates using an index measure of enforcement-related search intensity. This index is created by collecting and standardizing data for six different google trends topics related to enforcement activity and using principal components analysis to create a single index measure, which I standardize to have a mean of 0 and a standard deviation of 1. Estimates are negative and significant, as before. See Appendix B for detail on the measures used to construct this index.

6 Falsification Tests

As a final check, I conduct a series of falsification (or "placebo") tests that ask whether my difference-in-difference models would predict significant changes in attendance for students in groups not likely to be affected by the immigration enforcement environment. The results of these falsification tests are presented in Table 5.[9] In Connecticut, my falsification tests adapt equation 1 to consider differences in attendance for Black students relative to white students and students with disabilities (SWDs) relative to students without disabilities (non-SWDs). I do not detect significant effects for either outcome for either comparison. In Rhode Island, my falsification test compares changes in attendance for SWDs relative to non-SWDs. I find no significant effects for SWDs.

7 Conclusion

The consequences of the escalation of immigration enforcement activity under the second Trump administration are likely to fall heavily on families with school-age children. This paper presents early evidence that these actions are already affecting the attendance of public school students who are likely from immigrant families in two Northeastern states. In my Connecticut sample, I find small but significant decreases in average attendance for EL students relative to non-ELs and larger significant increases in chronic absenteeism following Trump's second inauguration. An alternative approach comparing Hispanic/Latino and white students generates similar results. In my Rhode Island sample, I find negative impacts on daily attendance rates for EL students and present evidence that declines in attendance for ELs are associated with increases in I.C.E. search intensity. I bolster both sets of finding by showing they are robust to alternative specifications and presenting null effects for placebo tests.

My results are particularly concerning given concerted efforts to regain ground in attendance outcomes following the Covid-19 pandemic. At its peak in SY 2021-22, nearly a third of EL students in Connecticut were chronically absent, as were 22.8% of non-ELs. The state has made substantial improvements since then, reducing chronic absenteeism for ELs by 8.9 percentage points. Nonetheless, substantial disparities persist. Extrapolating from my sample to the state

[9]Analytic samples used in these models are defined in the same way as the EL/non-EL samples for their respective student groups.

– and from monthly to annual chronic absentee rates – my estimates (+0.83 percentage points) suggest that were it not for this intensified enforcement activity, the gap in chronic absenteeism for ELs and non-ELs would have fallen to near pre-pandemic (SY 2018-19) levels.[10]

The magnitude of my results also suggest the potential for substantial spillover effects on non-immigrant students. Goodman (2014) shows that peer absences can be as consequential for student outcomes as a student's own absences, estimating that four additional peer absences per year reduce math achievement by 0.20 standard deviations. In my Rhode Island sample. I estimate that daily school-level absences for EL students increased by 7.3, on average, in the second Trump presidency. This is all the more striking given that my results likely understate the true magnitude of these effects.

The limitations of this study suggest several avenues for future work. The use of aggregate, publicly reported attendance data in this work limits my ability to examine heterogeneity by grade level or student characteristics, which could be important for understanding which students bear the brunt of these effects. Future work using student-level administrative data could clarify which students are most affected and whether these disruptions in attendance translate into longer-run effects on academic outcomes.

In a country where 25% of children come from immigrant families, intensified enforcement activity can be expected to impact schools and students in schools nationwide. My findings corroborate emerging evidence from California and Florida, suggesting that the effects of the current enforcement environment are not geographically isolated. Policies that seek to insulate schools and families from the broader enforcement environment may help mitigate the damage of intensified enforcement on educational outcomes. As immigration policy continues to evolve, the costs of enforcement activity to schools and students should be considered in policy debates.

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[10]The statewide gap in annual chronic absenteeism for EL and non-EL students in SY 2024-25 was 7.5 percentage points and the gap in SY 2018-19 was 6 percentage points, though actual chronic absenteeism rates were lower for both EL and non-EL students in SY 2018-19 (Connecticut State Department of Education, 2025).

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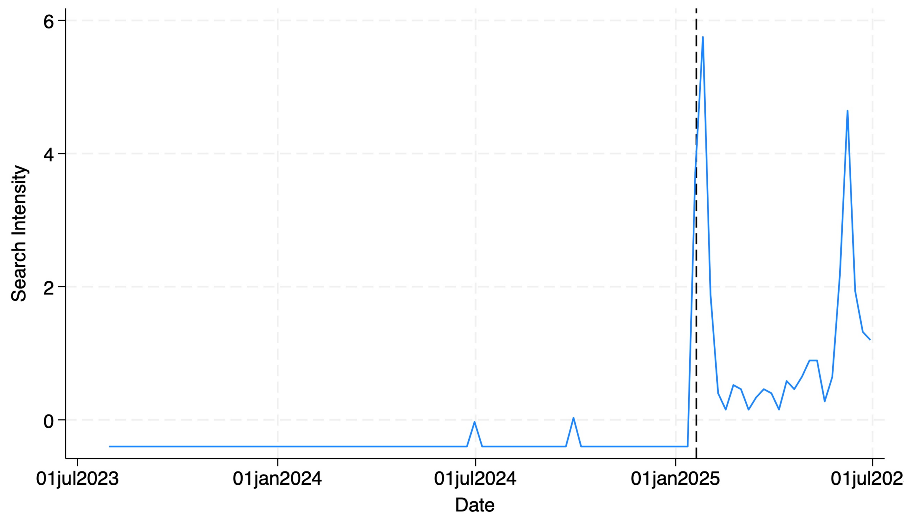
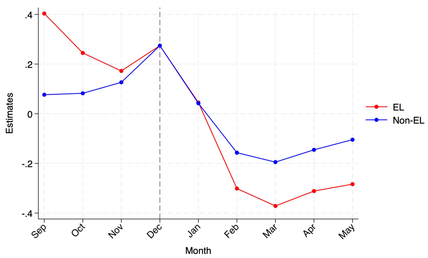
Figure 1: Immigration Customs and Enforcement Search Intensity



