Evaluating School Expenditures Near Affordable Housing Built For Families *

Kenneth Whaley
Department of Economics, University of South Florida
Tampa, Florida, USA
kennethwhaley@usf.edu

Abstract

I examine public schools near affordable housing made available through the Low-Income Housing Tax Credit (LIHTC) program. Analyzing a 21-year panel of elementary schools, I find that LIHTC rentals targeting families increase enrollment, causing schools to add more teachers and increase absolute spending. Despite LIHTC also causing identifiable student body composition changes, particularly in urban areas, estimates of the per-pupil spending change after LIHTC are attenuated by heterogeneity in school finance across space and time. To highlight the specific case in which a new batch of students with higher needs produces an unambiguous increase in per-pupil spending, I compute counterfactual spending measures under three prevalent school funding regimes. Had school spending policies remained fixed from the start of the sample, per-pupil spending would have decreased after LIHTC near schools in desirable neighborhoods.

JEL Classification: H75, R23, O18

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1 Introduction

The Low-Income Housing Tax Credit Program (LIHTC) has a budget of nearly $8 billion annually to support the construction of rental housing across the United States (Hollar 2019; Keightley and Stupak 2020). LIHTC construction in neighborhoods rich and poor leads to a question of how new developments affect essential functions of the public sector. Acknowledging the large share of LIHTC stock housing families, this paper is concerned with how the program interacts with local public schools. In a similar vein, the introduction of new residents to a neighborhood via housing policy has drawn the attention of economists studying a large-scale policy experiment known as Moving to Opportunity (Katz et al. 2001; Ludwig et al. 2008; Chetty et al. 2016; Aliprantis 2017; Pinto 2021).

To analyze the effect of LIHTC housing on schools, I employ a 21-year panel of school-level data that allows me to explore relationships masked by aggregation at the school district level. For example, by spatially merging the location of LIHTC developments to school attendance zones, I plausibly identify changes in enrollment, student body socioeconomic composition, and teacher counts that are caused by the availability of new affordable housing. However, because the relationship between student composition and per-pupil spending is subject to policy effects that go largely unobserved and change over time, estimates of the school spending response to LIHTC housing are attenuated to zero. To clear this econometric hurdle I use the data to model within-district expenditure variation as an outcome of within-district composition differences across schools for any given year. In doing so I document three school funding regimes that predict how districts change per-pupil spending in response to demographic shocks at a given school.

The event-study design of this paper takes the announcement of LIHTC project approval as exogenous. Following Atkins and O'Regan (2014), I use observable characteristics of the units made available with each apartment complex to identify LIHTC developments built to serve families. I find that a new LIHTC family development causes statistically significant increases in enrollment (40-50 students or 4-6%), teacher headcounts (3-5%), and high-need student enrollment (50-60 students). The composition changes are larger at initially low-need schools, defined as those where less than half of students qualify for free or reduced lunch. Further, low-need schools near city centers observe the largest student composition changes after LIHTC.

Given the increased enrollments, teacher counts, and changes to student body composition, I turn to evaluating changes to school expenditures after LIHTC. When the school expands, one might expect absolute spending to increase as the total budget grows. I find that absolute spending increases 3-4%, primarily at schools where enrollment and teacher count increases are statistically significant. Per-pupil spending is a common measure of school quality and is linked to student composition when studying the adequacy of school spending for different population groups (Chingos and Blagg 2017; Blagg et al. 2022). Despite the demographic changes, a naive event study model fails to identify changes to per-pupil spending after LIHTC construction, even at places subject to clear composition shocks.

I argue that the null per-pupil spending results are more likely due to fundamental flaws in panel data models, and less likely due to school districts funding new students (of higher financial needs) at the same level as existing students at a school receiving new LIHTC. As LIHTC occurs at different times in the sample period, estimates for the per-pupil spending response are potentially biased by differences in how schools are funded in any given year. Such changes in the policy environment are observed in raw data patterns that indicate the per-pupil spending response to student composition shocks will depend on when and where new housing is built. Not only do urban, suburban, and rural districts fund schools differently, but the changes in the funding patterns for each locale vary across time. Without controlling for policy changes my model suffers from the textbook forbidden comparisons problem (Sun and Abraham 2021; Goodman-Bacon 2021; Roth et al. 2023).

To deal with bias from comparing schools exposed to different funding environments at different points in time, I design an approach that holds policy environments fixed to leverage only the variation in student body composition. I find three prevalent school funding regimes defined by the relationship between per-pupil spending and student body socioeconomic composition. The first is the inverse U case, in which an increase in high-need student share causes per-pupil spending to rise at certain schools and fall in others. The second is the case where the per-pupil spending change associated with increased high-need student share is always positive, but diminishing. The third is the linear case, in which the per-pupil spending response to an increase in high-need student share is positive and constant. In the first counterfactual case, the composition changes caused by LIHTC result in substantial per-pupil spending declines. In the second and third case, per-pupil spending only increases at schools initially categorized as low need (high income).

By tracing out differential composition changes to schools that receive new LIHTC, I extend a literature that explores housing options as access mechanisms to middle and high-income schools (Di and Murdoch 2013; Ihlanfeldt and Mayock 2019). Unique to affordable housing construction in low-need (high-income) areas is that subsequent increases in per-pupil spending are required to support a new batch of students with higher needs. My contribution is to show such a spending response only occurs in select policy environments, because the sorting of high-income households away from LIHTC development would otherwise cause per-pupil spending to decline. The idea that housing policy can move students to opportunity is undermined if the resources available to new students decline upon arrival. With empirical evidence that school spending matters (Hoxby 2001; Jackson et al. 2016; Lafortune et al. 2018), and households are willing to pay for better-financed schools (Barrow and Rouse 2004; Cellini et al. 2010; Bayer et al. 2020), my results explain why housing policy may not produce the expected outcomes for residents moving to desirable neighborhoods.

Where to build affordable housing is a fundamental question in LIHTC program evaluation (Baum-Snow and Marion 2009). The breadth of the program has drawn economists to explain how LIHTC affects neighborhoods through private real estate markets (Ellen et al. 2007; Eriksen and Rosenthal 2010), and a variety of neighborhood amenities (Freedman and Owens 2011; Freedman and McGavock 2015). Di and Murdoch (2013) are among the only studies of school quality responses to the construction of LIHTC, finding that school ratings on average do not change using data from Texas during the first half of my sample period. Diamond and McQuade (2019) find large welfare gains from LIHTC in low-income areas, and relatively small welfare losses in high-income areas, but do not include changes to schools in their welfare calculations.

The remainder of this paper is as follows. In Section 2 I describe the data and institutional details that connect affordable housing to schools. I detail the causal effect of LIHTC on enrollment, student composition, and teacher counts in Section 3. In Section 4, I lay bare my counterfactual research design and the per-pupil spending response to LIHTC under three common funding regimes. I conclude the paper in Section 5.

2 Data and Program Details

2.1 LIHTC Data

A database of annual LIHTC activity is maintained by the Texas Department of Housing and Community Affairs. The data provides the year each housing development became board-approved, the total number of rental units (by bedroom count) in each complex, the latitude and longitude of each location, and if the development serves a specific target population.[1] Since the target population designation is inconsistent over time, I use the distribution of units by bedroom count to characterize LIHTC developments by type (Atkins and O'Regan 2014). Family-targeted LIHTC announcements are used for the main analysis of the paper as senior-designated LIHTC is not predicted to influence schools directly.

The LIHTC sites are spatially merged to school attendance zones using the following two-step procedure. First, ArcGIS software is used to geocode the latitude and longitude data for each site as a point on the map of Texas census blocks.[2] After assigning the appropriate

[1]Target populations include senior housing and housing for individuals with developmental needs.
[2]The census block shapefile is provided by IPUMS National Historical Geographic Information System.

census block to each LIHTC site, I utilize a publicly available file that matches the census block to school attendance zones across the US.[3] With each housing development matched to a school zone, I aggregate annual LIHTC activity at the school level by year of project approval.[4] Details on LIHTC sample construction, the location of LIHTC development during my sample period, and the family housing designation are shown in Appendix Section B.

2.2 Elementary School Data

The school data are a sample of public elementary schools in Texas from 2000-2020. The data is publicly available through the Texas Education Agency Academic Excellence System (2000-2012) and Academic Performance Reporting (2013-2020). Each repository stores data for the primary purpose of evaluating Texas public school performance. An advantage of this data is the campus-level unit of observation, allowing me to exploit rich variation in school spending and student composition across neighborhoods within a school district. The data are consistent across performance systems, yielding a 21-year panel of elementary school observations for the variables of interest.

In the data, I observe total spending, enrollment, and racial demographics annually at each school beginning in 2000. All expenditure values are deflated to the year 2015. In addition to data provided by the Texas performance reporting systems, I add teacher counts provided by the National Center of Education Statistics (NCES). NCES monitors teacher counts for all schools to analyze class sizes and labor market trends over time. Full-time equivalent teacher counts include full-time staff and the full-time equivalent of part-time staff. NCES also provides data describing the counts of students receiving free or reduced lunch at each elementary school. This measure is traditionally used as either a proxy for the concentration of low-income students in a school, or to categorize schools as low, medium,

[3]The School Attendance Boundary Information System: IPUMS, University of Minnesota, William and Mary.

[4]Schools exposed to LIHTC shocks before 2000 are excluded from the sample

or high poverty. In this paper, I use the share of students qualifying for lunch subsidies to study changes in student body composition over time, and to categorize schools as low-need vs. high-need at the start of the sample period.

2.3 The Analysis Sample

I restrict the sample to non-charter, non-open enrollment schools with available attendance zone boundary information.[5] The sample restrictions yield an unbalanced panel of 3,013 elementary or middle schools from 2000 to 2020. Summary stats are reported in Table 1. Column one of Table 1 describes all schools in the sample, a total of 61,119 schools $\times$ year observations. Column two includes observations in which less than half of enrollment qualifies for free or reduced lunch, or *low-need* schools. Column three includes schools with greater than 50% of the enrollment as income qualifying, or *high-need* schools.

Table 1 shows the similarities in the two school types across many characteristics. The likelihood of a LIHTC development is 21% in low-need school zones and 25% in high-need school zones. The average number of units in a family development is 133, and high-need schools receive 13 more units than low-need schools on average. Enrollment counts, student-teacher ratios, and per-pupil spending are all roughly the same level when pooling the data for the entire sample period. The average school in the sample has 58% of students qualifying for free or reduced lunch. For comparison, the US average for the 2019-2020 school year is 52%, 59% in California, 56% in New York, and 57% in neighboring Louisiana.[6]

2.4 Funding Formulas Link Neighborhoods to Schools

Given that high-need schools have nearly 200 more high-need students, a natural question is why average per-pupil expenditures are the same across the two school types. By 2020 in Texas, local property taxes provide 50% of school district revenue, 44% come from the state,

[5] I also exclude any schools that experienced LIHTC construction before the year 2000. This sample restriction removes less than 40 schools.

[6] https://nces.ed.gov/programs/digest/d22/tables/dt22_204.10.asp

and the remaining 6% from the federal government.[7] School districts manage federal, state, and local tax revenues by allocating dollars for individual schools to spend. Understanding that different student populations have different funding needs, the variation in per-pupil spending across schools in the same district has been well documented (Roza et al. 2004, Owens et al. 2016, Chingos and Blagg 2017).

How districts allocate dollars to schools may appear idiosyncratic, but can be described by a funding formula that considers enrollment counts, a base allotment for each student, and additional funding for student populations requiring more resources. This includes non-native English speakers, students in poverty, special education students, and those in gifted and talented programs. In Texas, the base allotment depends on grade level and is adjusted upwards for students requiring more resources and downwards if average daily attendance decreases.[8] Once a school receives funds, the principal and school administrators have discretion over how the money is spent. Appendix B.2 provides an example of the funding formula determination for Houston Independent School District, one of the largest in Texas.

The underlying motivation of this paper is the link between student income composition and per-pupil spending at a school. School funding formulas are the mechanism by which neighborhood changes are translated to school finances, and formula changes over time are difficult to observe directly for large panel data. This point is illustrated in Figure 1. For each plot, the schools are binned based on the share of students qualifying for free or reduced lunch. The mean level of per-pupil spending is then plotted for each bin across the distribution of schools, in five-year intervals from the beginning of the sample period. In the year 2000, the curve is inverse U-shaped, suggesting an increase in high-need student share would increase per-pupil spending at the lower end of the distribution but decrease per-pupil spending at schools with the highest concentration of high-need students. For the remainder of the

[7] 2020 Texas Public School Finance Overview: Annual Report

[8] Appendix Figure B3 is an example of this process for Houston Independent School District, one of the largest school districts in Texas.

sample, the relationship is strictly increasing, and nearly linear by 2020.

The curves in Figure 1 are averages across all schools in the sample, and Appendix Figures A1-A3 replicate the plots separately for city center, suburban, and rural locales. One might expect heterogeneity in this relationship of interest as schools in different locales face different labor markets, cost structures, and political economies. Together the figures document substantive changes in the relationship across locale and time. Of the 15 subfigures in Appendix Figures A1-A3 two predominant patterns emerge. An inverse U was present across all locales for the year 2000 and 6 of the 15 panels, and a positive but diminishing relationship was present in 5 of 15 panels. If LIHTC family development changes the student composition at a school, the change in per-pupil spending will depend on when and where the new rental units are built.

2.5 LIHTC Rental Housing in Neighborhoods of All Types

Created as part of the Tax Reform Act of 1986 and managed by the Internal Revenue Service, the general goal of the LIHTC program is to increase the supply of rental housing in the US. I identify no less than five stakeholders in the development of housing through LIHTC. The federal government allocates tax credits to state housing authorities that manage the application process and distribute tax credits to selected real estate developers. The developers sell tax credits to passive investors in exchange for operational cash flow at an estimated 75 cents for every dollar of the tax credit, and investor tax benefits are realized over ten years post-investment (Eriksen 2009). Finally, the renters, are only subject to income limits when applying for units held for reduced rent. Developers may choose to rent all or a fraction of units in a complex at below-market rent.

When developers apply for tax credits, site location has well-known implications for cost subsidies and affordability (Adkins et al. 2017). For one, subsidy amounts are determined as a percentage of total cost basis - applicable development costs that do not include the cost of land. Secondly, building in a qualified census tract yields higher incentives through a basis boost, an automatic increase of the total cost basis by up to 30% (Keightley and Stupak 2020). Both program attributes incentivize development in low-income neighborhoods, though there is reliable evidence that LIHTC itself does not cause concentrated poverty (Ellen et al. 2007, Freedman and McGavock 2015). Lang (2012) argues that relatively lower land costs in low-income areas dominate the effect of qualified census tract, status since land costs are not subsidized.

Who lives in LIHTC? Program guidelines require either 20% of tenants to earn less than 50% of the metro area median income or at least 40% of tenants to earn less than 60% area median income. Although developers are not required to rent most units to income-qualified tenants, the amount of tax credits received increases with the percentage of units held below the rent limit[9] One-third of all US LIHTC units house at least one child under 18 (Hollar 2019), and if each school-aged LIHTC resident attends the geographically assigned school, it is worth asking how if the timing of LIHTC development produces identifiable changes in school income composition. LIHTC developments reserved for senior housing are not predicted to influence school compositions, and I use senior housing as a placebo test to rule out spurious correlation disguised as real effects in my event-study results.

Table 2 contains descriptive information on the variation in LIHTC timing and the income-qualifying enrollment share in the year LITHC received project approval. The approval year for the first LIHTC build in the school zone is considered the event year, and I document substantial heterogeneity in the pre-period student composition at schools receiving affordable housing. The bottom section of Table 2 shows that 60% of LIHTC occurs near high-need schools, and 40% near low-need schools. Further, LIHTC occurs in cities, suburbs, and rural areas.[10] Throughout the analysis I explore the heterogeneity in the effect

[9]Rent limits are complex, but generally set 50% or 60% of the local income criteria, adjusted for household size. An area of concern is the actual affordability of LIHTC units, as the rent is determined by the median income of an entire metropolitan area, while locally a neighborhood that receives LIHTC could be very poor. Housing studies have shown that the share of LIHTC units that exceed fair market rents can exceed 30% in many cities (Cummings and DiPasquale 1999).

[10]There are 9 locale categories: big city, big city suburbs, midsize city, midsize city suburbs, large town, small town, rural, and rural remote. I aggregate the categories for the analysis of heterogeneity.

of LIHTC on schools across the various neighborhood types.

3 Estimation

I set out to identify changes at schools that experience new LIHTC family housing development. Denoting the event-year by the year tax credits are awarded for a project, let Y_{ijt} be the outcome of interest for school i, in district j, year t. To trace out the dynamic effects of new LIHTC family housing I estimate the event-study

$$Y_{ijt} = \sum_{\tau=-6}^{15} \pi_\tau (D_i \times 1[\tau_t = \tau]) + \gamma_i + \gamma_t + \epsilon_{ijt}. \tag{1}$$

D_i is a dummy equal to one if the school zone ever receives family LIHTC, interacted with a set of lag and lead indicators each equal to one in the year that a school is $\tau \in [-6, 15]$ years pre or post tax credit allocation. School zones that are never treated have the property $(D_i \times 1[\tau_t = \tau]) = 0$ since $D_i = 0$ for all untreated years. It follows that π_τ is a set of event-study coefficients, one for each event-year τ, that estimate the dynamic treatment effect of LIHTC on the school outcomes of interest. By including the two-way fixed effects γ_i and γ_t, the π_τ estimates trace-out the within-school changes over time, caused by LIHTC availability.

