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The Effect of the Second Trump Administration and the Attendance of Immigrant-Origin Students

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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 are likely from immigrant families. Using a difference-in-differences design that compares English learners (ELs) and non-English learners, I find negative effects on the attendance of EL students in both Rhode Island and Connecticut. In Connecticut, average monthly attendance declined by 0.07 standard deviations and chronic absenteeism increased by over half a percentage point. In Rhode Island, daily absences for EL students increased by close to 4%. I present corroborating evidence that anxiety/awareness of enforcement activity, as proxied by data from google searches, relate to increases in absences. Together with other recent work, these findings suggest that immigration enforcement activities under the second Trump presidency are having disruptive effects on students and schools in a variety of settings nationwide.

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The Effect of the Second Trump Administration and the Attendance of Immigrant-Origin Students

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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 are likely from immigrant families. Using a difference-in-differences design that compares English learners (ELs) and non-English learners, I find negative effects on the attendance of EL students in both Rhode Island and Connecticut. In Connecticut, average monthly attendance declined by 0.07 standard deviations and chronic absenteeism increased by over half a percentage point. In Rhode Island, daily absences for EL students increased by close to 4%. I present corroborating evidence that anxiety/awareness of enforcement activity, as proxied by data from google searches, relate to increases in absences. Together with other recent work, these findings suggest that immigration enforcement activities under the second Trump presidency are having disruptive effects on 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 to intensify federal immigration enforcement activity, taking steps to make good on his campaign promises to crack down on unauthorized immigration. In the months since taking office, Trump has escalated the anti-immigrant rhetoric of his administration and taken steps to increase the severity of enforcement activities, heightening anxiety among documented and undocumented immigrants alike.

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

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immigrants (Urban Institute, 2019). This includes 5.3 million children – 85% of whom were born in the United States – who live with at least one undocumented parent (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 for children in immigrant families, 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).

Several studies from earlier periods of enforcement activity have found negative effects of immigration enforcement on school attendance (Kirksey & Sattin-Bajaj, 2021; Bellows, 2019; Kirksey, 2020). School attendance can suffer in heightened enforcement environments if families fear that leaving home or sending their child to school increases their risk of detention or family separation. These concerns have recently been made more salient given the Trump's reversal of the long-running policy of Immigration Customs and Enforcement (ICE) agents to avoid making arrests near "sensitive sites" such as churches or schools. Effects on school attendance are concerning for several reasons. First, school attendance is related to a variety of important longer-term life outcomes, including educational attainment, economic well-being, and crime (Aucejo & Romano, 2016; Liu et al., 2021; Jacob & Lefgren, 2003; Ansari et al., 2020). Negative effects on attendance are also likely precursors of negative effects on other educational outcomes, such as student test scores (Goodman, 2014). In addition, research has found that increases in absences have negative spillover effects on one's peers, meaning that disruptions to the attendance of students in immigrant families are likely to negatively impact the learning of their non-immigrant classmates (Goodman, 2014).

This paper provides early evidence on the effects of the immigration enforcement environment under the second Trump administration on the attendance of children from immigrant families. Using school-level attendance data from Connecticut and Rhode Island, I estimate the effect of the second Trump presidency on the attendance of English learners relative to non-English learners using difference-in-difference models. I find evidence that the second Trump administration has negatively impacted the attendance of students who are likely from immigrant families. In Connecticut, the average attendance of English learners declined by 0.07 standard deviations and chronic absenteeism increased by about 2% relative to the sample mean after the start of Trump's second presidency. In Rhode Island, daily absences increased by close to 4% after Trump's second inauguration. I show supporting evidence 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 these concerns are driving changes in attendance outcomes.

This paper is most closely related to recent work by Dee (2025) that looks at the impacts of the second Trump presidency on the attendance of students in five high-immigrant school districts in the Central Valley of California. Using an event-study approach, Dee finds that student absences in these districts increased by 22 percent during the recent period of enforcement activity. My study, which differs both methodologically and geographically from Dee's, also finds negative effects on student attendance in this very different context, suggesting recent enforcement activities are having broad-based effects on students and schools in the United States.