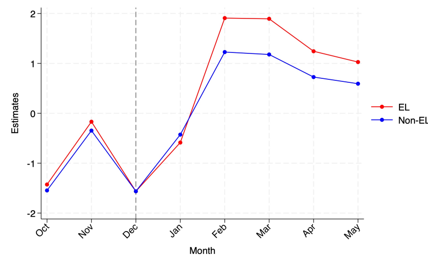
Google trends search measure for "United States Immigration and Customs Enforcement (Federal Agency)" for Rhode Island, as described in text. Measure is standardized to have a mean of 0 and standard deviation of 0. Dashed line corresponds to date of second Trump inauguration.

Figure 2: Residual Variation in Attendance Outcomes (Connecticut)

(a) Attendance

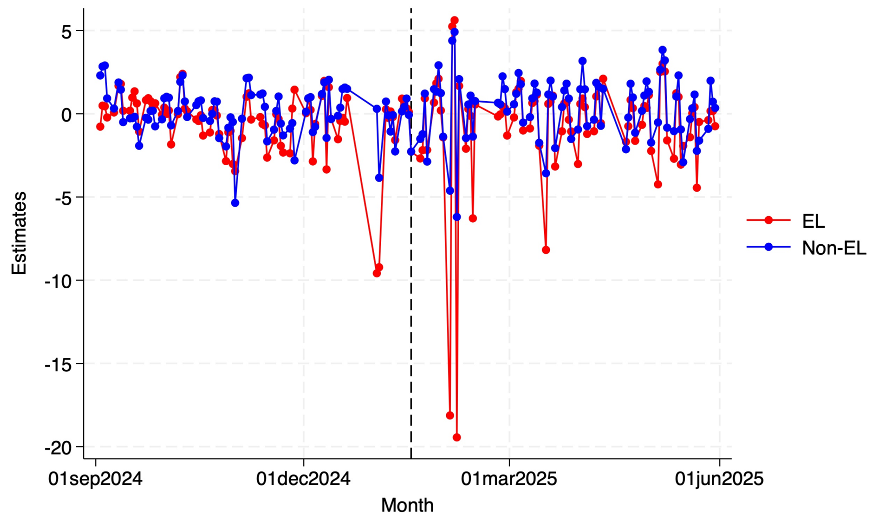


(b) Chronic Absenteeism



Average residual variation in attendance outcomes for Connecticut sample, adjusting for school year x group, month x group, and school fixed effects, as described in text. Averages are weighted by the number of students in each group, as are the regressions used to generate predicted values. Point estimates are re-centered so that they are equal for EL and non-ELs in December. This is done by subtracting the El/non-EL difference in outcomes in December from all EL points. There is one fewer month plotted for chronic absenteeism because chronic absenteeism is first reported starting in October.

Figure 3: Residual Variation in Attendance Outcomes (Rhode Island)



Average residual variation in (calculated) attendance rates for Rhode Island sample, controlling for school year, month x group, school x group, weather, illness, and holiday controls, as described in text and table notes for Table 4. Point estimates are re-centered so that they are equal for EL and non-ELs on January 17, 2025 (the last school day before Trump's inauguration). This is done by subtracting the EL/non-EL difference on that day from all EL points. Averages are weighted by the number of students in membership in each group as of SY 2023-24, as is the regression used to generate predicted values.

Table 1: Sample Descriptive Statistics

	Connecticut		Rhode Island	
	Full State	Sample	Full State	Sample
A. Coverage	(1)	(2)	(3)	(4)
Schools	958	526	349	50
Districts	188	79	65	14
All Enrollment	470,986	294,683	133,382	31,563
Share of All Enrollment	1.00	0.63	1.00	0.24
Total EL Enrollment	53,885	46,709	19,492	10,979
Share of Total EL Enrollment	1.00	0.87	1.00	0.56
B. School Characteristics				
Average Enrollment	497.345	560.234	390.126	630.140
obs	[947]	[526]	[349]	[50]
Share White	0.500	0.350	0.516	0.153
obs	[916]	[507]	[347]	[50]
Share Black	0.145	0.162	0.098	0.170
obs	[726]	[469]	[310]	[50]
Share Hispanic	0.302	0.405	0.310	0.590
obs	[933]	[526]	[342]	[50]
Share Asian	0.065	0.075	0.030	0.028
obs	[596]	[348]	[312]	[47]
Share Free or Reduced-Price Lunch	0.450	0.539	0.453	0.724
obs	[872]	[504]	[344]	[50]
Share English Learners	0.128	0.167	0.140	0.359
obs	[817]	[526]	[312]	[50]
Share Special Education	0.169	0.167	0.250	0.164
	[944]	[526]	[348]	[50]

Summary statistics for schools included/excluded in estimation samples. For CT, summary data are from SY 24-25 demographic data. For RI, summary data are from SY 23-24 program membership files. Some school-level data is missing, hence the different number of observations for some characteristics.