The results to follow are robust to the inclusion of group specific linear time trends.[11] All Figures include the event-time coefficients π_τ plotted relative to the period prior to LIHTC approval ($\tau_t = -1$), along with 95% confidence intervals for each estimate. In presenting the results I first analyze changes to total enrollment counts and show that the average 133 unit LIHTC family development causes first-order changes to schools by increasing the student body size. Such enrollment changes will require more teachers, and higher absolute

[11] I interact a linear time trend with the locale categories to control for heterogeneous trends in the outcome: big city, big city suburbs, midsize city, midsize city suburbs, large town, small town, rural, and rural remote. An additional trend is included for NCES defined high-poverty schools, those with over 75% of students qualifying for free or reduced lunch.

spending, but I am most interested in relative per-pupil spending changes that are driven by changes in student composition. After estimating the effect of LIHTC on per-pupil spending I conduct a simple placebo test using LIHTC senior housing as the event time, to rule out mechanical changes in the outcomes as a byproduct of the research design. Lastly, I discuss heterogeneity in the results across city center, suburban, and rural locales.

3.1 Results: Enrollment and Student Body Composition Changes

Figure 2 illustrates the first-order observable impacts of LIHTC on school enrollment. Taking the enrollment headcount as an outcome in the upper panel, the average school receiving new LIHTC family housing experiences an enrollment increase of between 30-40 students. The increase becomes clear about four years following the project announcement, and peaks at year 8. The bottom panel of Figure 2 shows the percentage increase in enrollment after LIHTC is between 4 to 6%. The timing patterns of enrollment increases are a combination of three factors. The time to build is measured by the period between the project announcement and when units come online, the sorting of households that can begin as soon as knowledge of the development is public, and the classroom onboarding of children who live in new LIHTC family units.

To show how the onboarding and matriculation of LIHTC residents potentially shape the enrollment timing, Figure 3 is a visual representation of the enrollment changes by grade. Comparing differences in the timing by grade level is informative about the arrival of new LIHTC residents into the school. Changes to the first-grade enrollment are sharp and distinguishable at year 4 as class sizes increase up to 7%, with equivalent increases in years 5-8. This indicates the presence of children in some households who are not of school age when they move into new housing. As the enrollment effects are delayed for second and third graders, we can see a pattern generated by this batch of students matriculating through the school. The enrollment changes are the latest, and smallest, for the fourth and fifth-grade classes. It could be that the LIHTC residents attending the school in first grade change schools before fourth and fifth grade, or that other students are exiting the school during this window. I explore evidence for which students sort out of schools by analyzing the nature of composition changes at treated schools.

To begin the analysis of sorting and composition changes I first illustrate heterogeneity in the enrollment change for low-need and high-need schools. In Figure 4 I show that the net change in enrollment is larger at initially high-need schools, where the increase is near 50 students or 6-8%. The increase at low-need schools is visually identifiable but not statistically significant. The net enrollment increase means that the influx of new students from LIHTC combined with sorting inflows is larger than the outflow of students from households leaving the school.

To elaborate on this point, the top panel of Figure 5 illustrates the change in the count of income-qualifying students after LIHTC. The increased headcount of income-qualifying students is statistically significant at nearly 50 students by year 5, and increasing afterward. Since this effect is larger than the net enrollment increase for low-need schools, there must be out-migration of high-income students who do not qualify for lunch subsidies. The composition changes at high-need schools follow a different pattern. Again comparing the upper panels of Figures 4 and 5, this time for high-need schools, the model predicts that the net enrollment increase of 50 students by year 5 is nearly equivalent to the increase in students that qualify for free lunch. This heterogeneity produces identifiable different composition changes shown in the bottom panel of Figure 5. At low-need schools, the share of students requiring lunch subsidies increases monotonically after new family LIHTC, while the composition of students at initially low-need schools remains the same.

3.2 Results: Teacher Headcount and School Spending

It is natural to assume that the enrollment increases and composition changes caused by new family LIHTC will result in changes to the school budget. Because Texas has set a maximum class size requirement for school districts, enrollment increases on the order of magnitude caused by LIHTC will require additional teachers.[12] In Figure 6 I take full-time equivalent headcount at each school as the outcome in my event study, and find that teacher counts increase on average 5% after new housing, following a similar pattern as enrollment. In the bottom panel, I show that teacher headcount increases occur in the places with the largest predicted enrollment increases. From this analysis, it appears that districts can flexibly increase teacher headcounts to meet enrollment requirements.

To measure the spending change caused by an increase in school size, I define absolute spending as the total spending in a given year divided by the school's enrollment at the start of the sample. Variation in the absolute spending measure indicates changes to the school's total budget. As predicted and shown in Figure 7, the hiring of additional teachers increases total expenditures. The lower pane of Figure 7 shows the absolute spending increase is largest in high-need schools where the enrollment effects are largest. Because enrollment growth and absolute spending growth rates after LIHTC are roughly the same, average per-pupil spending does not change in an identifiable way following LIHTC. Figure 8 shows that despite differences in the student body composition changes, there is no per-pupil spending change at low-need or high-need schools in the years following LIHTC.

3.3 Results: Heterogeneity by Neighborhood Locale

The location of new LIHTC is built into annual planning goals for state housing agencies. A feature of the program is that LIHTC is not concentrated in city centers, and many states recognize the need for affordable family housing in suburbs and rural areas. In this section, I reproduce the results of my study across different neighborhood types under the hypothesis that the sorting response of households and the way districts fund schools may be systematically different across neighborhood types. The results are presented in Supplementary Appendix A.

[12] Texas Education Code Section 25.112 was amended in July 2001 to cap the student-teacher ratio at 22:1 for grades 4 and below. Table 4 shows the effect of the amendment on schools in my sample. In 2001, over 35 schools had a student-teacher ratio over 22. By 2002 that number decreased to 3 and never rose higher than 7 for the remainder of the sample.

The first-order effects - enrollment and teacher counts - are largely similar across locales. The average net enrollment increase is between 5-8%, and teacher count increases follow the enrollment shocks. The heterogeneity lies in the composition changes, however, which differ substantially across locale and are only identified in city centers. At low-need schools in city centers, the composition change that follows family housing development produces long-term changes to the school. Such composition changes are not observed in suburban schools - where neighborhoods that get family LIHTC follow a different trajectory relative to the control group before the event date. At rural schools the pre-trends are comparable but LIHTC produces no real composition change at sample schools. As in the headline analysis, there are no well-identified changes to per-pupil spending following LIHTC in any locale.

3.4 Discussion: Bias in Observed School Spending Responses

Why are no per-pupil spending changes identified even in places with clear composition changes after LIHTC family housing? One explanation is that composition changes I find are a false positive type 1 error, meaning there are no true composition changes caused by LIHTC and thus no reason to expect per-pupil spending to change. Alternatively, if the composition results are truly well identified the spending results may suffer from attenuation bias for reasons unique to how schools are funded over time. In this section, I show that the classification of LIHTC family housing (as opposed to senior housing) drives the results, not the model design. Then, I argue that heterogeneity in how schools are funded across neighborhood locale and overtime must be controlled for to understand how composition changes from LIHTC will affect per-pupil spending.

In Figures 9-11 I take the timing of LIHTC senior designated housing as the event-year in my model. All family-designated LIHTC is dropped from the sample and all never-treated schools are used as the reference group. Together the figures show that senior housing produces no changes to student composition, absolute spending, or per-pupil spending. Further, the lower pane of each figure shows that the null effect of senior housing is present in both initially low-need and high-need school zones. This simple but powerful result is evidence in favor of the idea that affordable family housing is the specific subset of the LITHC program that interacts with schools. By testing this natural assumption I can state plainly that the composition changes identified after family LIHTC are not indicative of type 1 error.

If the composition changes are indeed representative, it could be the case that districts are systematically spending the same amount per pupil for new students who arrive after LIHTC, even though a substantial portion of the newly arriving students will qualify for need-based spending. Relying on the composition changes identified in the analysis of Section 3.3, this must particularly be true at low-need city center schools that undergo the most substantive composition change. Further, we must also consider that high-need students are assigned additional funding from federal not local sources. If the per-pupil spending response is a true null, then the federal dollars districts receive are completely crowding out local spending at the school level. I next turn to analyzing the relationship between variation in per-pupil spending and student composition across schools in the same district, to unpack why the per-pupil spending response to composition changes at a particular school depends on the timing and location of the demographic shock.

4 Counterfactual Analysis of School Funding Systems

In this section I detail how analyzing the school expenditure response to neighborhood change requires understanding that policy dictating public school finance can vary at any given point in time. Revisiting Figure 1, we see that the raw data relationship between per-pupil spending and the share of income-qualifying students differs across the sample period. Further, Appendix Figures A1-A3 show that this relationship changes differently across time based on neighborhood type. Since LIHTC occurs at different points during the sample period across different neighborhood types, identifying an average relationship between within-school student body composition changes and per-pupil spending requires accounting for such dynamic factors.

Consider that the expectation for per-pupil spending in a given year, $E[S_{ijt}]$, can be expressed as a function of the observed high-need student share, F_{ijt}, and year-specific policy parameters. The first is the district-specific base spending level per pupil, $\underline{\mathrm{S}}_{jt}$. The second is a year-specific funding weight that determines the spending increase or decrease associated with each high-need student, ω_t. If I assume that unobserved, idiosyncratic determinants of per-pupil spending are normally distributed with mean zero, I can write the expectation for school spending in a given year as

$$E[S_{ijt}] = (1 - F_{ijt})\underline{\mathrm{S}}_{jt} + F_{ijt}(1 + \underbrace{\omega_t}_{\text{Policy Weight}})\underline{\mathrm{S}}_{jt}. \tag{2}$$

It is ω_t that determines the predicted response to composition changes after LIHTC development. I test this hypothesis in two steps. First, I estimate the empirical analog of ω_t by exploiting the within-district relationship between per-pupil spending and the share of income-qualifying students for each school year. Under the assumption that school districts would fund a marginal change in the high-need student share *within* a school in the same way as it does *across* schools in a given year, the estimates from the first stage can be used to compute counterfactual measures of school spending under the school funding system that prevailed in a given year.

I proceed by outlining the framework for creating the counterfactual measures, then use the LIHTC-induced composition shocks to show how school spending would change under the most prevalent funding regimes. The first case is the funding system in place at the start of the sample, a non-linear case as predicted by the inverse U-shape in the first panel of Figure 1. The second is the non-linear case in which an increase in the share of high-need students produces a positive but diminishing increase in per-pupil spending. Lastly, I analyze the linear case, in which a marginal change in high-need student share would produce a constant, unambiguous increase in per-pupil spending. I conclude this section by discussing the implications of my findings for the intersection of housing policy and education finance.

4.1 Research Design

To estimate the marginal change in spending for a marginal increase in high-need students, I employ district fixed effects θ and estimate the model (separately for each year t)

$$Log(S_{ijt}) = \alpha_{0t} + \alpha_{1t}F_{ijt} + \alpha_{2t}F_{ijt}^2 + X_{ijt}'\beta + \theta_{jt} + v_{ijt}. \tag{3}$$

Other observed explainers of spending differences across schools in the same district, X_{ijt}, include the share of Latino students and the total enrollment size. Conditional on X_{ijt}, the within-district change in spending due to a marginal increase in F_{ijt} is

$$\widehat{\omega}_t = \widehat{\alpha}_{1t} + 2\widehat{\alpha}_{2t}F_{ijt}. \tag{4}$$

Equation 4 says the funding weight $\widehat{\omega}_t$ for the marginal high-need student introduced to any school depends on the incumbent proportion of high-need students. The district-specific base spending level for each school, $\widehat{\underline{\mathrm{S}}}_{jt}$, can also be obtained from Equation 3 as

$$\widehat{\underline{\mathrm{S}}}_{jt} = \underbrace{\widehat{\alpha}_{0t}}_{\text{State Base Spend}} + \overbrace{\widehat{\theta}_{jt}}^{\text{District Heterogeneity}}. \tag{5}$$

Substituting 4 and 5 into 2 we get predicted school spending as a deterministic function of the high-need student share,

$$\widehat{S}_{ijt} = [\widehat{\alpha}_{0t} + \widehat{\theta}_{jt}][1 + \widehat{\alpha}_{1t}F_{ijt} + 2\widehat{\alpha}_{2t}F_{ijt}^2]. \tag{6}$$

Equation 6 assigns each school a predicted spending level based only on F_{ijt} and the year-specific policy parameters $\widehat{\alpha}_{0t}, \widehat{\theta}_{jt}, \widehat{\alpha}_{1t}, \widehat{\alpha}_{2t}$. When the relationship is non-linear, the prediction for the signs is $\widehat{\alpha}_1 > 0$ and $\widehat{\alpha}_2 < 0$. In the linear case $\widehat{\alpha}_1 > 0$ and $\widehat{\alpha}_2 = 0$. Upon estimating the policy parameters, which are exogenous to any particular school in a given year, I can then use the LIHTC shocks to generalize the school spending response to any neighborhood change that shifts school composition.

4.2 First Stage: Estimating the Policy Parameters

Estimates for the parameters of interest in Equation 6 are presented in Table 3. Results obtained by pooling all years of data are presented in column one, and separately for selected years moving left to right. Each specification includes district fixed effects and controls for enrollment size and Latino population share. In the results shown for each specification, standard errors are clustered at the district level. The estimates are for the policy parameters $\widehat{\alpha}_1$ and $\widehat{\alpha}_2$.

The first row of results in Table 3 suggests that a school with no current high-need students will experience an increase in per-pupil spending for a small increase in the high-need student share. If the share of high-need students were to increase from 0 to 0.1, per-pupil spending would increase by 3.67% percent on average across all years. Qualitatively, the second row of estimates describes the shape of the relationship for a given year. The negative, statistically significant estimates in all columns suggest that the per-pupil spending increase associated with an increase in high-need student share is diminishing across all sample years.

The non-linear estimates imply the potential existence of a threshold high-need enrollment share in which a marginal increase would cause per-pupil spending to decline. The threshold is the quadratic OLS turning point, $\tilde{F}_t = -\frac{1}{2}\frac{\widehat{\alpha}_{1t}}{\widehat{\alpha}_{2t}}$. If $\tilde{F}_t \in (0, 1]$, the support of the high-need student share, then the composition change caused by LIHTC may cause per-pupil spending to rise in some cases and fall in others. If $\tilde{F}_t > 1$, then the relationship remains non-linear but at no point along the support of the high-need student share would a small increase cause per-pupil spending to fall. In the linear case, $\widehat{\alpha}_{2t} = 0$ and the threshold $\tilde{F}_t$ does not exist as per-pupil spending is strictly increasing in the share of high-need students.

Table 3 contains the computed values $\tilde{F}_t$ for the pooled sample and the selected years. For the pooled sample, any school with an incumbent high-need student share of 0.737 or above would expect new LIHTC to cause a decrease in per-pupil spending because of the change in composition. The threshold is lowest in 2000 (0.502) and also exists in 2015 (0.856). For the years 2005, 2010, and 2020, any school receiving new LIHTC would experience a per-pupil spending increase due to the change in student composition. I examine the precision of the threshold results by plotting the marginal effect of a small increase in income-qualifying student share on per-pupil spending, at different points along the $(0, 1]$ support, with the 95% confidence interval in Figure 12. Estimates above the horizontal dashed line indicate that the marginal effect of a small increase in high-need student share on per-pupil spending is positive. In all years the marginal spending increase is diminishing, and in two of the five years, there is the potential for a marginal spending decrease at schools above the threshold.

From this analysis, I now have the policy parameters needed to construct the counterfactual spending panel for the three cases of interest. Recall from Equation 6, I take the observed share of income-qualifying students in a given year along with estimates from the models in Table 3 to construct new panels of spending for each school under three regimes.[13] For the inverse U case I take the parameters from the model in column two, which predict a threshold of 0.502 at which the LIHTC-induced composition change will cause per-pupil spending to fall. For the case of diminishing (but always positive) marginal spending changes I use the parameters from column six. For the linear case, I take $\hat{\alpha}_1$ from column 6 and set $\hat{\alpha}_2 = 0$ so that the marginal spending change is constant across the distribution of schools.

4.3 Results: Counterfactual Spending Changes After New LIHTC

After the first stage, I am left with three 21-year panels of counterfactual spending data for my sample of schools. I employ my event study specification taking each counterfactual spending measure as an outcome. By using the counterfactual measures to hold the policy

[13] As shown in Equation 5, the other two parameters $\widehat{\alpha}_{0t} + \widehat{\theta}_{jt}$ are obtained from the constant term and the coefficients for each district fixed effect that coincide with models of Table 3.

environment constant, I am exploiting just the LIHTC-induced variation in student composition to reveal the spending changes in each of the three scenarios. In each subsection to follow I present the average spending response, heterogeneity by initial need status, and analyze city centers, where the composition shocks are most clearly defined.

4.3.1 Case 1 : The Inverse U

The first non-linear case is the one in which per-pupil spending is increasing in the high-need student share, up until a threshold is reached and per-pupil spending begins to fall. This case prevailed at the start of the sample period, has an empirical threshold at roughly 50%, and carries fairly obvious predictions given that 60% of LIHTC family housing occurs above the threshold (Table 2). Under this regime, one would expect the average LIHTC development would cause per-pupil spending to fall. Indeed, Figure 13 shows that the composition change after LIHTC would cause spending to fall 20% by year 5 and almost 40% in the long run.