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 share (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 Providence, where over 38% of all students are classified 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-related policies, including allowing undocumented immigrants to get driver's licenses and qualify for in-state tuition at public colleges and universities.

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.[1] Since attendance data is not reported separately for immigrants or the children of immigrants, I proxy for children in immigrant families using students identified as English learners (ELs). This likely underestimates the actual population of children in immigrant families since most children who are initially classified as ELs are later reclassified as English proficient and other children in immigrant families will never be classified as ELs. This could bias against detecting effects in my difference-in-differences models.

In Connecticut, I have access to monthly school-level data on average daily rates and the share of students who were chronically absent, which is defined as missing 10% or more of school days, by student group (i.e., ELs and non-ELs). My analytic sample in Connecticut covers school year (SY) 2021-22 to

[1] 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`.

SY 2024-25 (4 school years), through May 2025. For Rhode Island, I have daily school-level data on the number of absences by student group for SYs 2023-24 and 2024-25 (2 school years).[2] My analytic samples include about 58% of comparable schools in Connecticut and about 15% of comparable schools in Rhode Island. Missing data appears to be due in some cases to data suppression rules for small sample sizes.[3] In Rhode Island, I exclude observations from schools with less than 100 absence observations reported for both EL and non-EL students in the school year. In Connecticut, I exclude observations from schools with less than 6 months of average attendance rate data for ELs and non-ELS in the school year and set to missing chronic absenteeism rates for schools with less than 5 months of chronic absenteeism data. In both states, I drop schools with enrollment $<$ 100 students. Both samples include some charter schools. Summary statistics for schools in my sample are presented in Appendix Table A1.

[Figure 1 about here: google search intensity]

I use data on search intensity for terms related to immigration enforcement from Google Trends as a proxy for anxiety/awareness of enforcement activity in Rhode Island, following prior work using Google Trends data (Bacher-Hicks et al., 2021, 2022). Google Trends-based measures may be preferable in this context to alternative approaches – such as using data on immigration raids or arrests – for several reasons. First, while there have been some higher-profile immigration arrests, there have not been many or any large-scale raids in Rhode Island in 2025 to date. Second, in this period of great uncertainty, search data may be a better expression of anticipation of enforcement activity than actual enforcement actions, though the two are correlated.[4] Google Trends data come from a random sample of searches 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 this data for Rhode Island only because in Rhode Island I have access to daily (as opposed to monthly) outcome data. I download Google Trends data for the state of Rhode Island from August 2021-July 2025. Two measures used to construct my index measure come from google "topics" as opposed to individual search terms. Google topics are considered more reliable and expansive indicators of search intensity related to a topic because they take into account acronyms, common misspellings, and

[2] I drop observations from August because there are very few attendance dates in this month.

[3] In Connecticut, the schools in my sample represent an estimated 87% of all EL enrollment in the state among comparable schools with non-missing EL data. In Rhode Island, that figure is 60%.

[4] Appendix Figure A1 plots my preferred index of enforcement-related search intensity against ICE arrest data in Rhode Island. The correlation between immigration arrests and my search index is about 0.25. One reason the two variables are not more strongly correlated is that arrests were relatively frequent in the pre-period, when search intensity was much lower. This is consistent with the Trump administration driving anxiety/awareness of enforcement activity above and beyond what would be predicted given actual changes in enforcement activity.

(most importantly) searches in other languages (Google News Initiative, 2025).[5] I also use Google Trends data on individual search terms, including those that are geographically specific – such as "ICE in Rhode Island" and "ICE in Providence" – which I select based on the availability of data and recommended related searches. (A complete list of terms used for the index is available in Appendix A). I use principal components analysis to generate index measures of enforcement search intensity, which I standardize to have a mean of 0 and a standard deviation of 1. Figure 1 plots my preferred measures of search intensity over time. Relative search intensity for immigration enforcement-related terms 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. I also use Google Trends data to proxy for inclement weather using searches for "snow," "storm," and "school closings." I use these search intensity measures to create an index of inclement weather using principal components analysis, which I standardize, as before.