Table 2: Effects on English Learner Attendance Outcomes in Connecticut

	Average Attendance Rate			Chronic Absenteeism Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
AfterxEnglish Learner	0.75***	0.15*	-0.37***	-1.64***	0.74***	0.83***
	(0.12)	(0.06)	(0.07)	(0.40)	(0.22)	(0.25)
After	-0.52***	-0.42***	-0.34***	2.86***	2.39***	2.38***
	(0.06)	(0.05)	(0.04)	(0.25)	(0.24)	(0.26)
English Learner	-0.41*			1.31**	-6.24***	-6.93***
	(0.18)			(0.50)	(1.06)	(0.96)
Month, Year FE	X			X		
Month, Year x EL FE		X			X	
Month x EL, Year x EL FE			X			X
School FE	X		X	X		X
r2	0.77	0.78	0.78	0.74	0.75	0.75
N	40,976	40,976	40,976	27,424	27,424	27,424
Outcome Means (Sample)						
English Learners	91.2	91.2	91.2	29.6	29.6	29.6
Non-English Learners	92.6	92.6	92.6	26.0	26.0	26.0

Estimates of difference-in-difference models comparing EL and non-EL students (equation 1) in Connecticut sample. Analytic dataset is limited to school-by-group-by month observations for EL and non-EL students for months Sep-May (average attendance) or Oct-May (chronic absenteeism) for SY's 21-22 to 24-25. Chronic absenteeism rate refers to share of students who miss more than 10% of school days. Year FE refers to school year fixed effects. Month (Year) x EL fixed effects are indicator variables for combinations of month (school year) and EL status. Regressions are weighted by the number of students in the student group using analytic weights in Stata, as are reported outcome means. + p< 0.10, * p< 0.05, ** p<0.01, *** p<0.001.

Table 3: Effects on Hispanic/Latino Attendance Outcomes in Connecticut

	Average Attendance Rate			Chronic Absenteeism Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
AfterxHispanic/Latino	0.89***	-0.03	-0.21***	-1.01**	2.51***	1.30***
	(0.10)	(0.04)	(0.05)	(0.34)	(0.17)	(0.20)
After	-0.67***	-0.32***	-0.25***	2.49***	0.97***	1.46***
	(0.07)	(0.04)	(0.03)	(0.27)	(0.19)	(0.17)
Hispanic/Latino	-1.63***	-1.60***	-1.50***	8.09***	3.97***	4.36***
	(0.08)	(0.19)	(0.20)	(0.30)	(0.81)	(0.76)
Month, Year FE	X			X		
Month, Year x Hispanic/Latino FE		X			X	
Month x Hispanic, Year x Hispanic/Latino FE			X			X
School FE	X		X	X		X
r2	0.74	0.76	0.76	0.73	0.74	0.75
N	66,540	66,540	66,540	45,733	45,733	45,733
Outcome Means (Sample)						
Hispanic	91.5	91.5	91.5	28.5	28.5	28.5
White	94.7	94.7	94.7	14.8	14.8	14.8

Estimates of difference-in-difference models comparing Hispanic/Latino and white (non-Hispanic/Latino) students in Connecticut sample (adapted from equation1). Analytic dataset is limited to school-by-group-by month observations for Hispanic/Latino and non-Hispanic/Latino white students for months Sep-May (average attendance) or Oct-May (chronic absenteeism) for SY's 21-22 to 24-25. Chronic absenteeism rate refers to share of students who miss more than 10% of school days. Year FE refers to school year fixed effects. Month (Year) x Hispanic/Latino fixed effects are indicator variables for combinations of month (school year) and Hispanic/Latino status. Regressions are weighted by the number of students in the student group using analytic weights in Stata, as are reported outcome means. + p< 0.10, * p< 0.05, ** p<0.01, *** p<0.001.

Table 4: Effect on English Learner Attendance Outcomes in Rhode Island

	(1)	(2)	(3)	(4)	(5)	(6)
After x EL	-0.93	-2.05***	-1.97***			
	(0.58)	(0.49)	(0.48)			
After	0.13	0.50*	1.53***			
	(0.24)	(0.19)	(0.23)			
ICE Search Intensity x EL				-0.57***	-0.56***	-0.53***
				(0.11)	(0.13)	(0.13)
ICE Search Intensity				0.19**	0.19**	0.36***
				(0.06)	(0.06)	(0.07)
Month FE	X			X		
Month x EL FE		X	X		X	X
Year FE	X	X	X	X	X	X
School FE	X	X	X	X	X	X
Holiday, Weather, Illness Controls			X			X
Placebo Search Controls						X
r2	0.55	0.55	0.61	0.55	0.55	0.61
N	26,440	26,440	26,440	26,440	26,440	26,440
Outcome Means (Sample)						
English Learners	87.0	87.0	87.0	87.0	87.0	87.0
Non-English Learners	87.0	87.0	87.0	87.0	87.0	87.0

Estimates of difference-in-differences models comparing EL and non-EL students in Rhode Island (equations 2 and 3). Analytic sample consists of school-by-group-by-date observations for EL and non-EL students covering months Sep-May for SY's 23-24 to 24-25. ICE Search intensity is the standardized google trends measure of searches for Immigration and Customs Enforcement. Year FE refers to school year fixed effects. Month x EL fixed effects are indicators combinations of month and EL status. Holidays controls are indicators for days around school breaks (see Appendix Table A2 for a complete list). Weather, sickness, and placebo search controls are as described in text. Regressions are weighted by the number of students in the student group using analytic weights in Stata, as are reported outcome means. + p< 0.10, * p< 0.05, ** p<0.01, *** p<0.001.