The middle panel of Figure 13 shows the distribution of the effect across high and low-need schools. Per-pupil spending is predicted to decrease at high-need schools following a marginal increase in the share of high-need students. However, because LIHTC does not produce major composition changes at these schools, the per-pupil spending decrease is imprecisely identified. However, there are large spending decreases at initially low-need schools. The bottom panel of Figure 13 shows that initially low-need schools in city centers, where the sharpest composition changes occur, would incur the largest spending decrease after LIHTC.

4.3.2 Case 2: Diminishing Spending Increases

The second counterfactual models a world in which an increase in the share of high-need students always produces an increase in per-pupil spending, but the increase is diminishing for high-need schools. The shape of this curve is defined in the bottom panel of Figure 12. The marginal effect at a school with no high-need students would be to fund the new batch of high-need students at about 45% higher than the current level. As the share of high-need students approaches 1, the marginal effect tends to zero.

A clear prediction of the diminishing case is for large spending increases to occur at initially low-need schools relative to high-need counterparts after new LIHTC is built. Figure 14 shows that in this regime the average effect is unclear because of predicted spending increases at low-need schools and predicted decreases at high-need schools. Because spending decreases are associated with positive income growth at a school, the initially high-need schools that receive LIHTC shock and incur spending decreases are marginal schools. Meaning that the magnitude of the spending decrease is likely larger than the spending increase that would have occurred if LIHTC increased the share of high-need students.

4.3.3 Case 3: The Constant Marginal Spending Response

The last case I explore is that of a constant marginal increase in per-pupil spending in response to a small change in the share of high-need students. The prediction is that any school, regardless of initial student body composition, will receive increased per-pupil spending if LIHTC introduces more high-need students on net. This extreme case is not present for any years of the sample for Texas but does represent a potential policy position.

As Figure 15 shows, because the average school receiving LIHTC experiences an increase in income qualifying share, per-pupil spending is predicted to rise on average after LIHTC. Notably, the spending increases occur at the schools expected to have the largest composition changes. Initially, low-need schools, particularly those near city centers, would experience the largest expenditure increases in the years following new LIHTC housing under this regime.

4.4 Discussion: Implications for School and Housing Policy

Sections 4.3.1-4.3.3 detail the extent of changes to per-pupil spending after LIHTC composition shocks, under different counterfactual funding regimes. Because composition changes caused by LIHTC are strongest at initially low-need schools, most of the identifiable changes in per-pupil spending occur at these schools as well.

The results yield substantiative implications for the intersection of school and housing policy. If affordable housing is to be viewed as a way to *move to opportunity* then the resources to support the new batch of students at the receiving school must be at a sufficient level to produce better outcomes for students. Had the system of funding present in 2000 remained in place for the duration of the sample, resources available at initially desirable schools would have overwhelmingly declined after LIHTC arrived.

In practice, LIHTC occurs across neighborhoods of all types. While per-pupil spending is only one measure of school quality, a reasonable claim is that decreases in per-pupil spending after the introduction of new high-need students to the schools is not an equitable outcome. In two of three counterfactual cases, per-pupil spending is predicted to increase at initially low-need schools after the LIHTC composition change. With nationally sampled data at the school level, my approach could be used to estimate which funding regimes are most prevalent nationally. Because there might be regional heterogeneity in the composition changes that follow LIHTC, an extension of this work could examine how schools across the nation are responding to LIHTC composition shocks.

Measuring the financial resources of a school purely by fiscal budget has limitations. Schools in richer areas are likely to have access to a larger pool of private resources that do not register on publicly available financial data. The prediction for the level of undocumented resources following LIHTC is ambiguous. If private resources indeed fall with increases in high-need student share, then the real spending change at initially low-need (high-income) schools could be understated by my results.

5 Conclusion

This paper provides evidence of enrollment increases and student body composition changes at elementary schools near new affordable housing. The net enrollment increases are estimated to be 5-8%, which require districts to fulfill additional teacher positions as required by law. While new hiring increases absolute expenditures on average, the composition changes do not yield identifiable changes to per-pupil spending after LIHTC.

I argue that the null results of my naive event study are not reflective of real per-pupil spending changes after LIHTC. Instead, the result reflects substantial heterogeneity in the composition changes across neighborhood types and unobserved changes in the public financing of schools over time. A core contribution of this paper is to test how per-pupil spending changes following LIHTC, holding the policy regime fixed to one of three different cases. If LIHTC housing shifts the composition of a school by introducing more high-need students, per-pupil spending will only increase when the school finance system is tailored to spend more money for students of higher need. In the prevalent case where the per-pupil spending response to high-need student increases is non-linear, the average school will incur per-pupil spending decreases after new LIHTC housing.

The counterfactual funding regimes are constructed from Texas sample estimates but represent three policy environments that could exist anywhere across the US. Thus the results can be used to analyze the per-pupil spending response to any exogenous neighborhood composition change under each of the funding regimes. In the case of LIHTC, a nearly $8 billion-a-year housing program, the composition changes that follow new family housing create considerable financial spillovers at US public schools.

Given the composition of who lives in LIHTC (Hollar 2019), it is an extension for future work to understand how LIHTC changes the racial composition of schools in urban, suburban, and rural areas. If LIHTC housing is predicted to change racial composition, at least part of the out-sorting of high-income households after LIHTC comes from preferences over race. Given the simultaneity of such changes along many dimensions, there is more to be learned about demographic changes caused by LIHTC (Davis et al. 2019; Dizon-Ross 2020).

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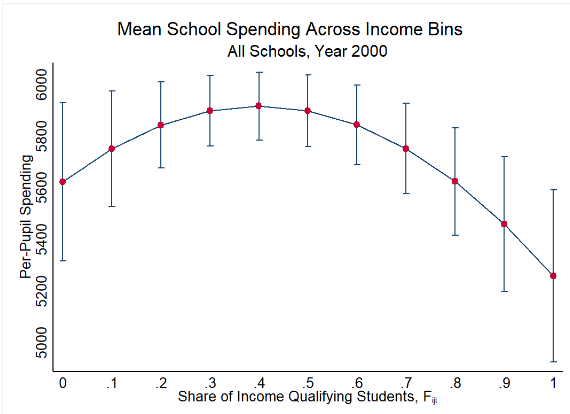
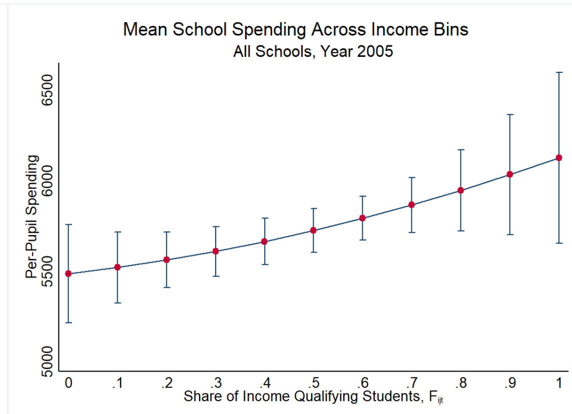
Figures

Figure 1: Per-Pupil Spending Across the Distribution of Schools by Need

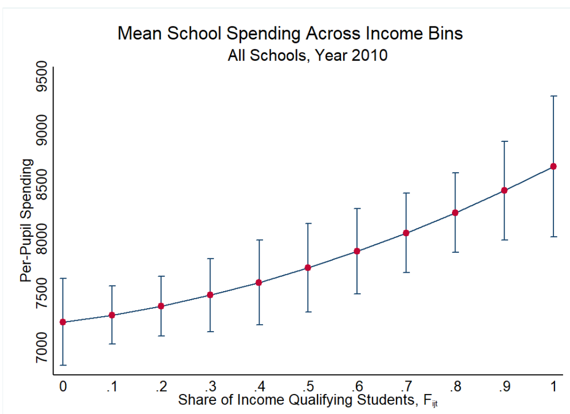
(a)



(b)



(c)



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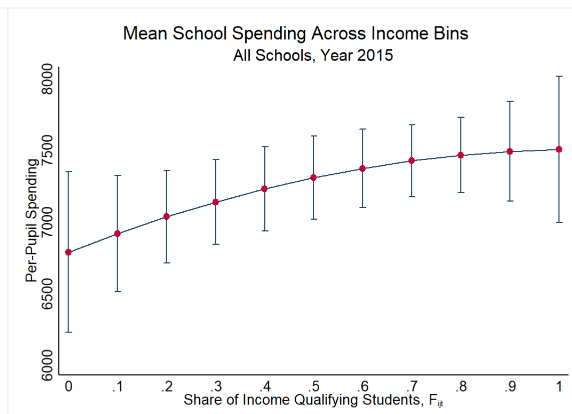

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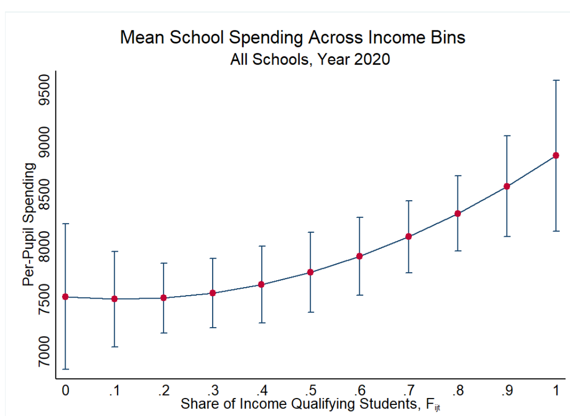
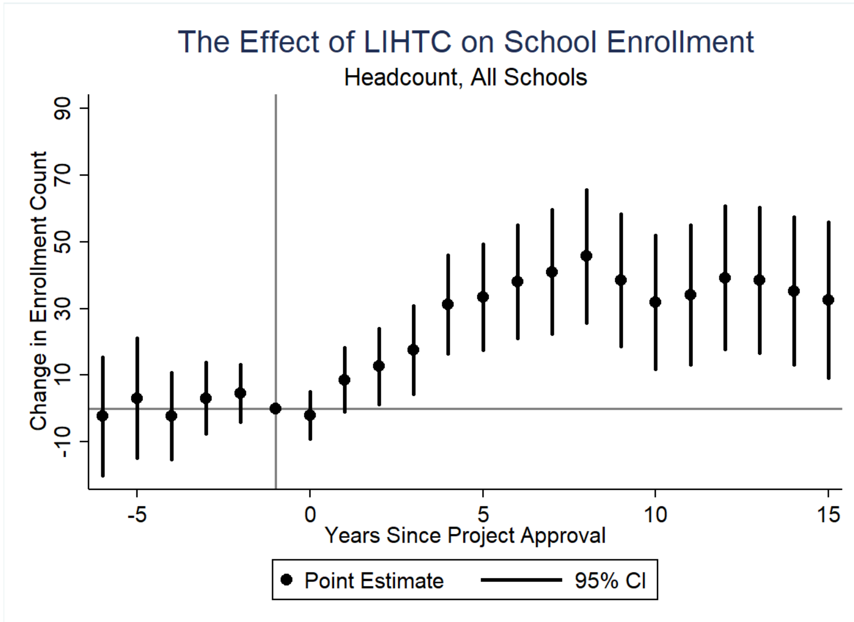


Notes: Income bins categorize schools based on the share of high-need students across the range shown on the x-axis. Each panel presents estimates of the unconditional mean per-pupil spending level for each bin in a given year, along with the standard error.

Figure 2: Affordable Housing Increases School Size

(a)



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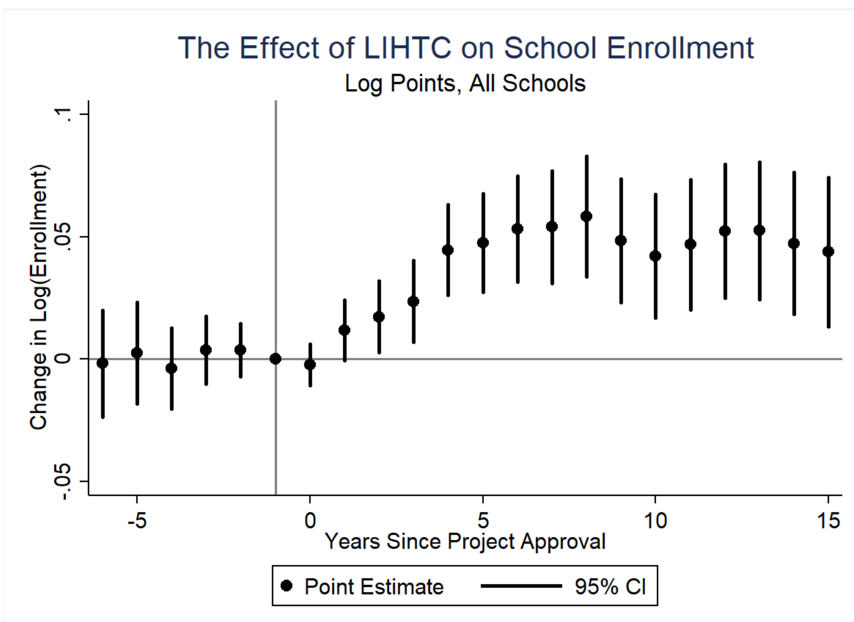
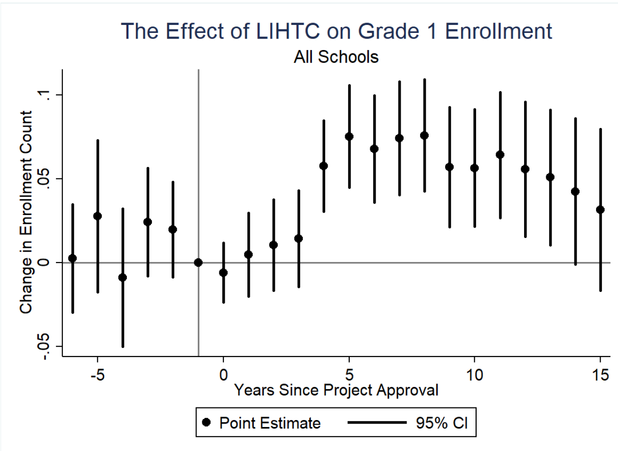


Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. In the upper panel the outcome is enrollment count in levels, and in the lower panel the outcome is enrollment count in logs. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city centers, small city centers, big city suburbs, small city suburbs, large towns, small towns, and rural remote areas. 95% confidence intervals are shown, with observations clustered at the school level.

Figure 3: Enrollment Changes by Grade

(a)



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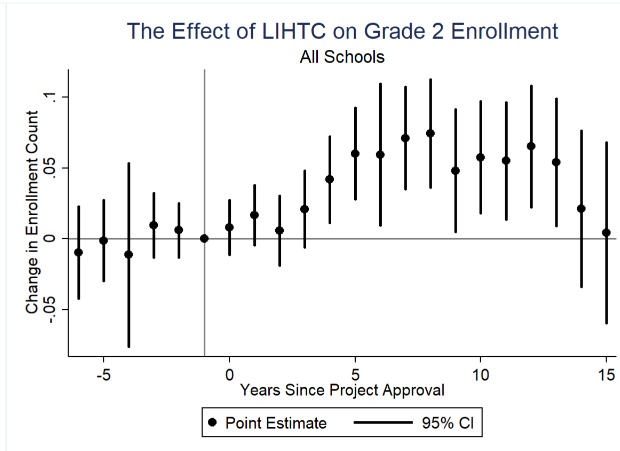

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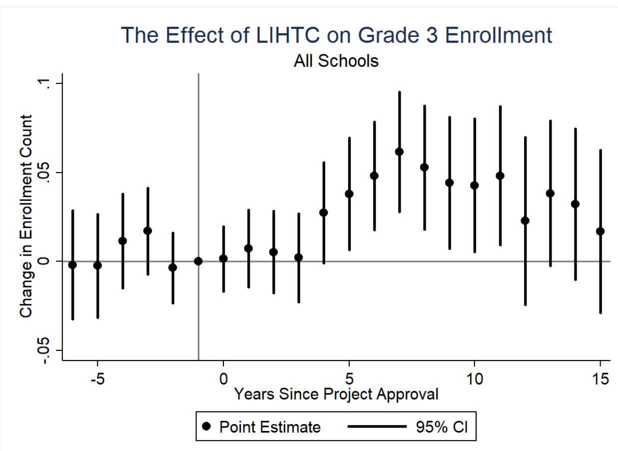

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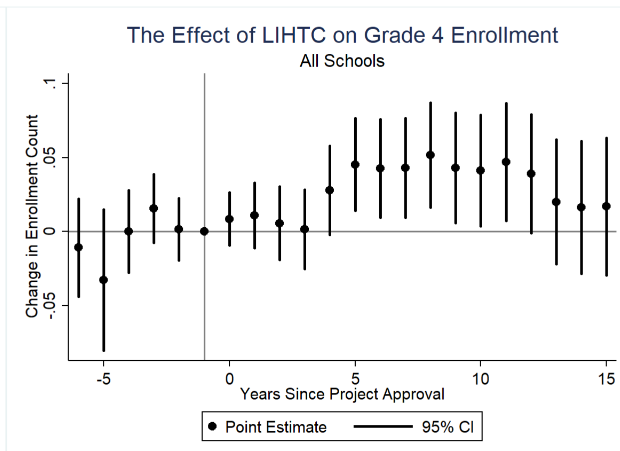

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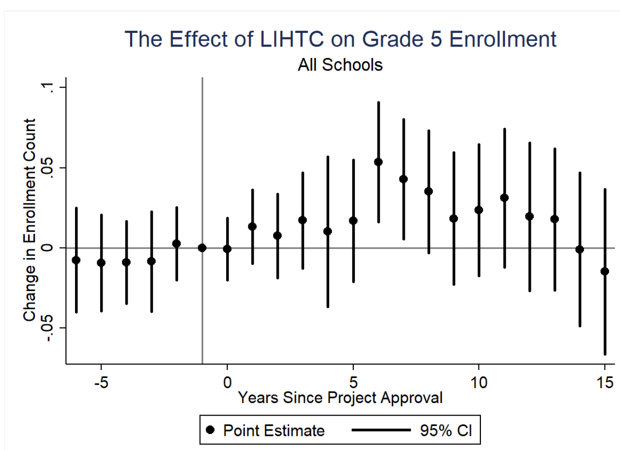
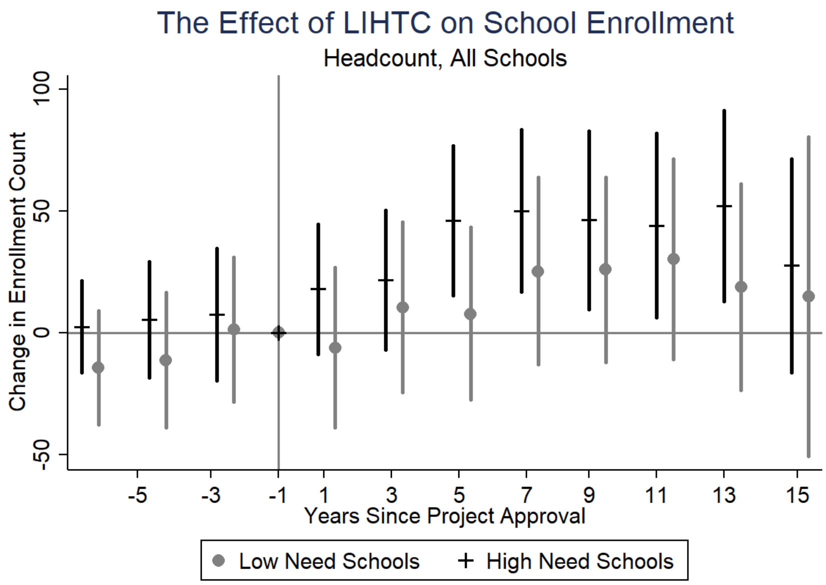


Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. In all panels the outcome is enrollment count in logs and each figure tracks changes to the enrollment for a particular grade level. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city centers, small city centers, big city suburbs, small city suburbs, large towns, small towns, and rural remote areas. 95% confidence intervals are shown, with observations clustered at the school level.