4 Methods

Identification in both states is based on a difference-in-differences design that compares changes in attendance outcomes for EL and non-EL students over time. In Connecticut, where outcome data are available at the month-by-school-by-student-group level, my models assess whether the attendance of EL students has changed relative to that of non-ELs since the start of the second Trump presidency. 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 $Attend_{smyg}$ is the attendance measure (average attendance or chronic absenteeism rate) for students in group g (EL or non-EL) at school s in month m in school year y. $After_{my}$ is an indicator that is equal to 1 if the observation falls in or after January 2025.[6] β_2 is the coefficient of interest, representing the difference in the attendance outcome of EL students relative to non-ELs. μ_{mg} is a complete set of month fixed effects interacted with indicators for EL observations. 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.[7] λ_{yg} is a fixed effect for the student group and school year, which accounts for year-to-year variation in the student group population over time.

[5] The topics that contribute to my index measures are "United States Immigration and Customs Enforcement" and "Deportation."

[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] As an alternative, I interact an indicator for school month (i.e., order of month in the regular school year Sep-June) with an indicator for EL observations. Positive point estimates in column 2 of Table 1 suggest that the attendance of EL students typically improves relative to that of non-EL students over the course of the school year.

This could be relevant given that districts in Connecticut have seen increases in EL students in recent years. θ_s are school fixed effects which I include to adjust for time-invariant differences in attendance across schools. 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.

To assess parallel trends, I adapt Equation (1) to include period-specific dummies for each month in the SY 2024-25 before/after January 2025 (up to May 2025, the latest available data). I interact these "pre" and "post" period indicators with an indicator for being an EL or non-EL observation, as follows:

$$Attend_{smyg} = \sum_{k=-5}^{3} \kappa_k^{EL} 1(Month = k) + \sum_{k=-5}^{3} \kappa_k^{NonEL} 1(Month = k) + \mu_{mg} + \lambda_{yg} + \theta_s + \epsilon_{smyg}, \tag{2}$$

Here, k indexes month relative to January 2025 and is 0 in January 2025 and -4 in September 2025. (All observations from before SY 2024-25 are assigned a k value of -5.)[8] The omitted category is $k = 0$, so coefficients are estimated relative to January 2025. The terms κ_k^{EL} capture the month-over-month residual variation in the attendance outcome for EL students and the terms δ_k^{NonEL} do the same for non-English Learners. I plot point estimates of $\widehat{\kappa}_k^{EL}$ and $\widehat{\kappa}_k^{NonEL}$ for months in SY 2024-25 to visualize patterns for EL and non-EL students.

In Rhode Island, the outcome data are the (log) number of absences at a school reported for EL and non-EL students on each day for the past two school years (SY 23-24 and SY 24-25). Using these more granular outcome data, I start by adapting equation (1) to estimate changes in daily EL absences after January 20, 2025, as follows:

$$LnAbsences_{sdg} = \alpha_1 After_d + \alpha_2 AfterxEL_{dg} + \gamma X_{dg} + \omega_{mg} + \theta_{sg} + \lambda_{yg} + \epsilon_{sdg}, \tag{3}$$

Here, d indexes the calendar date (e.g., March 2, 2025) in month m and school year y. $After$ is an indicator for date observations that come after January 20, 2025. The outcome – $LnAbsences$ – is the natural log of the number of absences reported for students in school s on calendar date d in the EL or non-EL group (g) plus one. X_{dg} is a vector of date-level controls that includes (1) indicators for days before and after recurring school breaks and the interactions of these terms with indicators for EL status (see Appendix Table A2 for detail) and (2) the index of inclement weather search intensity based on Google Trends data, as described, and the interaction of this index with an indicator for EL observations. θ_{sg} are fixed effects for each school-by-group combination. These are included to adjust for differences in the number of students in each group at

[8] Since chronic absenteeism is available only beginning in October of each year, there are only 3 pre-period months for this outcome and pre-SY 2024-25 observations are assigned a value of -4.

a school.[9] I also include school year by group fixed effects, as before. α_2 is the coefficient of interest. Standard errors are clustered by school and regressions are weighted by the number of students in the student group using analytic weights in Stata.[10]

To estimate parallel trends, I adapt this equation to include calendar date-specific indicators for each day before/after Trump's inauguration in school year 2024-25, as in equation (2):

$$LnAbsences_{sdg} = \sum_{j=-140}^{149} \delta_j^{EL} 1(Date = j) + \sum_{j=-140}^{149} \delta_j^{NonEL} 1(Date = j) + \gamma X_{dg} + \omega_{mg} + \theta_{sg} + \epsilon_{sdg}, \quad (4)$$