Table 5: Falsification Tests

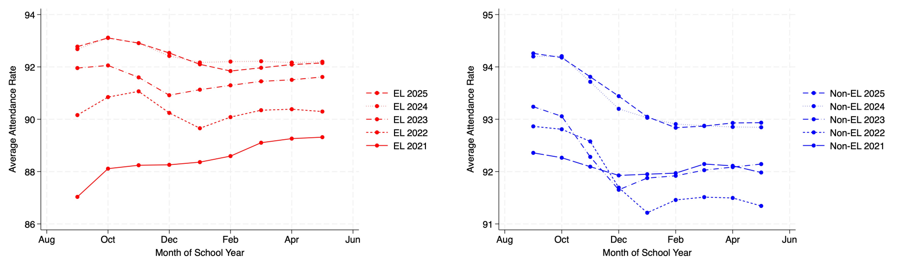
	Attendance (CT)		Chronic Absenteeism (CT)		Attendance (RI)	
	(1)	(2)	(3)	(4)	(5)	(6)
AfterxBlack	-0.10		-0.59			
	(0.06)		(0.36)		-0.02	
After x Students with Disabilities		0.03		0.04	(0.31)	
		(0.04)		(0.14)	0.69***	
After	-0.22***	-0.22***	2.11***	1.95***	(0.17)	
	(0.04)	(0.02)	(0.37)	(0.09)		-0.05
Search Intensity x Students with Disabilities						(0.09)
						0.09+
Search Intensity						(0.05)
r2	0.75	0.84	0.71	0.82	0.64	0.64
N	36,192	65,727	18,461	48,920	33,101	33,101

Presents results from falsification tests, as described in text. Outcomes are as follows: attendance rates in CT (columns 1-2), chronic absenteeism rates in CT (columns 3-4), and attendance rates in RI (columns 5-6). Columns 1 and 3 adapt equation 1 to compare Black and white students, swapping in an indicator for Black for an indicator for ELs. Columns 2 and 4 do the same for students with (SWDs) and without disabilities (non-SWDs), swapping in an indicator for SWDs for the indicator for ELs. Columns 5 and 6 adapt equations 2 and 3 to compare SWDs and non-SWDs, swapping in an indicator for SWDs for the indicator for ELs. All regressions are weighted by the number of students in the group. Standard errors are clustered by school.
+ p< 0.10, * p< 0.05, ** p<0.01, *** p<0.001.

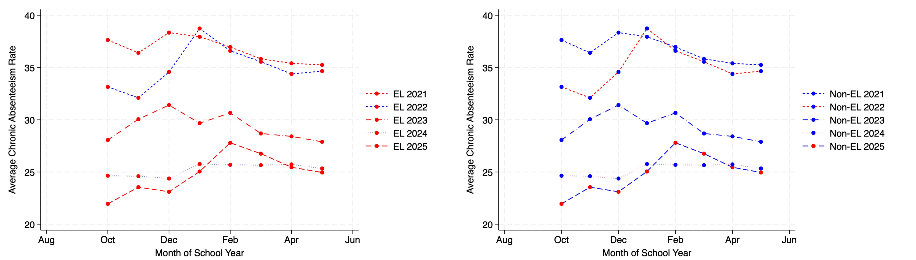
Last updated: December 18, 2025

Figure A1: Attendance Metrics by Year (Connecticut)

(a) Average Attendance Rates



(b) Average Chronic Absenteeism Rates

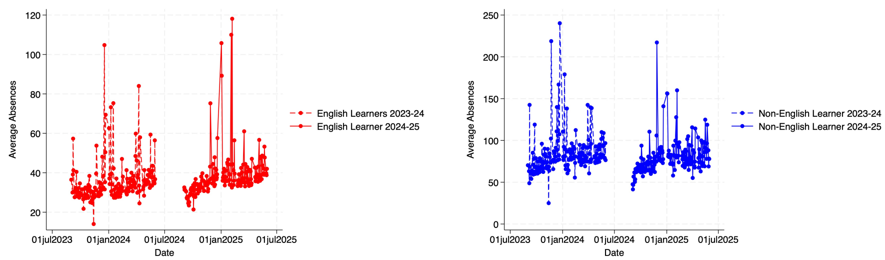


Average outcome by month/school year for students in each group. Average is constructed by taking school-level data in a sample and collapsing by month and student group, weighting by the number of students in the group using analytic weights. Year in legend refers to spring of school year.

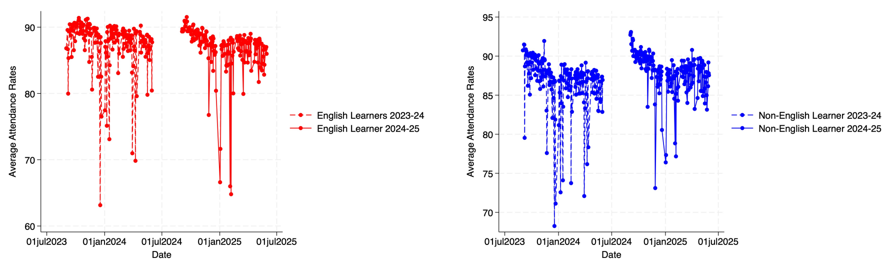
Immigration and Customs Enforcement search intensity measure is created from Google Trends data, as described in text. Rhode Island immigration arrest data come from the Deportation Data Project (see Appendix A).