Figure 4: Heterogeneity In Enrollment Changes After LIHTC

(a)



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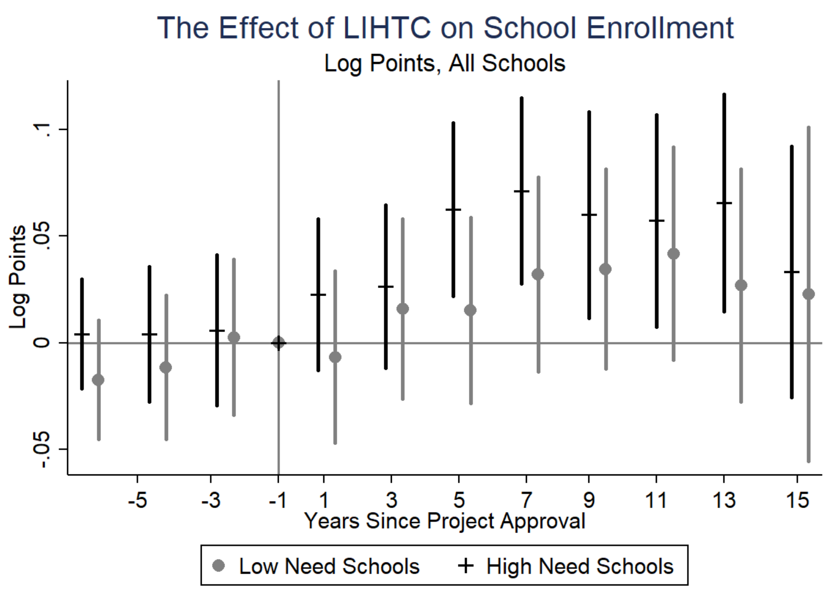
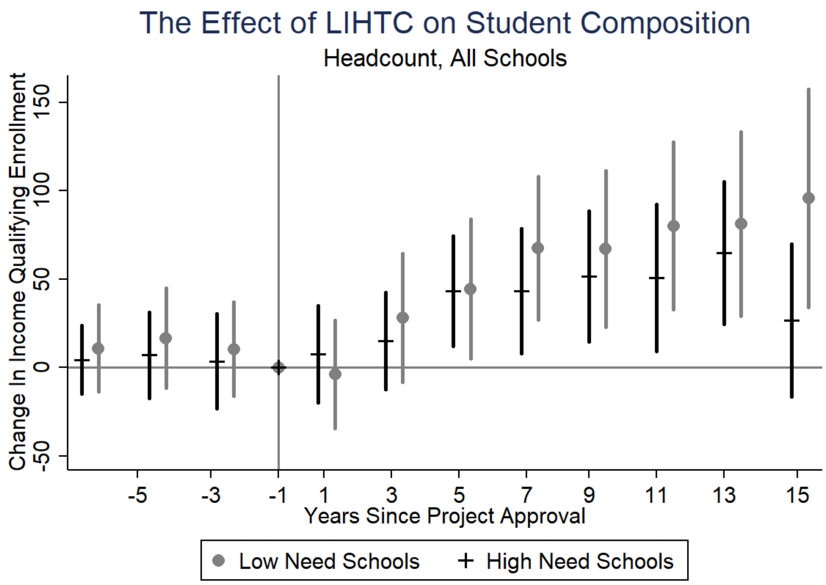


Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. High-need schools are categorized at the start of the panel and have over 50% of students that qualify for free or reduced lunch. The remainder of schools are categorized as low-need. In the upper panel the outcome is enrollment count in levels, and in the lower panel the outcome is enrollment count in logs. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city centers, small city centers, big city suburbs, small city suburbs, large towns, small towns, and rural remote areas. 95% confidence intervals are shown, with observations clustered at the school level.

Figure 5: Heterogeneity In Composition Changes After LIHTC

(a)



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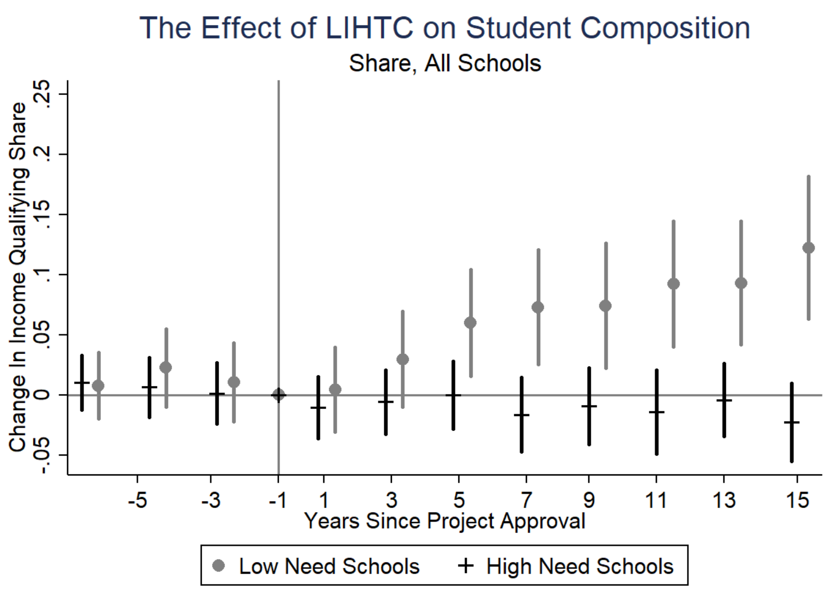
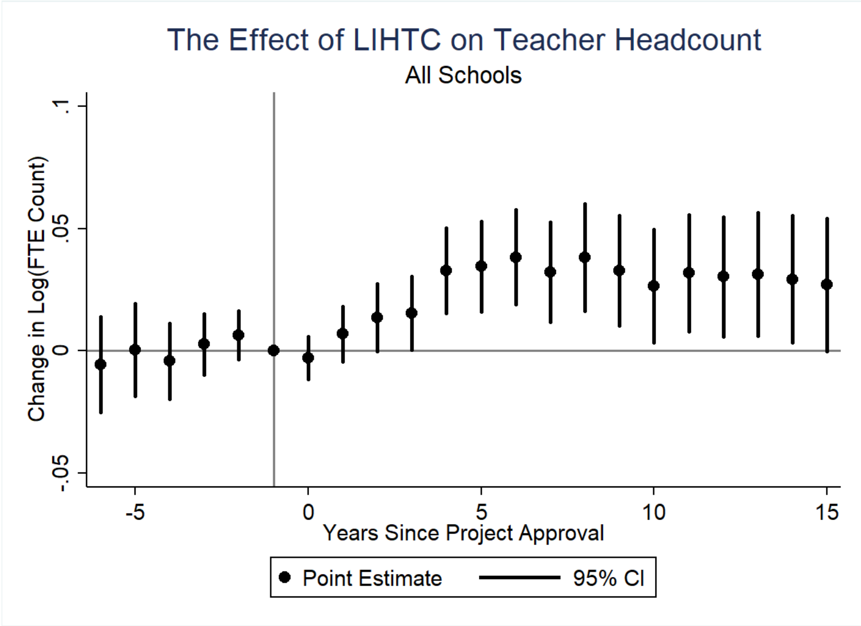


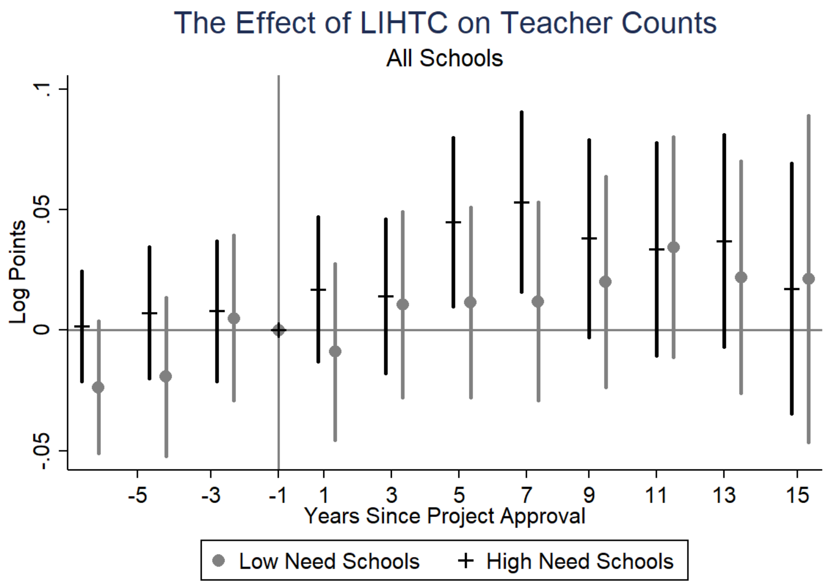
Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. High-need schools are categorized at the start of the panel and have over 50% of students that qualify for free or reduced lunch. The remainder of schools are categorized as low-need. In the upper panel the outcome is high-need student headcount, and in the lower panel the outcome is high-need student share. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city centers, small city centers, big city suburbs, small city suburbs, large towns, small towns, and rural remote areas. 95% confidence intervals are shown, with observations clustered at the school level.

Figure 6: Heterogeneity In Teacher Counts After LIHTC

(a)



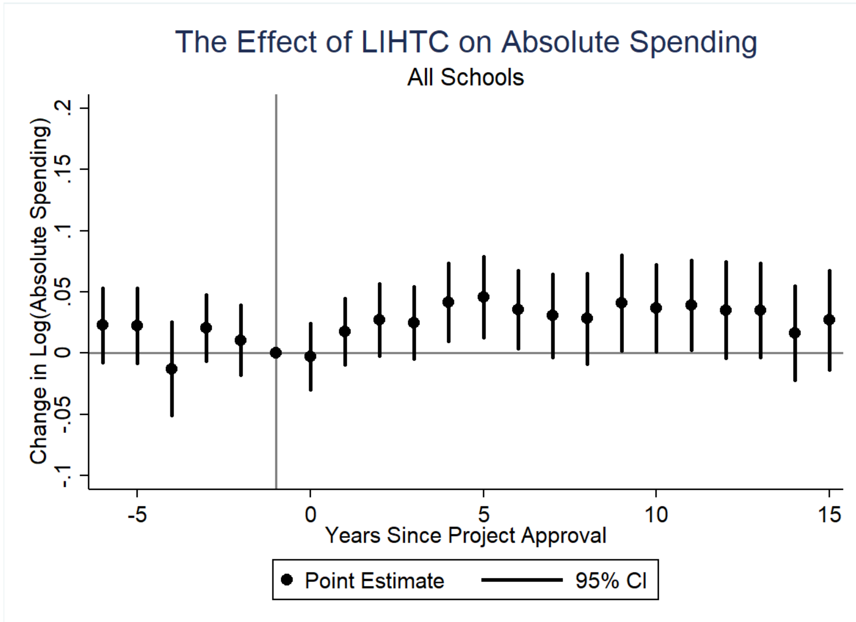
(b)



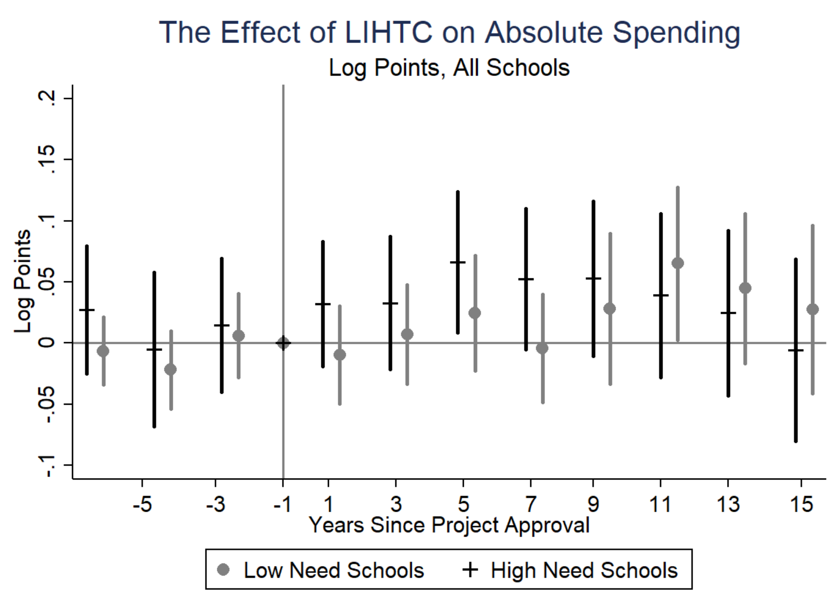
Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. High-need schools are categorized at the start of the panel and have over 50% of students that qualify for free or reduced lunch. The remainder of schools are categorized as low-need. In both panels the outcome is the count of full time equivalent (FTE) teachers in logs. Full time equivalent include full time teachers and part time teachers as a fraction of full time working hours. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city centers, small city centers, big city suburbs, small city suburbs, large towns, small towns, and rural remote areas. 95% confidence intervals are shown, with observations clustered at the school level.