Here j indexes, dates indexes days before/after January 20, 2025 (j=0) and is set to the same value ($j = -140$) for all observations from SY 2023-24. When estimating this model, I specify $j = -3$ (i.e., January 17, 2025, the last pre-inauguration school day) as the omitted category. I plot $\widehat{\delta}_j^{EL}$ and $\widehat{\delta_j}^{NonEL}$ to assess parallel trends.

The availability of sub-monthly data in Rhode Island also allows me to assess whether changes in attendance after the election of Donald Trump relate to increased anxiety/awareness of enforcement activity, proxied by google search intensity. To answer this question, I estimate the following model:

$$LnAbsences_{sdg} = \alpha_1 SearchICE_d + \alpha_2 SearchICExEL_{dg} + \gamma X_{dg} + \omega_{mg} + \kappa_{yg} + \theta_{sg} + \epsilon_{sdg}, \quad (5)$$

where $SearchICE_d$ is the Google Trends-based measure of enforcement search intensity, which varies by week. X_{dg} is a vector of day-level controls, including the controls described in Equation 3. In this equation, X_{dg} additionally includes standardized values of Google Trends data for search intensity for several "placebo" search topics (i.e, J.D. Vance, tariff, and the Department of Government Efficiency). These are included to address concerns that searches about immigration enforcement might correlate with factors driving general interest in the news/the Trump administration's actions. The coefficient of interest in this specification is α_2. Since interest peaks substantially after the start of the second Trump presidency, most of the identifying variation for α_2 should come from the post-period.

[9]The number of EL or non-EL students could change from year to year, which would affect the expected number of absences for students in that group. As a robustness check, I estimate models that include fixed effects for school-by-group-by-year dummies.

[10]Enrollment weights are average daily membership for EL and non-EL students in the school in the 2023-24 school year, the most recent available data. See `https://datacenter.ride.ri.gov/Home/FileDetail?fileid=1069`. Results are similar if I specify weights using frequency weights in Stata instead.

5 Results

5.1 Parallel Trends

I start by examining parallel trends. Figures 2A and 2B plot estimates of $\widehat{\kappa}_k^{EL}$ and $\widehat{\kappa}_k^{NonEL}$ (equation 2) by month for each attendance outcome in Connecticut. The average residual variation in attendance of EL and non-EL students in Connecticut follow similar patterns prior to January 2025 but sharply diverge thereafter, with EL students showing relative declines (2A). The residual variation in the share of students who are chronically absent shows the opposite trend: EL and non-EL students show similar trends in the beginning of the 2024-25 school year but ELs experience increases in chronic absenteeism beginning after January 2025 (2B). Student absences show a similar pattern of divergence in Rhode Island, as shown in Figure 2C, with EL student residual variation showing spikes in absences in the post-period.

[Figure 2 about here: DID estimates/trends]

5.2 Difference-in-Differences Estimates

Estimates from difference-in-differences models in Table 1 confirm the visual pattern shown in Figure 2. Point estimates from the preferred specification (column 3) indicate that the average attendance of EL students in Connecticut decreased by 0.231 percentage points in the months after the second Trump inauguration. This is a relatively small change compared to the sample mean – average attendance rates are above 90% in the sample – but is equivalent to a decrease of about 0.07 standard deviations based on the sample standard deviation. Results are similar in an alternative specification (column 2) that includes a school month-by-EL trend instead of period-by-group specific indicators for each calendar month. Meanwhile, rates of chronic absenteeism increased for EL students by more than half a percentage point (0.587 percentage points), an increase of about 2% relative to the sample mean.

[Table 2: CT DID Effects]

Negative effects are also significant and substantial in Rhode Island. In columns 1-3 of Table 2, I show estimates of changes in daily absences for EL students relative to non-ELs after Trump's inauguration. Preferred estimates (column 3) indicate that absences for ELs increased by approximately 3.87% relative to non-ELs after the start of the second Trump presidency. Columns 4-6 relate EL absences to my Google Trends-based measure of attention/awareness of enforcement activity. A one standard deviation increase in enforcement-related search intensity is related to an approximately 1.37% increase in absences for EL students. This is consistent with the hypothesis that changes in EL attendance relate to concerns about enforcement.