Figure A2: Attendance Metrics by Year (Rhode Island)

(a) Average Daily Absences



(b) Average Calculated Attendance Rates



Average outcomes are (A) daily absences (reported on website) and (B) calculated attendance rates, where attendance rates are calculated using membership by school/student group data from SY 2023-24. Average is constructed by taking school-level daily data and collapsing by month and student group, weighting by the number of students in that group using analytic weights.

Figure A3: Enforcement Search Intensity and ICE Arrests, Rhode Island

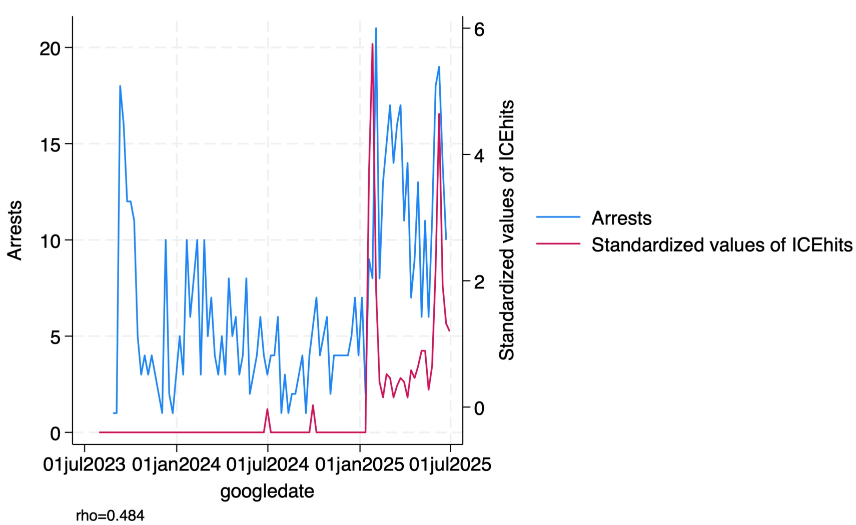
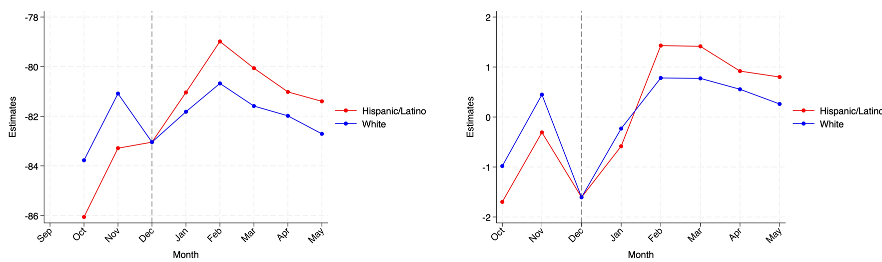


Figure A4: Residual Variation in Attendance Outcomes (Hispanic/White Students, Connecticut)

(a) Attendance (b) Chronic Absenteeism



Average residual variation in attendance outcomes for Connecticut sample, adjusting for school year x group, month x group, and school fixed effects, as described in text. Averages are weighted by the number of students in each group, as are regression used to generate predicted values. Point estimates are re-centered so that they are equal for Hispanic/Latino and white in December. This is done by subtracting the Hispanic/Latino and white student gap in December from all Hispanic/Latino points. There is one fewer month plotted for chronic absenteeism because this data is first reported starting in October.

Table A1: School Breaks/Holidays in RI Regressions

Holiday	SY 2023-24	SY 2024-25
Friday before September break	September 1, 2023	August 30, 2024
Friday before Columbus Day/Indigenous People's Day	October 6, 2023	October 11, 2024
Friday before Veteran's day	November 10, 2023	November 8, 2024
1-2 days before Thanksgiving break	Nov 22, 2023; Nov 21, 2023	Nov 26, 2024; Nov 27, 2024
1-2 days before winter break	Dec 21, 2023; Dec 22, 2023	Dec 19, 2024; Dec 20, 2024
1-2 days after winter break	Jan 2, 2024; Jan 3, 2024	Jan 2, 2025; Jan 3, 2025
Friday before MLK day	January 12, 2024	January 17, 2025
1-2 days before February break	Feb 15, 2024; Feb 16, 2024	Feb 13, 2025; Feb 14, 2025
1-2 days post February break	Feb 26, 2024; Feb 27, 2024	Feb 24, 2025; Feb 25, 2025
Good Friday	March 29, 2024	Occurred during spring break
1-2 days before April break	April 12, 2024; April 11, 2024	April 11, 2025; April 10, 2025
1-2 days after April break	April 22, 2024; April 23, 2024	April 21, 2025; April 22, 2025
Friday before Memorial Day	May 24, 2024	May 23, 2025
Source for calendar dates:	https://ride.ri.gov/sites/g/files/xkgbur806/files/2023-06/2023-2024RIDESchoolCalendar062123.pdf	https://ride.ri.gov/sites/g/files/xkgbur806/files/2024-01/SY2024-25%20RIDE%20Calendar_240131.pdf