Figure 7: Evaluating Absolute Expenditure Changes after LIHTC

(a)



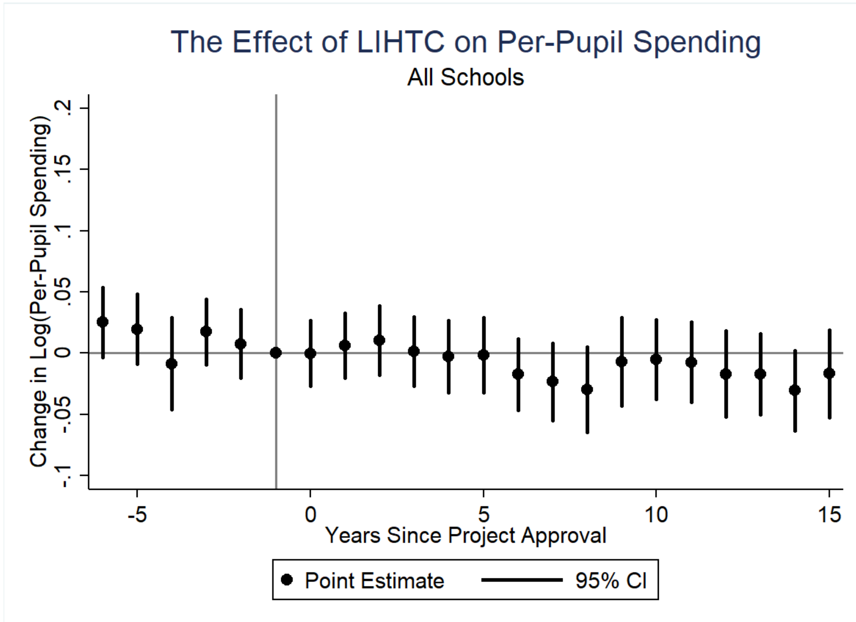
(b)



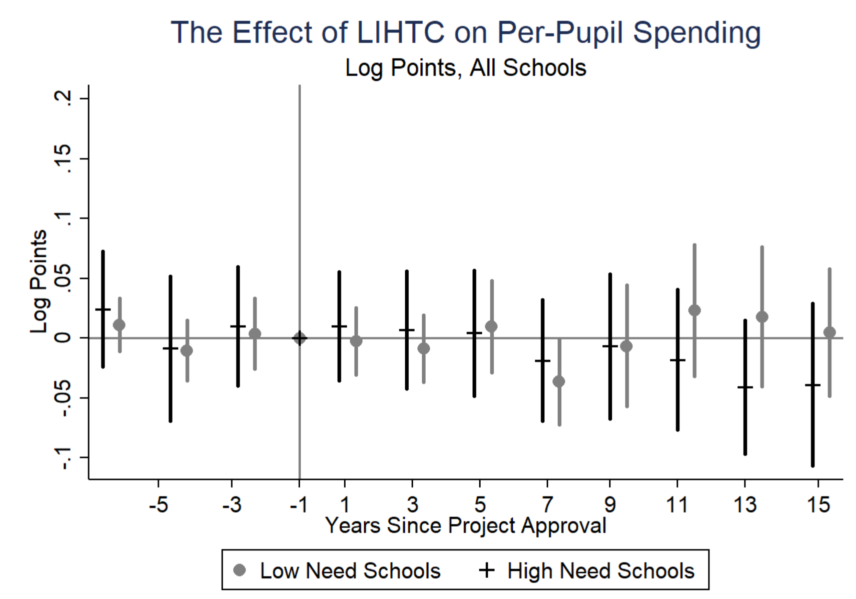
Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. High-need schools are categorized at the start of the panel and have over 50% of students that qualify for free or reduced lunch. In both panels the outcome is absolute spending logs. Absolute spending is defined as the total expenditure in a given year divided by school enrollment held fixed to the value from the first year of the panel. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city centers, small city centers, big city suburbs, small city suburbs, large towns, small towns, and rural remote areas. 95% confidence intervals are shown, with observations clustered at the school level.

Figure 8: Evaluating Per-Pupil Spending Changes after LIHTC

(a)



(b)

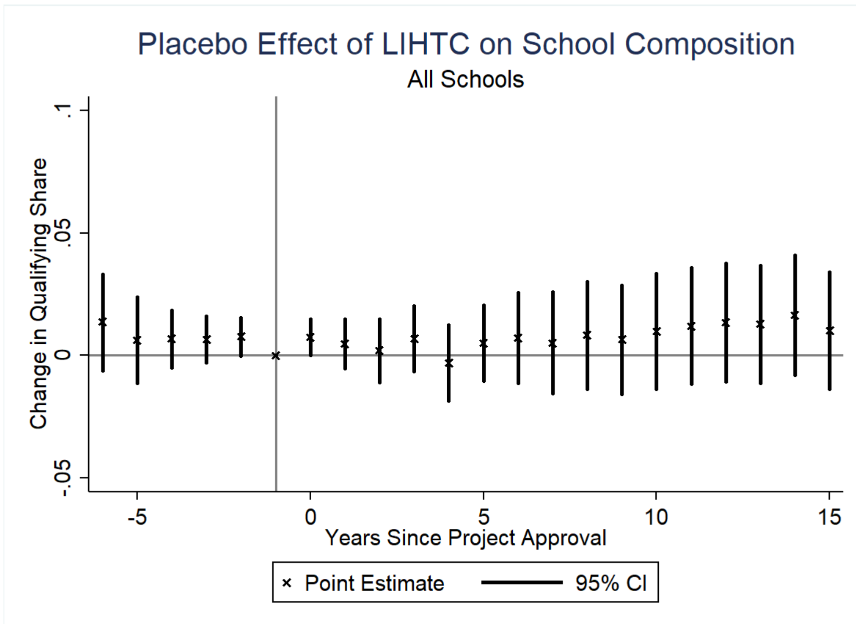


Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. High-need schools are categorized at the start of the panel and have over 50% of students that qualify for free or reduced lunch. In both panels the outcome is per-pupil spending logs. Per-pupil spending is defined as the total expenditure in a given year divided by school enrollment in the same year. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city centers, small city centers, big city suburbs, small city suburbs, large towns, small towns, and rural remote areas. 95% confidence intervals are shown, with observations clustered at the school level.

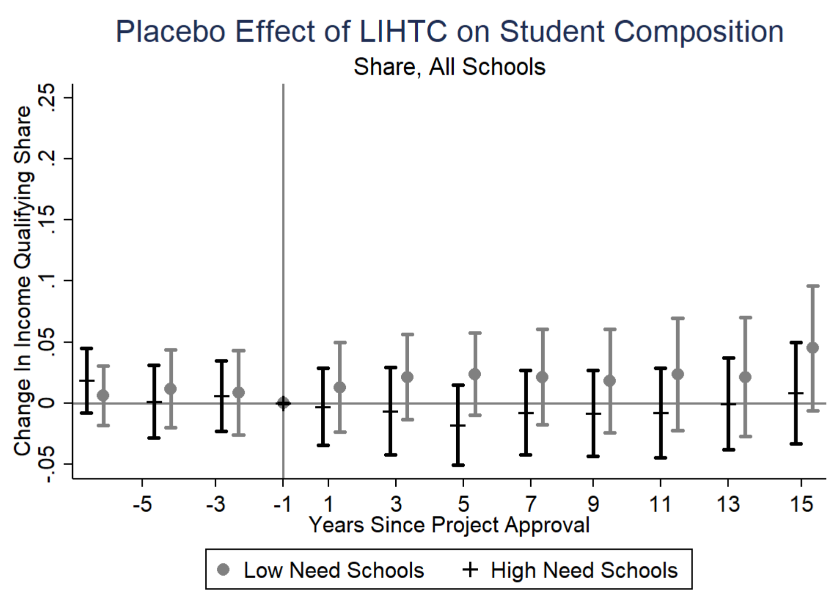
Placebo Figures

Figure 9: The Effect of LIHTC Senior Housing

(a)



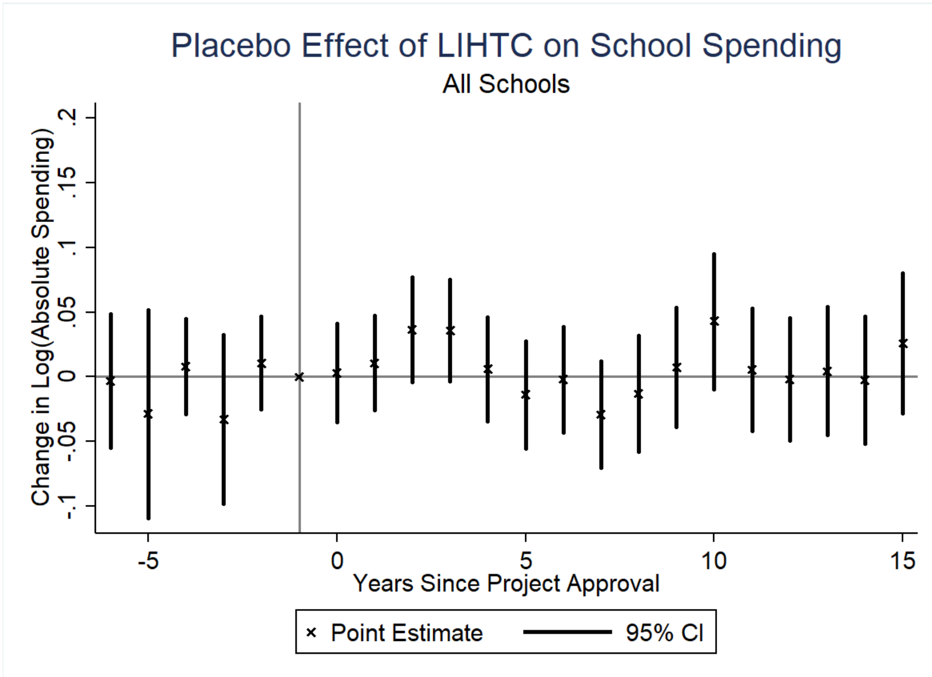
(b)



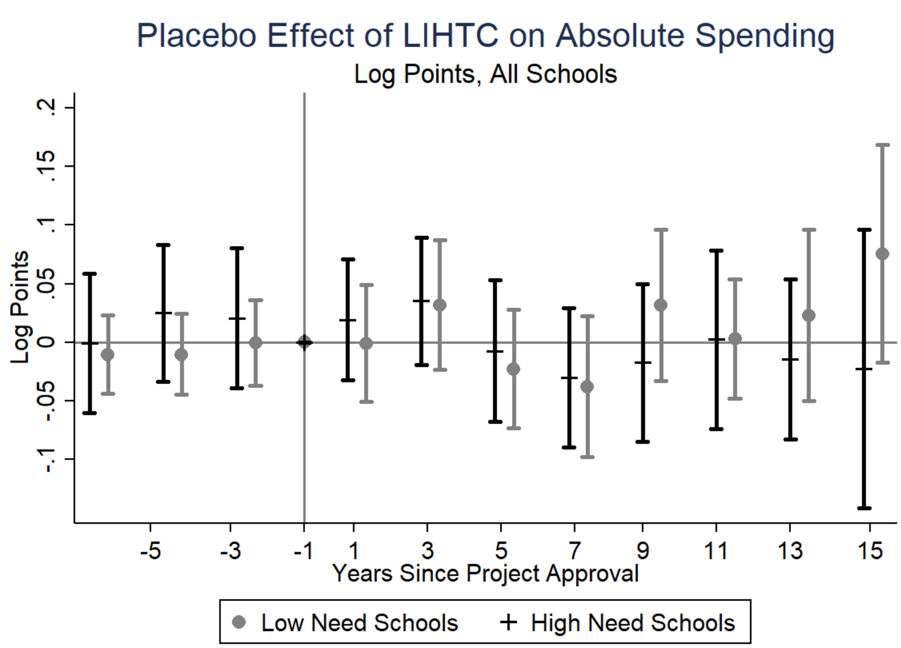
Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. The placebo event is LIHTC housing designated for seniors, and all family housing is dropped from the sample. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city centers, small city centers, big city suburbs, small city suburbs, large towns, small towns, and rural remote areas. 95% confidence intervals are shown, with observations clustered at the school level.

Figure 10: The Effect of Senior Housing on Absolute Spending

(a)



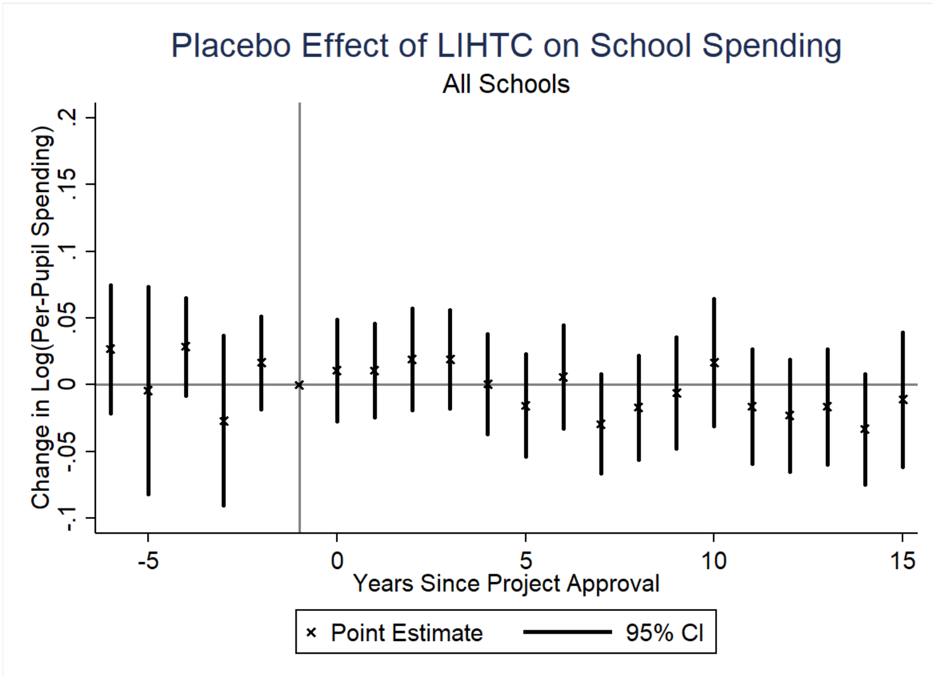
(b)



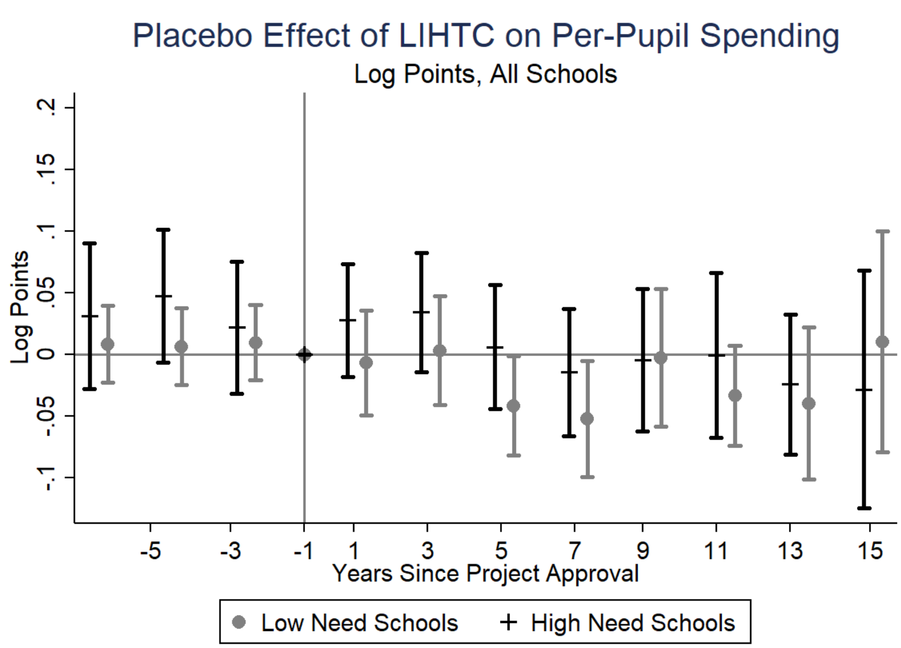
Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. The placebo event is LIHTC housing designated for seniors, and all family housing is dropped from the sample. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city centers, small city centers, big city suburbs, small city suburbs, large towns, small towns, and rural remote areas. 95% confidence intervals are shown, with observations clustered at the school level.

Figure 11: The Effect of Senior Housing on Per-Pupil Spending

(a)



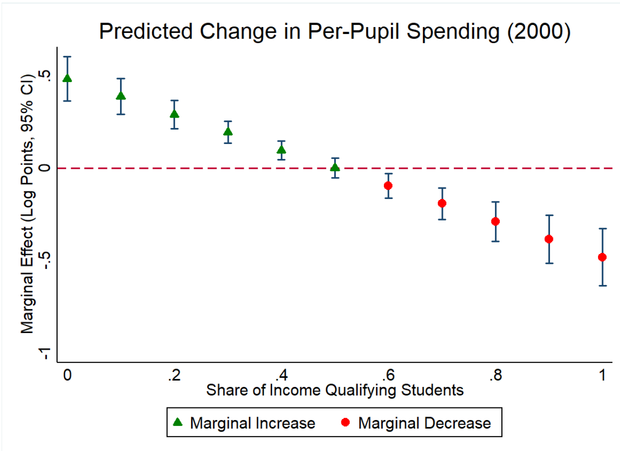
(b)



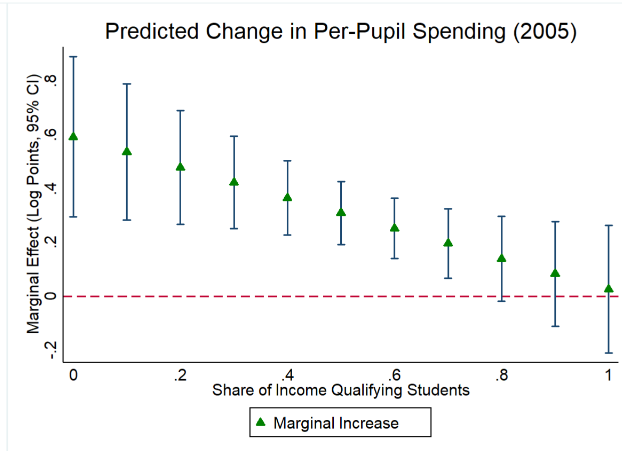
Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. The placebo event is LIHTC housing designated for seniors, and all family housing is dropped from the sample. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city centers, small city centers, big city suburbs, small city suburbs, large towns, small towns, and rural remote areas. 95% confidence intervals are shown, with observations clustered at the school level.