[Table 3: RI DID Effects]

5.3 Robustness

In Appendix Tables A3 and A4, I assess the robustness of these estimates to alternative specifications including: models estimated without analytic weights, models that weight by total enrollment, and models that drop observations out of concerns that results are driven by absences related to the February 3 "Day without Immigrants" observance, and models that include school by group by year fixed effects. Estimates generally remain of similar magnitude and significant across specifications, though effect estimates on chronic absenteeism in Connecticut (Panel B of Table A2) are sensitive to the choice of weights.

Tables A3 and A4 also report results from falsification tests. In Connecticut, my falsification test assesses whether I detect differences in attendance for Black students relative to White students after the start of the second Trump presidency. I do not detect significant effects. In Rhode Island, my falsification test assess whether I detect differences in absences for disabled students relative to non-disabled students and whether absences for disabled students are related to my Google Trends measure of enforcement-related search intensity.[11] Again, I do not detect significant effects.

6 Conclusion

Intensified immigration enforcement activity is likely to disproportionately impact families with school-age children. This paper presents early evidence that these actions are already affecting the attendance of children who are likely from immigrant families in two Northeastern states, corroborating other recent evidence from California. Using a difference-in-differences design that compares changes in outcomes for English learners and non-English learners, I detect significant and substantial declines in average monthly attendance (CT), increases in chronic absenteeism (CT) and increases in daily absences (RI) for EL students since the second Trump inauguration. These early findings suggest Trump's immigration agenda may have broad-based impacts on students and public schools in diverse contexts across the country.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used ChatGPT in order to draft reference citations and improve readability. After using this tool/service, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the published article.

[11] Absences by race and day are not available in Rhode Island.

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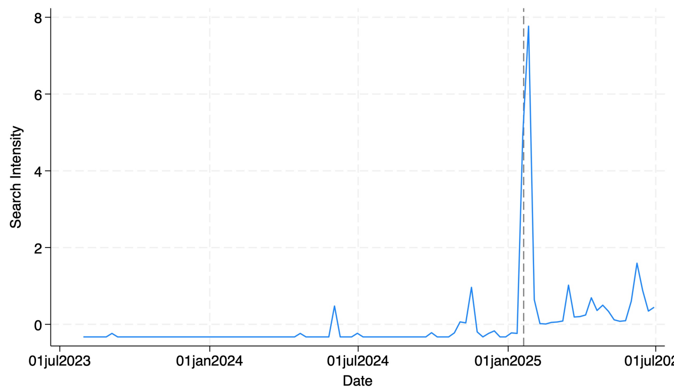
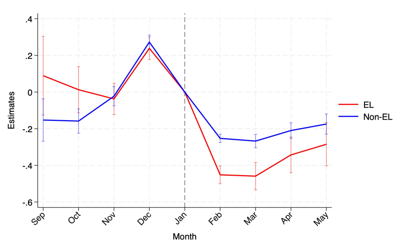
Figure 1: Immigration Enforcement Search Intensity (Rhode Island)



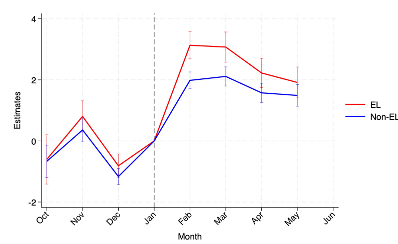
Index measure of immigration enforcement-related search intensity for Rhode Island, as described in text. Measure is standardized to have a mean of 0 and standard deviation of 0. Line corresponds to date of second Trump inauguration.