Table A2: Robustness: Connecticut

	Average Attendance Rate					Chronic Absenteeism Rate				
	Preferred	No Weights	Add School x Group FE	Limit to SY 2022-23 or Later	Drop Febuary 2025	Preferred	No Weights	Add School x EL FE	Limit to SY 2022-23 or Later	Drop Febuary 2025
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
A. English Learners vs. Non-English Learners										
After x English Learner	-0.37***	-0.25***	-0.37***	-0.12+	-0.38***	0.83***	0.51*	0.76**	0.38	0.78**
	(0.07)	(0.04)	(0.07)	(0.07)	(0.07)	(0.25)	(0.24)	(0.24)	(0.27)	(0.26)
After	-0.34***	-0.44***	-0.34***	-0.28***	-0.34***	2.38***	2.54***	2.39***	2.67***	2.25***
	(0.04)	(0.03)	(0.04)	(0.04)	(0.05)	(0.26)	(0.15)	(0.26)	(0.16)	(0.27)
r2	0.78	0.71	0.81	0.90	0.78	0.75	0.67	0.79	0.84	0.75
N	40,976	40,976	40,976	25,990	39,980	27,424	27,424	27,424	16,898	26,694
B. Hispanic/Latino vs. White										
After x Hispanic/Latino	-0.21***	-0.12***	-0.21***	-0.06	-0.22***	1.30***	0.96***	1.26***	0.62***	1.25***
	(0.05)	(0.03)	(0.05)	(0.05)	(0.05)	(0.20)	(0.18)	(0.20)	(0.18)	(0.21)
After	-0.25***	-0.33***	-0.25***	-0.25***	-0.24***	1.46***	1.59***	1.47***	2.27***	1.38***
	(0.03)	(0.03)	(0.03)	(0.02)	(0.03)	(0.17)	(0.15)	(0.17)	(0.12)	(0.18)
r2	0.76	0.68	0.78	0.88	0.76	0.75	0.67	0.77	0.85	0.74
N	66,540	66,547	66,540	40,490	65,052	45,733	45,733	45,733	28,033	44,580

Alternative specifications of difference-in-differences estimates comparing EL/non-EL (Panel A) and Hispanic/Latino and white (Panel B) students. All models include controls as described for preferred estimates in Tables 2 and 3 (columns 3 and 6) except where noted here or in the text. Columns 1 and 6 replicate preferred estimates from Tables 2 and 3. Columns 2 and 7 presents unweighted estimates. Column 3 and 8 adapt equation 1 to include school x group (i.e., English Learner or Hispanic/Latino) fixed effects instead of school fixed effects. Columns 4 and 9 drop data from SY 2020-21 and SY 2021-22 (pandemic). Columns 5 and 10 drop observations from February 2025, when the national "Day without Immigrants'' took place. Regressions are weighted by the number of students in the student group using analytic weights in Stata (except where noted), as are reported outcome means. + p< 0.10, * p< 0.05, ** p<0.01, *** p<0.001.

Table A3: Robustness: Rhode Island (After)

	Preferred	No Weights	Drop Feburary 3	Add Year x EL FE	Add School x EL FE	No Interacted Weather Controls
	(1)	(2)	(3)	(4)	(5)	(6)
After x English Learner	-1.97***	-2.12***	-1.84***	-0.53+	-1.90***	-1.99***
	(0.48)	(0.47)	(0.50)	(0.27)	(0.48)	(0.49)
After	1.53***	1.90***	1.40***	1.06***	1.51***	1.52***
	(0.23)	(0.43)	(0.23)	(0.23)	(0.23)	(0.24)
r2	0.61	0.67	0.61	0.61	0.64	0.61
N	26,440	26,440	26,371	26,440	26,440	25,864

	Assume EL Pop Grew 10%	Limit Sample (>100 Students in Group)	Impute Missing Attendance (75th Percentile)	Impute Missing Attendance (99th Percentile)	Limit Sample (Non-Missing for Both)	Outcome = Absences	Outcome = Absences
	(7)	(8)	(9)	(10)	(11)	(12)	(13)
After x English Learner	-0.96*	-1.90***	-1.61***	-1.57**	-1.82***	2.44	7.30***
	(0.44)	(0.49)	(0.46)	(0.47)	(0.48)	(2.32)	(1.51)
After	1.28***	1.52***	1.36***	1.33***	1.39***	-3.95**	-6.38***
	(0.25)	(0.23)	(0.21)	(0.21)	(0.25)	(1.32)	(1.10)
r2	0.65	0.61	0.54	0.53	0.61	0.61	0.82
N	27,008	25,864	28,680	28,680	24,934	27,008	27,008

Alternative specifications of difference-in-differences estimates comparing EL/non-EL students in Rhode Island (equation 2). All models include controls as described in Table 4 for preferred estimates (column 3), except where noted. Column 1 replicates preferred estimates from Table 4. All regressions are weighted by the number of students in the group, except where noted. Column 2 presents unweighted estimates. Column 3 drops observations from February 3, 2025. Column 5 swaps in school eyar x group fixed effects for school year fixed effects. Column 6 adapts equation 2 to include school x group fixed effects instead of school fixed effects. Column 6 includes main effect of standardized weather search intensity measures but omits interactions with EL status. Column 7 recalculates attendance rates and weights used in the regression to reflect 10\% growth in EL student populations from SY 23-24 to SY 24-25. Column 8 limits estimating sample to observations with at least 100 students in each student group. Column 9 imputes missing attendance rates as the 75th percentile of daily attendance rates. Column 10 does the same with the 99th percentile. Column 11 limits sample to days where both EL and non-EL absence data are reported. Columns 12 and 13 use the number of daily absences for students at the school in that group as the outcome instead of daily attendance rates for students in the school/group. Column 12 estimates equation 2 with this outcome as written. Column 13 uses school by group fixed effects instead of school fixed effects. + p< 0.10, * p< 0.05, ** p<0.01, *** p<0.001.