Figure 12: The Marginal Effect of an Increase in Income Qualifying Share

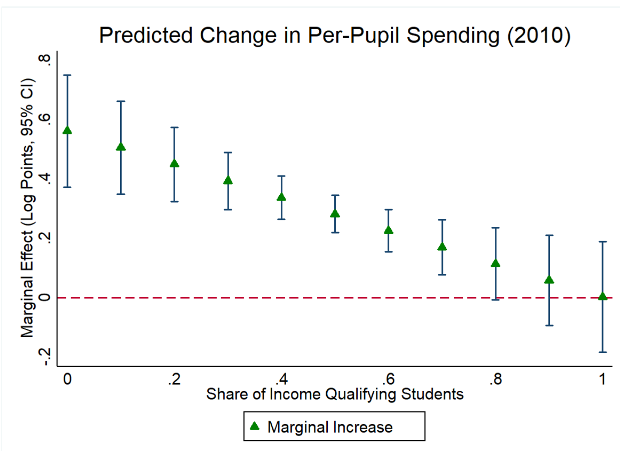
(a)



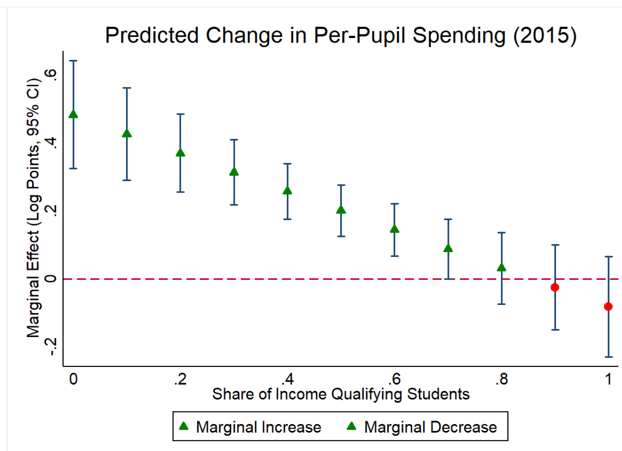
(b)



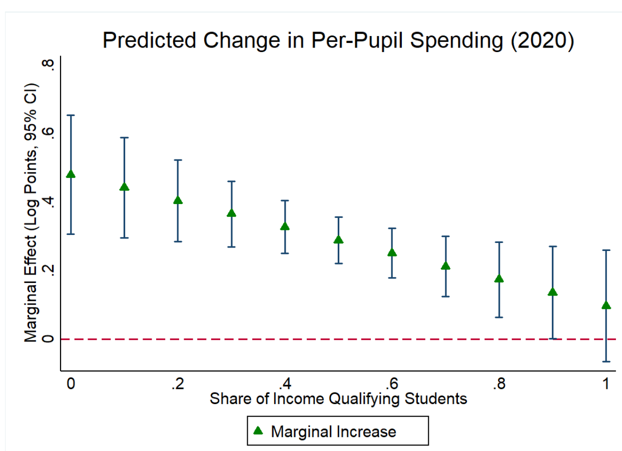
(c)



(d)



(e)

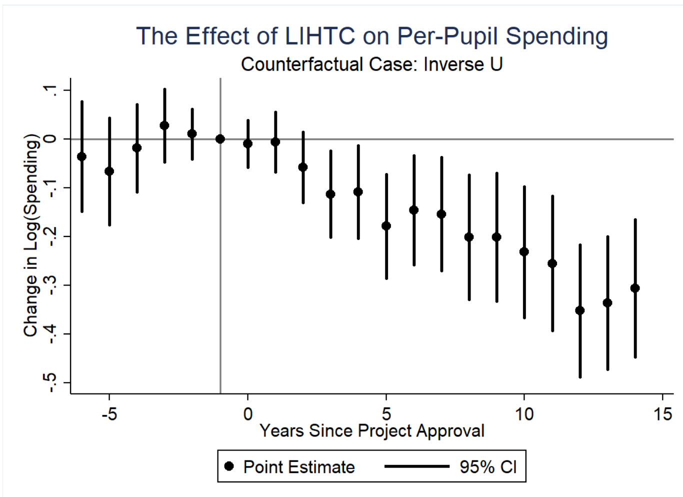


Notes: Each panel contains estimates of the marginal per-pupil spending response to a change in high-need student share. Because Model 3 is non-linear, the predicated spending change is not constant across the support of the variable shown on the X-axis. In three of the five years selected the per-pupil spending response is always positive, but two of the five years a small increase in high-need student share may cause per-pupil spending to decline at some schools. 95% confidence intervals are shown, with observations clustered at the school level.

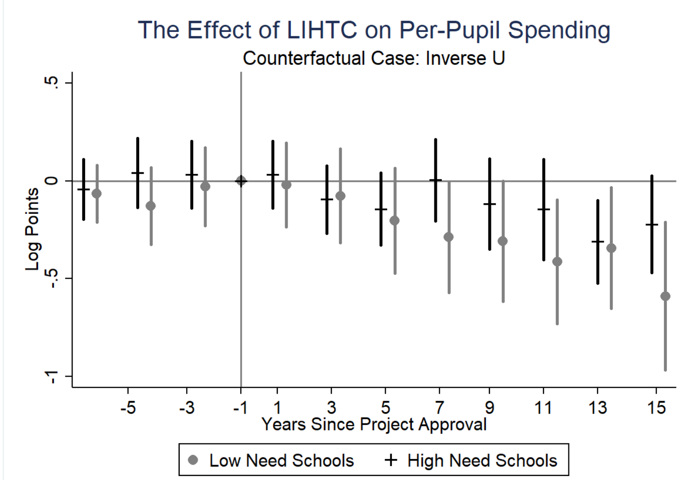
Counterfactual Estimates

Figure 13: (Counterfactual 1) LIHTC Causes Per-Pupil Spending to Decrease on Average

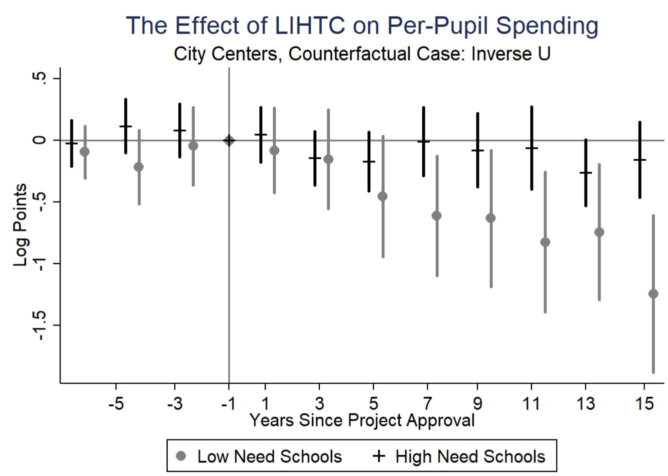
(a)



(b)



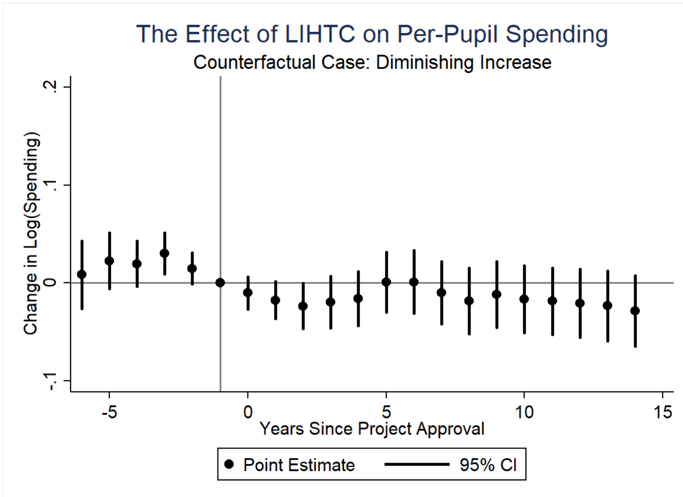
(c)



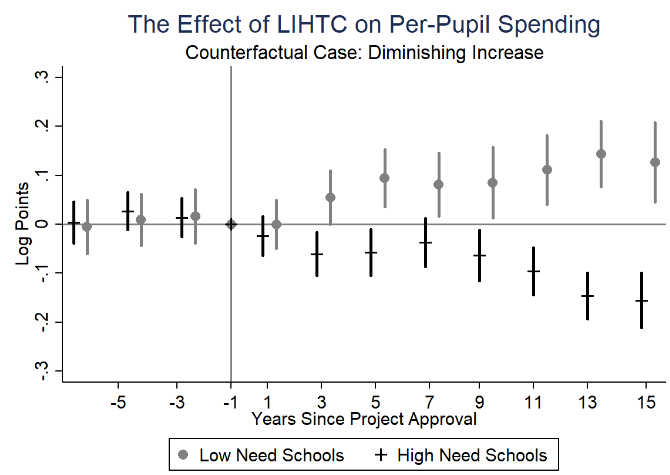
Notes: Event-study estimates of the change in spending caused by a LIHTC composition shock when schools are funded under the regime described in Section 4.3.1. High-need schools are categorized at the start of the panel and have over 50% of students that qualify for free or reduced lunch. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city centers, small city centers, big city suburbs, small city suburbs, large towns, small towns, and rural remote areas. 95% confidence intervals are shown, with observations clustered at the school level.

Figure 14: (Counterfactual 2) Heterogeneity in the Effects of New LIHTC Housing

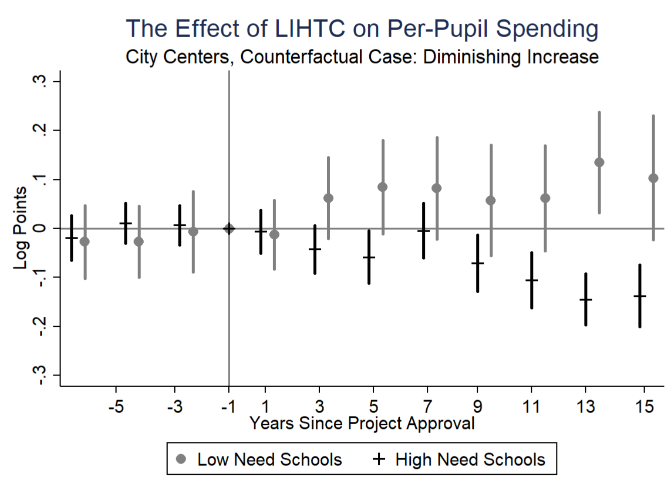
(a)



(b)



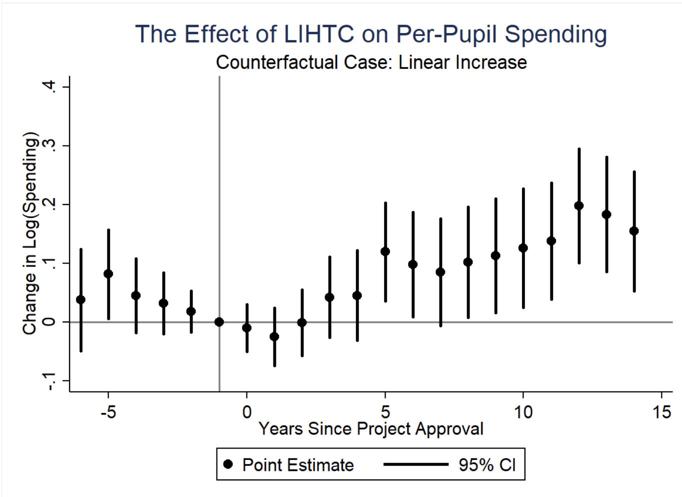
(c)



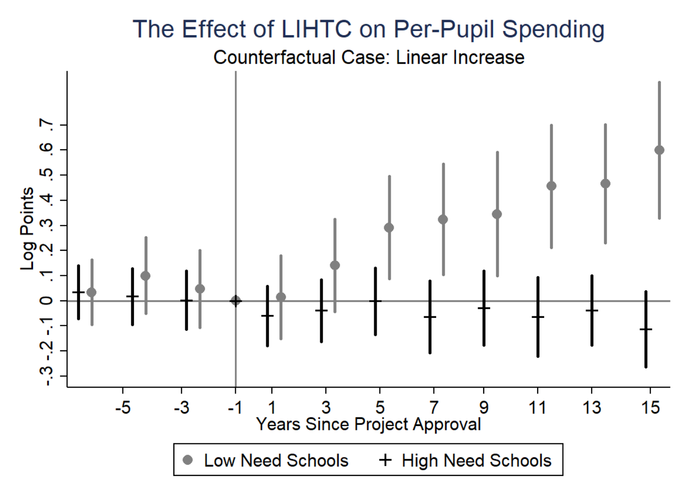
Notes: Event-study estimates of the change in spending caused by a LIHTC composition shock when schools are funded under the regime described in Section 4.3.2.High-need schools are categorized at the start of the panel and have over 50% of students that qualify for free or reduced lunch. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city centers, small city centers, big city suburbs, small city suburbs, large towns, small towns, and rural remote areas. 95% confidence intervals are shown, with observations clustered at the school level.

Figure 15: (Counterfactual 3) No Predicted Spending Decreases after LIHTC Housing

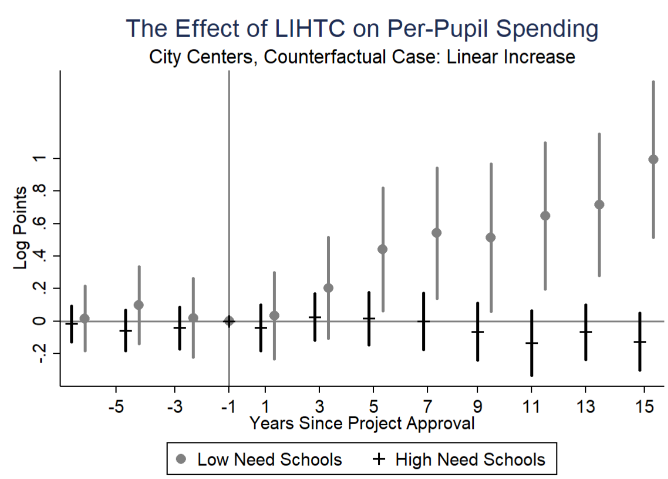
(a)



(b)



(c)



Notes: Event-study estimates of the change in spending caused by a LIHTC composition shock when schools are funded under the regime described in Section 4.3.3. High-need schools are categorized at the start of the panel and have over 50% of students that qualify for free or reduced lunch.Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city centers, small city centers, big city suburbs, small city suburbs, large towns, small towns, and rural remote areas. 95% confidence intervals are shown, with observations clustered at the school level.

Tables

Table 1: School Summary Statistics

	Full Sample	< 50% Income Qualifying Low-Need Schools	50%+ Income Qualifying High-Need Schools
Per-Pupil Spending	7,006.46	6,943.43	7,056.34
	(2580.7)	(2489.1)	(2650.0)
Enrollment	702.74	710.77	696.39
	(253.3)	(258.8)	(248.7)
Income Qualifying Count	397.76	283.51	488.19
	(252.1)	(206.8)	(248.0)
Income Qualifying Share	0.58	0.41	0.71
	(0.292)	(0.246)	(0.254)
Teacher Count	45.38	46.24	44.70
	(15.26)	(15.68)	(14.89)
Student-Teacher Ratio	15.42	15.28	15.52
	(3.272)	(1.839)	(4.059)
Any LIHTC	0.23	0.21	0.25
	(0.424)	(0.411)	(0.433)
Units per Development	133.57	125.02	138.40
	(88.139)	(84.261)	(89.941)
School×Year Obs.	61,119	26,798	34,321

Notes: Summary stats for the full sample of schools pooled across all periods are shown in column 1. Columns 2 and 3 divide the sample by initial share of students that qualify for free or reduced lunch. The sample is restricted to non-charter, non-open enrollment schools that serve elementary students.

Table 2: LIHTC Treatment at Sample Schools

Income Qualifying Share in the Event Year	**Count**	**Percent**	**Cumulative**
0-0.1	40	4.77	4.77
0.1-0.2	48	5.73	10.50
0.2-0.3	57	6.80	17.30
0.3-0.4	95	11.34	28.64
0.4-0.5	97	11.58	40.21
0.5-0.6	109	13.01	53.22
0.6-0.7	109	13.01	66.23
0.7-0.8	97	11.58	77.80
0.8-0.9	93	11.10	88.90
0.9-1	93	11.10	100

Notes: This table contains counts of LIHTC construction approved in schools within each bin of the high-need student share distribution. Only LIHTC housing targeting families are included in the counts.

Table 3: Within District Regression: All Schools

DV: Log(Per-Pupil Spending)	(1) All	(2) 2000	(3) 2005	(4) 2010	(5) 2015	(6) 2020
$\widehat{\alpha}_1$	0.367***	0.486***	0.593***	0.563***	0.485***	0.482***
	(0.075)	(0.061)	(0.152)	(0.097)	(0.081)	(0.089)
$\widehat{\alpha}_2$	-0.249***	-0.484***	-0.283*	-0.280**	-0.283***	-0.192*
	(0.069)	(0.065)	(0.123)	(0.090)	(0.068)	(0.079)
$\tilde{F}_t = -\frac{1}{2}\frac{\widehat{\alpha}_{1t}}{\widehat{\alpha}_{2t}}$	0.737	0.502	1.048	1.005	0.856	1.255
N	61123	2393	2680	2870	2870	2870
r2	0.312	0.456	0.160	0.487	0.422	0.436

Notes: Estimates from the non-linear regression Model 3 are presented for the policy parameters. The dependent variable is log(per-pupil spending) and the independent variable is the share of high-need students. $\widehat{alpha}_1$ is the marginal increase and $\widehat{alpha}_2$ models the non-linear effect. As standard in the OLS case where the non-linear effect is negative, the turning point $\tilde{F}_t$ is indicative of the threshold high-need student share in which a marginal increase would cause per-pupil spending to decline. Each model includes district fixed effects and controls for the share of Latino students and the school enrollment size.