Figure 2: Difference-in-Differences Estimates over Time

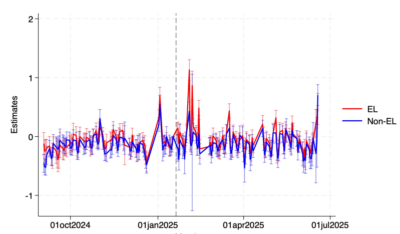
(a) Connecticut: Attendance



(b) Connecticut: Chronic Absenteeism



(c) Rhode Island: Log Absences



Plots coefficients for period/groups-specifics dummies (point estimates and 95% confidence intervals), as described in text. For Connecticut, the outcomes are monthly average attendance and chronically absent rates by student group. For Rhode Island, the outcome is daily log number of absences plus one by student group. Regressions are weighted by the number of students in the group. Standard errors are clustered by school

Table 1: Effect on Attendance and Chronic Absenteeism, DID Estimates (Connecticut)

	Attendance Rate			Chronic Absence Rate		
	(1)	(2)	(3)	(4)	(5)	(6)
AfterxEL	0.209+	-0.214***	-0.231***	-0.536	0.578*	0.587*
	(0.119)	(0.054)	(0.060)	(0.378)	(0.229)	(0.251)
After	-0.290***	-0.217***	-0.214***	2.372***	2.153***	2.151***
	(0.039)	(0.032)	(0.032)	(0.159)	(0.141)	(0.142)
EL	-1.156***			0.412		
	(0.212)			(0.569)		
School Month x EL		0.081***			0.041	
		(0.011)			(0.036)	
Month Dummies	X	X		X	X	
School Year Dummies	X	X		X	X	
School Dummies	X	X	X	X	X	X
Month x EL Dummies			X			X
School Year x EL Dummies			X			X
r2	0.071	0.861	0.862	0.795	0.796	0.796
N	35,628	35,628	35,628	24,183	24,183	24,183
Outcome Mean	92.74	92.74	92.74	26.87	26.87	26.87
Outcome SD	3.21	3.21	3.21	12.35	12.35	12.35

Estimates of DID models (equation 1) for attendance outcomes in Connecticut, as described in text, estimated in a dataset of school-by-group-by-month attendance outcomes. Average attendance rate ranges from 0 to 100. Chronic absence rate refers to share of students who miss more than 10% of schools days. School month refers to the order the month appears in a typical school year (i.e., September=1, October=2, etc.). Standard errors are clustered at the school level. Regressions are weighted by the number of students in the student group using analytic weights in Stata. Ourcome mean and standard deviation are unweighted. + p< 0.10, * p< 0.05, ** p<0.01, *** p<0.001.

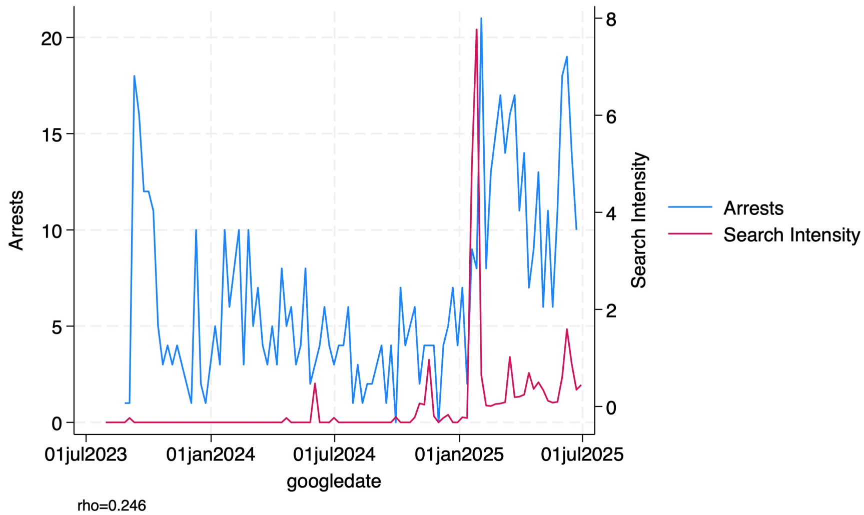
Table 2: Effect on Log Absences, DID Estimates (Rhode Island)