Table A4: Robustness: Rhode Island (Search Intensity)

	Preferred	No Weights	Drop February 3	Add Year x EL FE	Add School x EL FE	No Interacted Weather Controls
	(1)	(2)	(3)	(4)	(5)	(6)
ICE Search Intensity x EL	-0.52***	-0.52***	-0.45**	-0.11	-0.50***	-0.56***
	(0.13)	(0.12)	(0.14)	(0.07)	(0.13)	(0.13)
ICE Search Intensity	0.30***	0.38***	0.23**	0.17**	0.29***	0.40***
	(0.07)	(0.10)	(0.07)	(0.06)	(0.06)	(0.06)
r2	0.61	0.67	0.61	0.61	0.64	0.61
N	26,440	26,440	26,371	26,440	26,440	25,864

	Assume EL Pop Grew 10%	Limit Sample (>100 Students in Group)	Impute Missing Attendance (75th Percentile)	Impute Missing Attendance (99th Percentile)	Limit Sample (Non-Missing for Both)	Outcome: Absences (Equation 1)	Outcome: Absences (Add SchoolxEL FE)	Alternative Search Intensity Measure
	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
ICE Search Intensity x EL	-0.27*	-0.51***	-0.44**	-0.43**	-0.45***	0.71	1.88***	
	(0.12)	(0.13)	(0.13)	(0.13)	(0.12)	(0.60)	(0.46)	
ICE Search Intensity	0.26***	0.30***	0.25***	0.23***	0.25***	-0.85*	-1.49***	
	(0.07)	(0.07)	(0.06)	(0.06)	(0.07)	(0.37)	(0.34)	
Enforcement Search Intensity Index X EL								-0.33**
								(0.10)
Enforceent Search Intensity Index								0.12*
								(0.05)
r2	0.65	0.61	0.54	0.53	0.61	0.61	0.82	0.61
N	27,008	25,864	28,680	28,680	24,934	27,008	27,008	26,440

Alternative specifications of difference-in-differences estimates comparing EL/non-EL students in Rhode Island (equation 3). See table notes for Table A3. Column 14 uses an index-based measure of search intensity, as described in the text.
+ p< 0.10, * p< 0.05, ** p<0.01, *** p<0.001.

A. Data Citations

Connecticut School Attendance Data. Connecticut Department of Education. Available online at https://public-edsight.ct.gov/students/attendance-dashboard?language=en_US.

Connecticut School Directory, SY 2024-25. Connecticut Department of Education. Available online at https://data.ct.gov/Education/Education-Directory/9k2y-kqxn/about_data.

Connecticut School Enrollment Demographic Data, SY 2024-25. Connecticut Department of Education. Available online at https://public-edsight.ct.gov/students/enrollment-dashboard?language=en_US.

Deportation Data Project. Immigration and Customs Enforcement Data: ERO Administrative Arrests. Available online at https://deportationdata.org/data/ice.htmla. Accessed on July 29, 2025.
Google Search Intensity Measure for Rhode Island. Google Trends. Available online at https://trends.google.com/trends/. See Appendix B for details.

Rhode Island Attendance Data. Rhode Island Department of Education. Available online at https://www3.ride.ri.gov/attendance/public.

Rhode Island Student Membership by Program Eligibility Status, SY 2023-24. Rhode Island Department of Education. Available online at https://datacenter.ride.ri.gov/Home/FileDetail?fileid=1069.

Storm Database. National Centers for Environmental Information. Available online at National Centers for Environmental Information. Available online at https://www.ncdc.noaa.gov/stormevents/.

B. Google Trends Data Details

Google search data were collected for the state of Rhode Island for dates 7/30/2023-6/29/2025.

- Placebo Measures:
  - J.D. Vance (Topic),
  - Tariff (Topic),
  - Department of Government Efficiency (Federal agency)(Topic)
- Main Immigration Enforcement Measure (*). All measures listed here were used used to construct index measure for alternative enforcement-related search intensity measure in Appendix Table A4:
  - United States Immigration and Customs Enforcement (Federal Agency) (Topic)*
  - Deportation (Topic)
  - ICE raid
  - ICE in Rhode Island
  - ICE in Massachusetts
  - ICE in Providence
- Weather Search Measures:
  - snow (Topic)
  - storm
  - school closings
- Illness Search Measures:
  - Influenza (Topic)
  - Conjunctivitis (Topic) [pink eye]
  - Streptococcal pharyngitis (Topic) [strep throat]
  - Gastroenteritis (Topic)
  - Hand, Foot, and Mouth Disease (Topic)

Figure B1: Principal Components Analysis: Enforcement-Related Search Intensity Index

```
. pca  stdICEhits stdiceraid stdiceinRI stdiceinProvidence stdiceinMA stddeport

Principal components/correlation                 Number of obs    =        101
                                                 Number of comp.  =          6
                                                 Trace            =          6
    Rotation: (unrotated = principal)            Rho              =     1.0000
```

Component	Eigenvalue	Difference	Proportion	Cumulative
Comp1	3.17154	2.11527	0.5286	0.5286
Comp2	1.05627	.0495462	0.1760	0.7046
Comp3	1.00672	.449631	0.1678	0.8724
Comp4	.557089	.352458	0.0928	0.9653
Comp5	.204631	.200878	0.0341	0.9994
Comp6	.00375288	.	0.0006	1.0000