Table 4: The Effect of Class Size Limits

Year	**Overcapacity Schools**	**Percent of Total**
2000	10	12.50
2001	35	43.75
2002	3	3.75
2003	1	1.25
2004	2	2.50
2005	2	2.50
2006	2	2.50
2009	3	3.75
2010	1	1.25
2011	1	1.25
2012	3	3.75
2013	3	3.75
2014	4	5.00
2015	7	8.75
2016	3	3.75

Notes: Schools with a student-teacher ratio above 22 are considered over-capacity as the average class size is above the cutoff mandated by law in beginning with the 2002 school year. Because LIHTC causes material enrollment increases, districts are required to assign more teachers to treated schools.

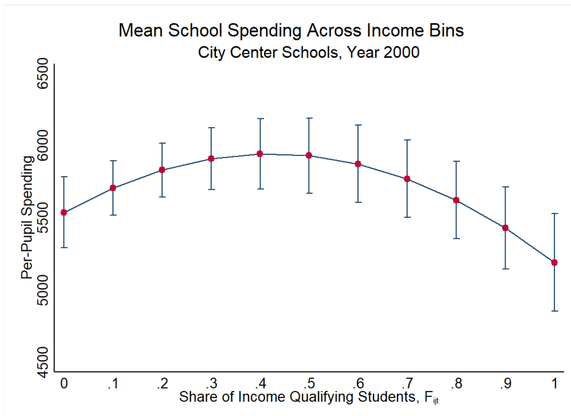
Supplementary Appendix

Local Housing Development and Money for Neighborhood Schools

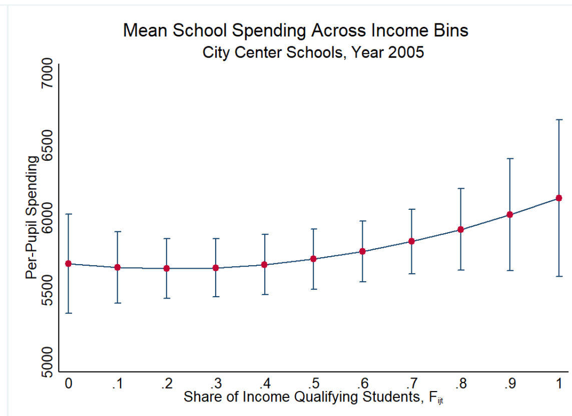
Kenneth Whaley

Figure A1: Citycenter Free Lunch Curves

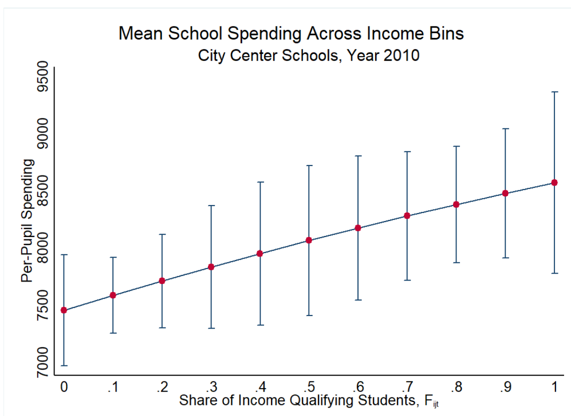
(a)



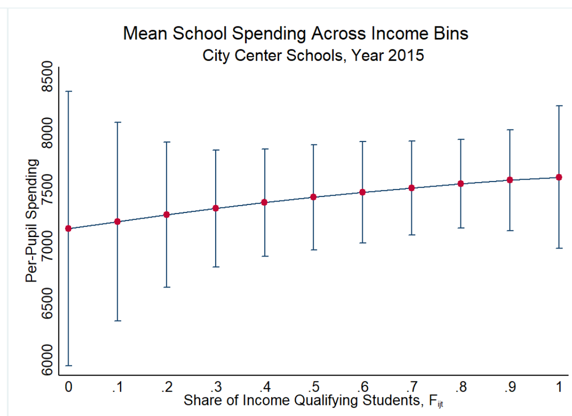
(b)



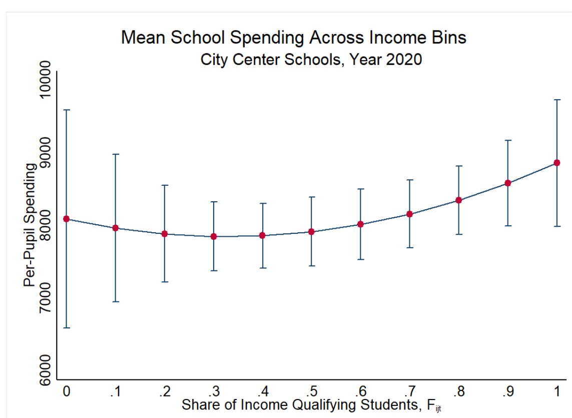
(c)



(d)



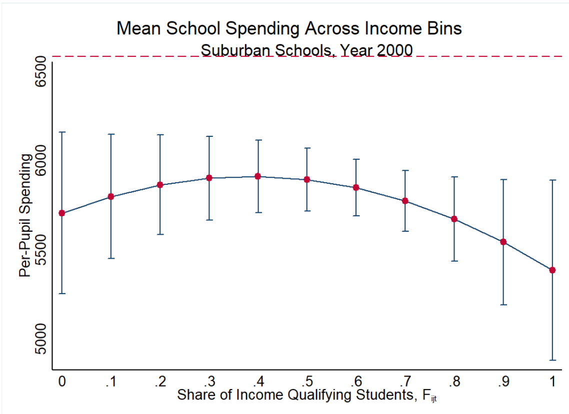
(e)



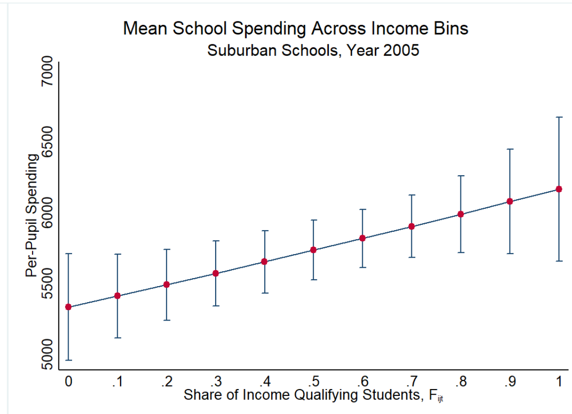
Notes: Income bins categorize schools based on the share of high-need students across the range shown on the x-axis. Each panel presents estimates of the unconditional mean per-pupil spending level for each bin in a given year, along with the standard error.

Figure A2: Suburbs Free Lunch Curves

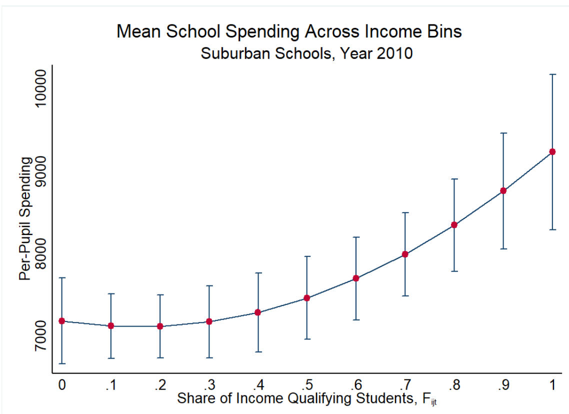
(a)



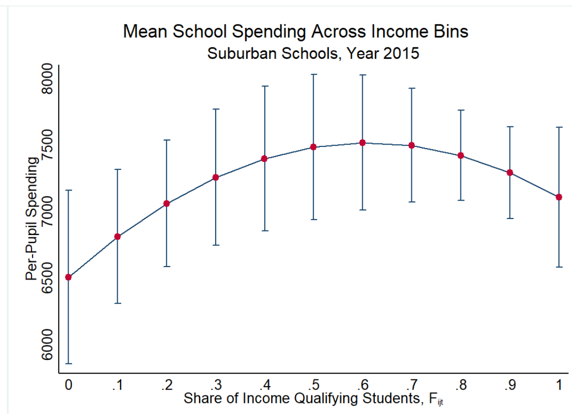
(b)



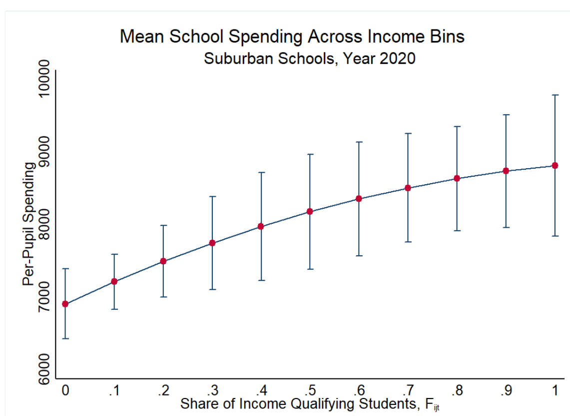
(c)



(d)



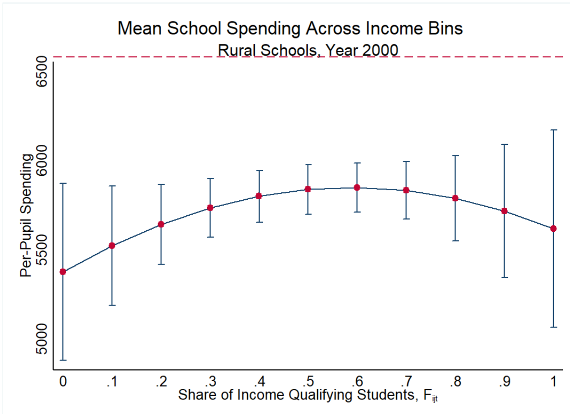
(e)

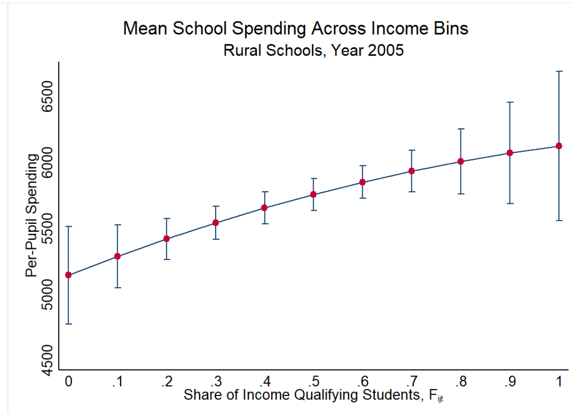


Notes: Income bins categorize schools based on the share of high-need students across the range shown on the x-axis. Each panel presents estimates of the unconditional mean per-pupil spending level for each bin in a given year, along with the standard error.

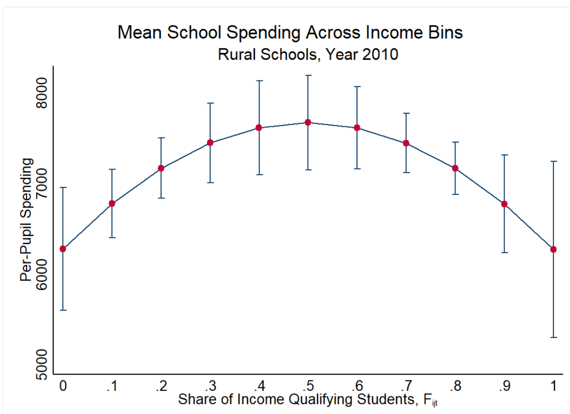
Figure A3: Rural Free Lunch Curves

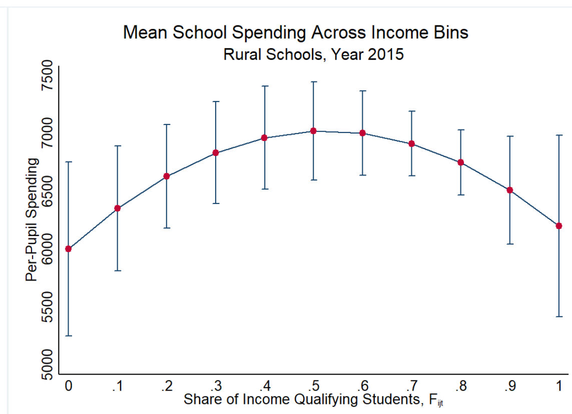
(a) (b)





(c) (d)





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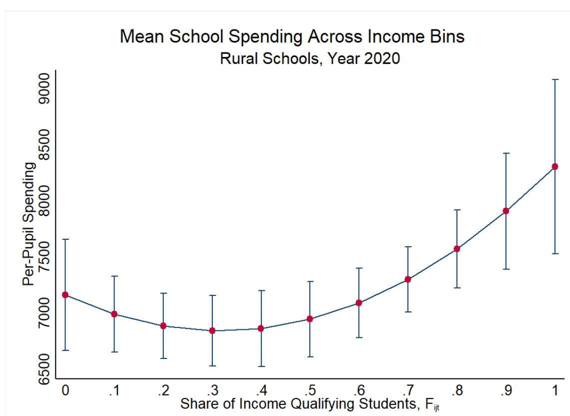
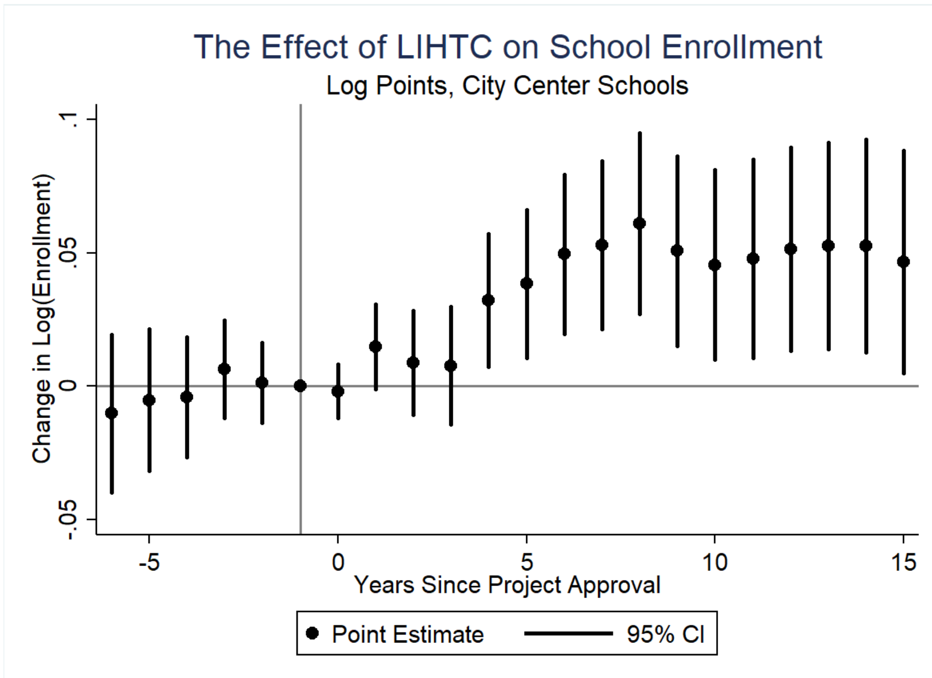


Notes: Income bins categorize schools based on the share of high-need students across the range shown on the x-axis. Each panel presents estimates of the unconditional mean per-pupil spending level for each bin in a given year, along with the standard error.