	(1)	(2)	(3)	(4)	(5)	(6)
After x EL	0.0964***	0.0404*	0.0387*			
	(0.0203)	(0.0195)	(0.0189)			
After	-0.0405*	-0.0225	-0.0132			
	(0.0189)	(0.0197)	(0.0184)			
Search Intensity x EL				0.0277**	0.0088	0.0137*
				(0.0086)	(0.0059)	(0.0058)
Search Intensity				-0.0183**	-0.0119+	-0.0025
				(0.0065)	(0.0060)	(0.0059)
Month, School Year Dummies	X			X		
School Year x EL Dummies	X	X	X	X	X	X
Month x EL, School Year x EL Dummies		X	X		X	X
Holiday, Weather Controls			X			X
Placebo Search Controls						X
r2	0.8439	0.845	0.856	0.8438	0.8451	0.8561
N	30,293	30,293	30,293	30,293	30,293	30,293
Outcome Mean	3.48	3.48	3.48	3.48	3.48	3.48
Outcome SD	0.71	0.71	0.71	0.71	0.71	0.71

DID estimates of school effects on attendance in Rhode Island (Equations 3 and 4). Outcome is natural log number of abseneces by school, day, and student group (+1). Estimating dataset consists of obserations at the schoolxdayxgroup level. Regressions are estimated with weights by student group (based on SY 23-24 data) using analytic weights in Stata. Standard errors are clustered by school. "After" refers to observations after January 20, 2025. SearchIntensity is the google trends search metric for searches for United Sttates Immigration and Customs Enforcement over time in Rhode Island, standardized to have a mean of 0 and a standard deviation of 1. Weather controls are Google Trends-based measures of searches for snow, storm, and school closings. Placebo searches are Google Trends-based measures of searches for J.D. Vance, tariff, and the Departent of Government Efficiency (DOGE). Ourcome mean and standard deviation are unweighted. + p< 0.10, * p< 0.05, ** p<0.01, *** p<0.001.

Last updated: September 10, 2025

Figure A1: Enforcement Search Intensity and ICE Arrests, Rhode Island



Search intensity measure is created from Google Trends data, as described in text. Arrest data comes from the Deportation Data Project (see Appendix A).

Table A1: Sample Summary Statistics

		Connecticut		Rhode Island	
		Full State	Sample	Full State	Sample
		(1)	(2)	(3)	(4)
Schools		886	506	355	53
Districts		164	75	64	13
Enrollment		499.661	558.595	390.126	628.038
	obs	[880]	[506]	[349]	[53]
Share White		0.479	0.349	0.516	0.155
	obs	[849]	[487]	[347]	[53]
Share Black		0.150	0.162	0.098	0.164
	obs	[695]	[452]	[310]	[53]
Share Hispanic		0.312	0.406	0.310	0.589
	obs	[877]	[506]	[342]	[53]
Share Asian		0.068	0.075	0.030	0.030
	obs	[568]	[338]	[312]	[49]
Share Free or Reduced-Price Lunch		0.464	0.542	0.453	0.739
	obs	[813]	[485]	[344]	[53]
Share English Learners		0.131	0.172	0.140	0.365
	obs	[783]	[506]	[312]	[53]
Share Special Education		0.170	0.167	0.250	0.169
	obs	[878]	[506]	[348]	[53]

Summary statistics for schools included/excluded in estimation samples. For CT, summary data are for SY 2024-25; not all data is available for all schools, hence the different number of observations. For RI, summary data is only available for SY 23-24. Initial sample in Rhode Island is limited to schools with non-missing attendance data for EL and non-EL students for at least 100 days in the school year. In both states, both columns are limited to schools with enrollment>=100. See Appendix A for additional detail on data sources for school summary statistics.

Table A2: 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 17, 2024	January 12, 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 A3: Robustness: Connecticut

	Robustness						Falsification Test
	Preferred Specification	No Weights	Weight by Enrollment	Drop February 2025	Frequency Weights	School x Yr x Group FE	Black vs. White
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A. Outcome =Attendance Rate							
After x EL	-0.231***	-0.133**	-0.189***	-0.217***	-0.231***	-0.230***	
	(0.060)	(0.041)	(0.048)	(0.065)	(0.060)	(0.061)	
After	-0.214***	-0.323***	-0.221***	-0.206***	-0.214***	-0.215***	-0.155***
	(0.032)	(0.028)	(0.034)	(0.034)	(0.032)	(0.032)	(0.028)
After x Black							-0.071
							(0.064)
obs	35,628	35,638	35,638	34,658	10,034,804	35,628	32,869
B. Outcome = Chronic Absenteeism Rate							
AfterxEL	0.587*	0.048	0.224	0.470+	0.587*	0.546*	
	(0.251)	(0.247)	(0.251)	(0.273)	(0.248)	(0.255)	
After	2.151***	2.594***	2.179***	2.084***	2.151***	2.159***	
	(0.142)	(0.149)	(0.144)	(0.154)	(0.141)	(0.145)	
obs	24,183	24,192	24,192	23,461	7,171,259	24,183	