Principal components (eigenvectors)

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6	Unexplained
stdICEhits	0.4969	0.1810	0.0014	-0.3148	-0.7882	0.0049	0
stdiceraid~s	0.5199	-0.1952	-0.0345	0.4168	0.1120	-0.7100	0
stdiceinRI~s	0.5182	-0.1970	-0.0351	0.4270	0.1152	0.7041	0
stdiceinPr~s	0.0587	0.9290	-0.1381	0.3147	0.1244	-0.0014	0
stdiceinMA~s	0.0081	0.1060	0.9861	0.1259	-0.0191	-0.0003	0
stddeporth~s	0.4591	0.1269	0.0776	-0.6557	0.5806	0.0042	0

```
. predict score, score
(5 components skipped)

Scoring coefficients
    sum of squares(column-loading) = 1
```

Variable	Comp1	Comp2	Comp3	Comp4	Comp5	Comp6
stdICEhits	0.4969	0.1810	0.0014	-0.3148	-0.7882	0.0049
stdiceraid~s	0.5199	-0.1952	-0.0345	0.4168	0.1120	-0.7100
stdiceinRI~s	0.5182	-0.1970	-0.0351	0.4270	0.1152	0.7041
stdiceinPr~s	0.0587	0.9290	-0.1381	0.3147	0.1244	-0.0014
stdiceinMA~s	0.0081	0.1060	0.9861	0.1259	-0.0191	-0.0003
stddeporth~s	0.4591	0.1269	0.0776	-0.6557	0.5806	0.0042

Details from principal components analysis process used to construct google trends-based index measure of immigration enforcement intensity for robustness check.

Figure B2: Enforcement-Related Google Search Trends

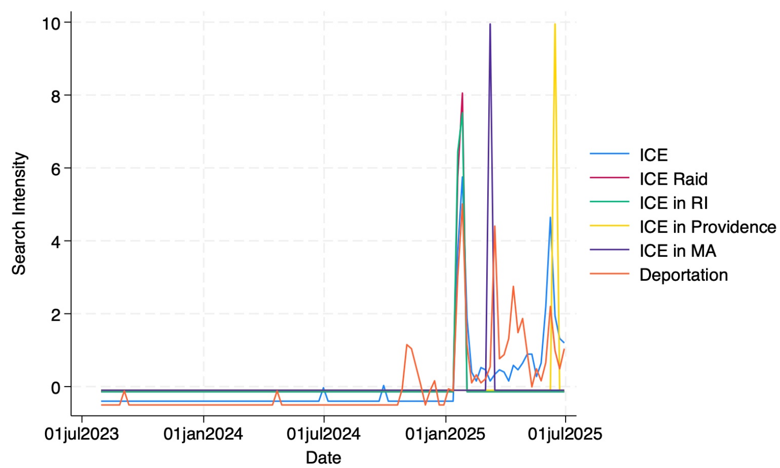


Figure B3: Weather-Related Google Search Terms

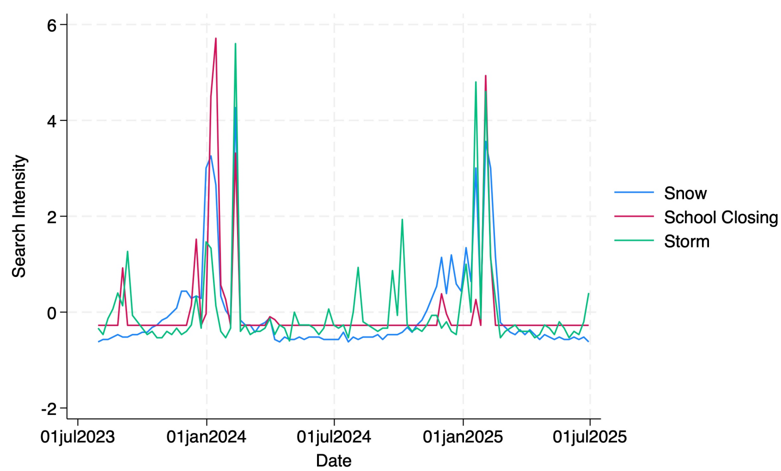


Figure B4: Sickness-Related Google Search Terms

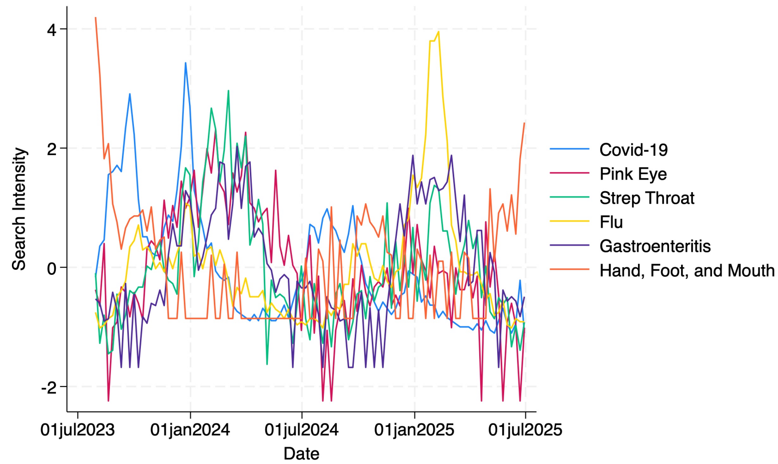


Figure B5: Placebo Google Search Terms