The outcome in Panel A is attendance rate and the outcome in panel B is the chronic absenteeism rate. Column 1 replicates results from preferred specificationsin Table 2 (columns 3 and 6). Column 2 shows esitmates without analytic weights. Column 3 weights by the total enrollment in the school instead of the number of students by student group. Column 4 drops observations from February 2025. Column 5 uses frequency weights instead of analytic weights. Column 6 uses schoolxgroup (i.e. EL or non-EL) fixed effects instead of school fixed effects. Column 7 presents results from a falsification test looking at differences in attendance rates for Black and white students estimated in a dataset of month-by-group-by-school observations for Black and white students. All controls are as in equation (1), with an indicator for "Black" substituting for the indicator for EL. I do not show results from falsification tests for chronic absenteeism because there are very few observations with chronic absenteeism data broken down at this level.
+ p< 0.10, * p< 0.05, ** p<0.01, *** p<0.001.

Table A4: Robustness: Rhode Island

	Preferred	No Weights	Weight by Enrollment	Drop Feb 3	Frequency Weight	School x Year x EL FE	Outcome = # of Absences	Falsification: Disabled vs. Non-Disabled
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
After x EL	0.0387*	0.0289+	0.0222	0.0353+	0.0387*	0.0412*	1.6389	
	(0.0189)	(0.0167)	(0.0173)	(0.0190)	(0.0189)	(0.0195)	(1.1207)	
After	-0.0132	0.0010	-0.0038	-0.0160	-0.0132	-0.0126	-0.8466	-0.0084
	(0.0184)	(0.0177)	(0.0189)	(0.0182)	(0.0184)	(0.0184)	(1.0899)	(0.0143)
After x Disabled								0.0175
								(0.0192)
obs	30,293	30,293	30,293	30,207	10,182,563	30,293	30,293	37,258
Search Intensity x EL	0.0137*	0.0074*	0.0102+	0.0130*	0.0138*	0.0142*	0.8301*	
	(0.0058)	(0.0036)	(0.0053)	(0.0058)	(0.0058)	(0.0060)	(0.3167)	
Search Intenstiy	-0.0025	0.0033	-0.0004	-0.0027	-0.0025	-0.0024	-0.5287	0.0010
	(0.0059)	(0.0034)	(0.0052)	(0.0058)	(0.0058)	(0.0058)	(0.3192)	(0.0041)
Search Intensity x Disabled								0.0060
								(0.0038)
obs	30,293	30,293	30,293	30,207	10,182,563	30,293	30,293	37,258

Column 1 replicates preferred specification estimates from Table 3. Column 2 shows estimates without weights. Column 3 weights by total enrollment at the schol. Column 4 drops observations from February 3, 2025. Column 5 uses schoolxyearxEL fixed effects instead of schoolxEL fixed effects. The outcome for Column 6 is the number of absences. Column 7 uses absences as the outcome instead of log absences. Column 8 shows results from a falsification exercise estimating effects on the attendance of special education students relative to non-special education students, substituting an indicator for special education students for the indicator for EL students in equations 3 and 4. (Note that RI reports these students under the "Disabled" group name). Standard erorrs clustered by school. + 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: [Topics/Terms below] for Rhode Island. Google Trends. Available online at https://trends.google.com/trends/.

- Placebo - Topics: J.D. Vance, Tariff, Department of Government Efficiency (Federal agency)
- Enforcement Activity Index Measures: United States Immigration and Customs Enforcement (Federal Agency), Deportation, ICE agents, ICE raid, ICE in Rhode Island, ICE in Massachusetts, ICE in Providence
- Weather Index Measures: snow, storm, school closings

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/.