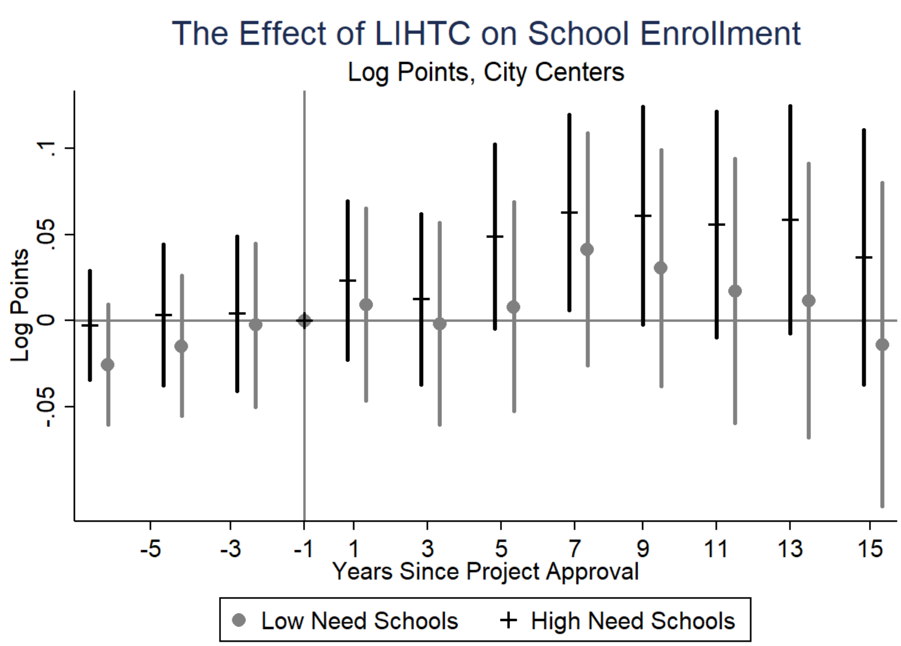
Analysis of City Center Schools

Figure A4: City Center Enrollment Shocks

(a)



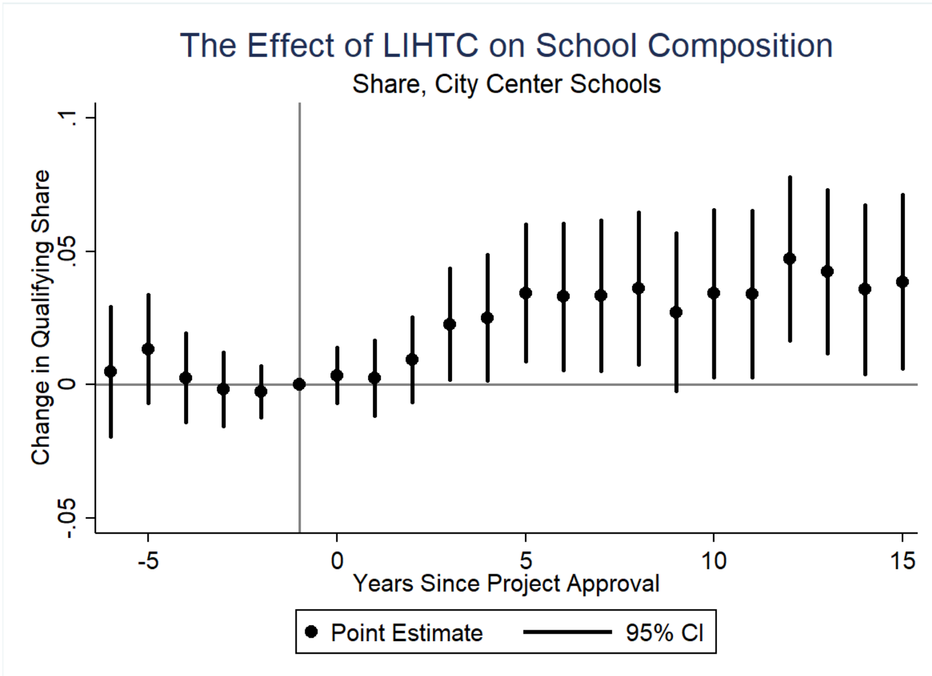
(b)



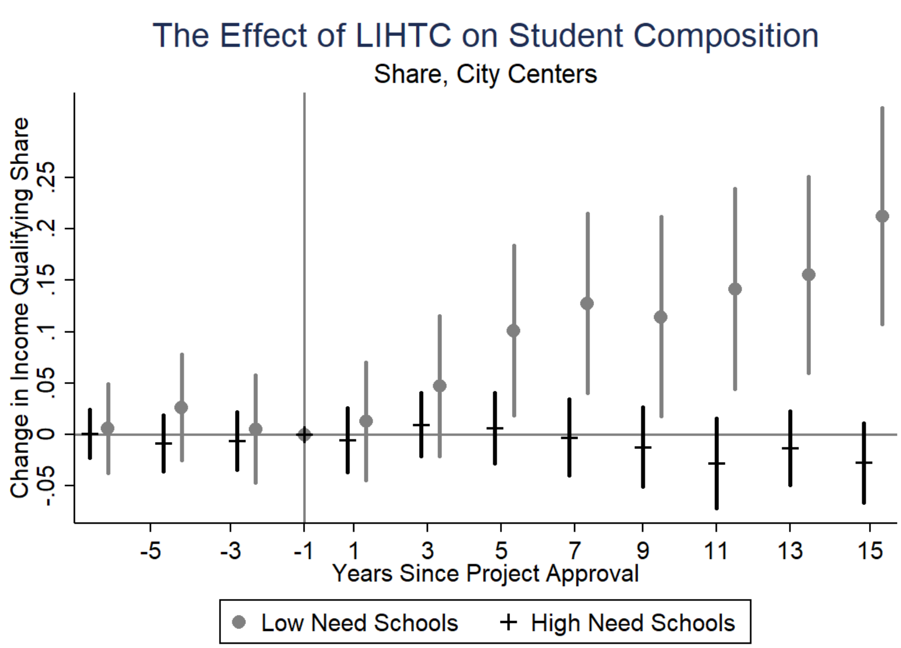
Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. High-need schools are categorized at the start of the panel and have over 50% of students that qualify for free or reduced lunch. The remainder of schools are categorized as low-need. In the upper panel the outcome is enrollment count in levels, and in the lower panel the outcome is enrollment count in logs. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city centers and small city centers. 95% confidence intervals are shown, with observations clustered at the school level.

Figure A5: City Center Composition Shocks

(a)



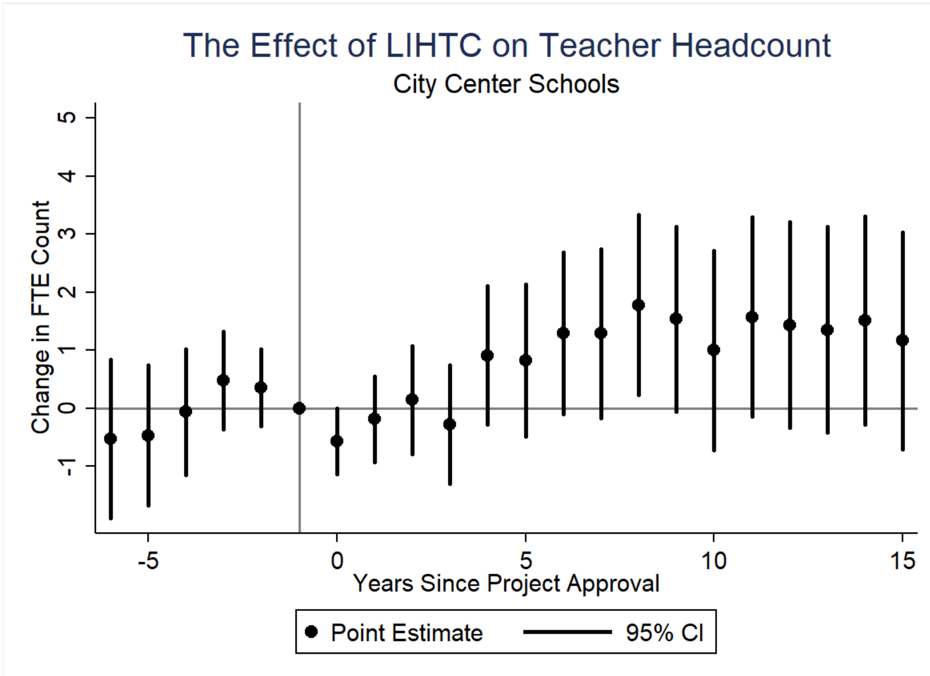
(b)



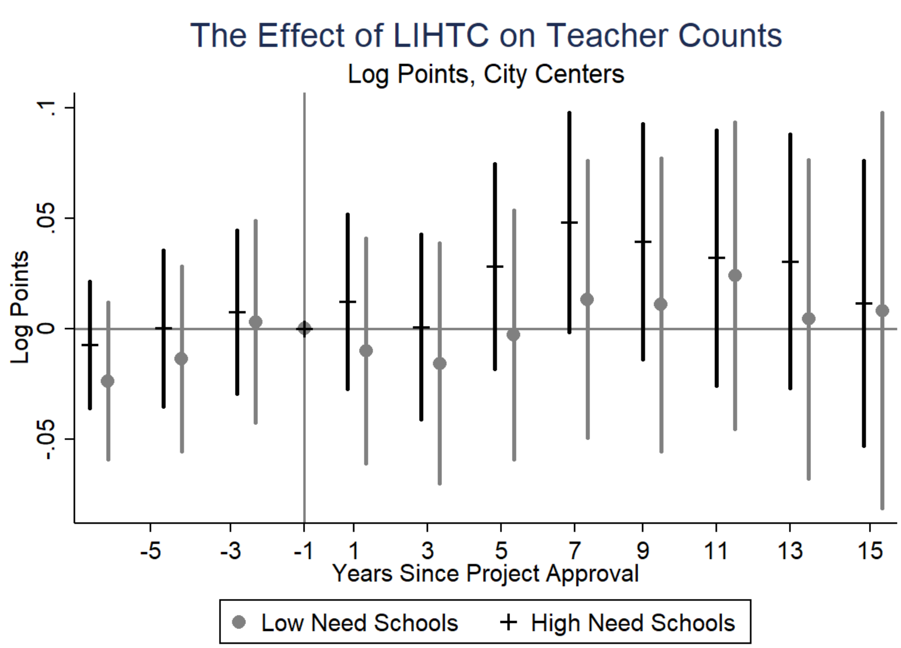
Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. High-need schools are categorized at the start of the panel and have over 50% of students that qualify for free or reduced lunch. The remainder of schools are categorized as low-need. In both panels the outcome is high-need student share. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city centers, and small city centers. 95% confidence intervals are shown, with observations clustered at the school level.

Figure A6: City Center Teacher Shocks

(a)



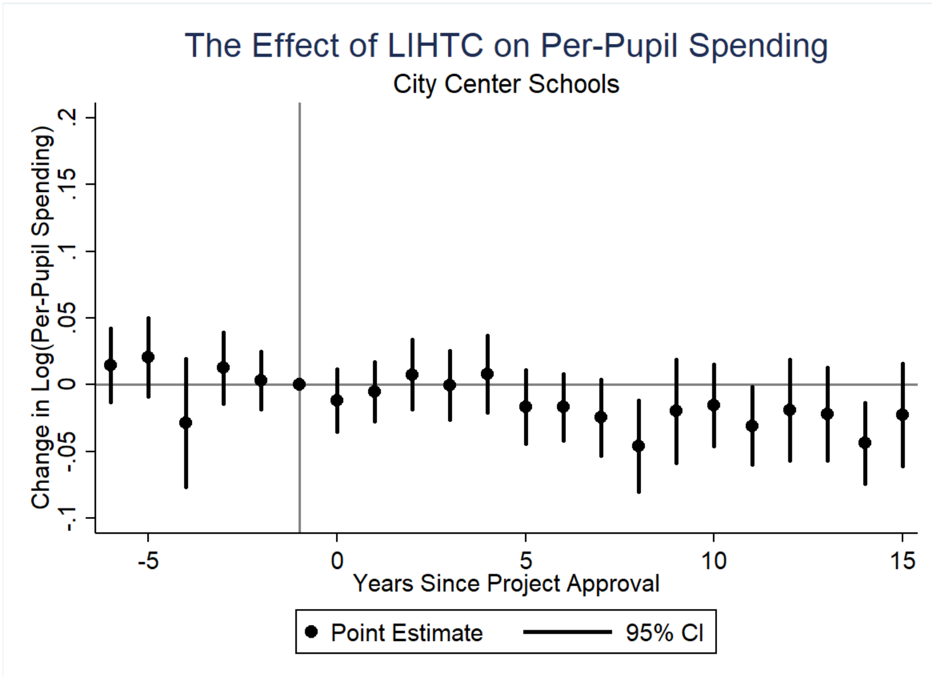
(b)



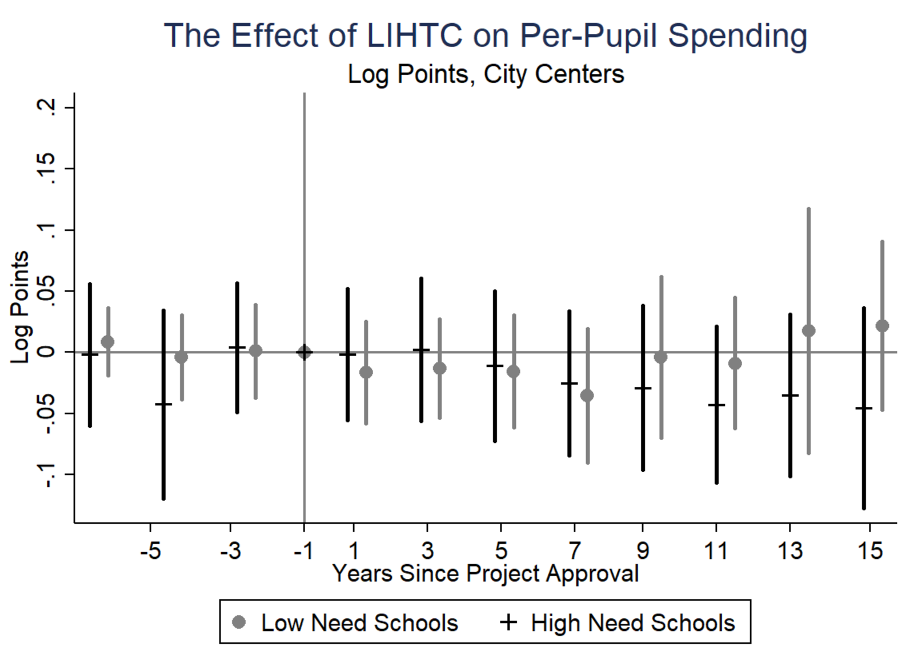
Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. High-need schools are categorized at the start of the panel and have over 50% of students that qualify for free or reduced lunch. The remainder of schools are categorized as low-need. In both panels the outcome is the count of full time equivalent (FTE) teachers in logs. Full time equivalent include full time teachers and part time teachers as a fraction of full time working hours. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city centers and small city centers. 95% confidence intervals are shown, with observations clustered at the school level.

Figure A7: City Center Spending Shocks

(a)



(b)

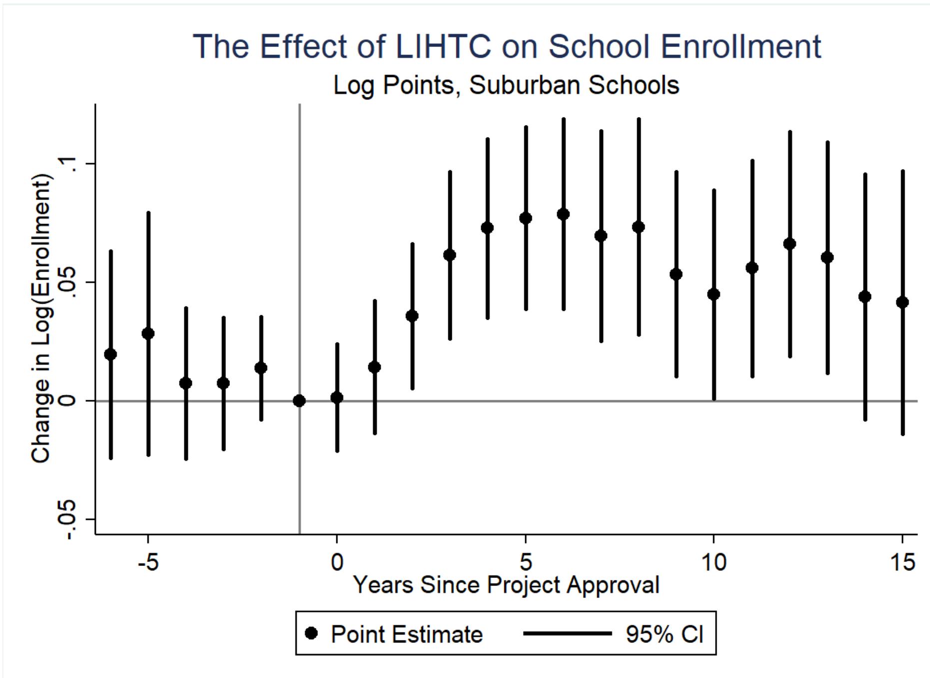


Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. High-need schools are categorized at the start of the panel and have over 50% of students that qualify for free or reduced lunch. In both panels the outcome is per-pupil spending logs. Per-pupil spending is defined as the total expenditure in a given year divided by school enrollment in the same year. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city centers and small city centers. 95% confidence intervals are shown, with observations clustered at the school level.

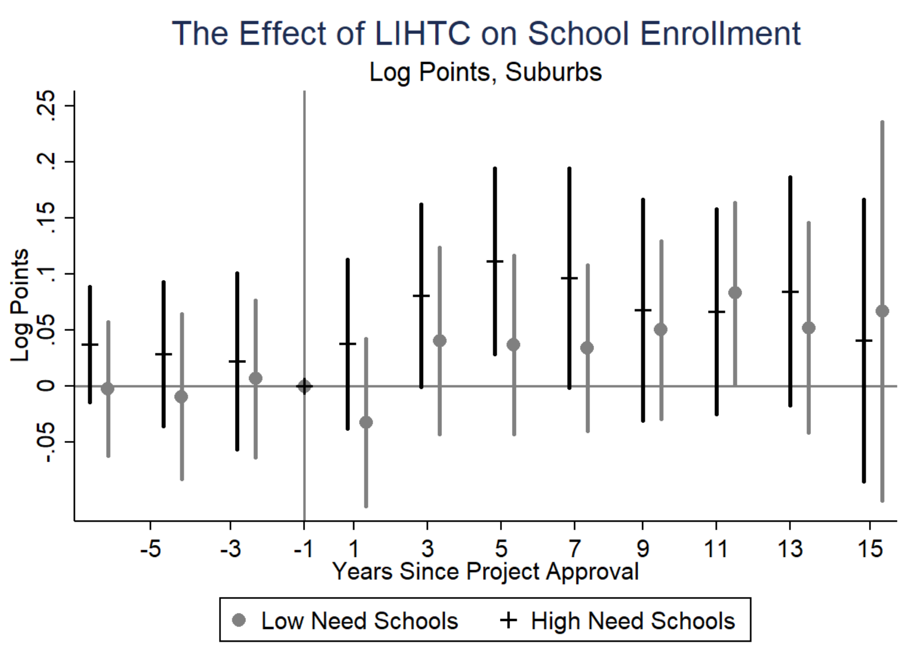
Analysis of Suburban Schools

Figure A8: Suburban Enrollment Shocks

(a)



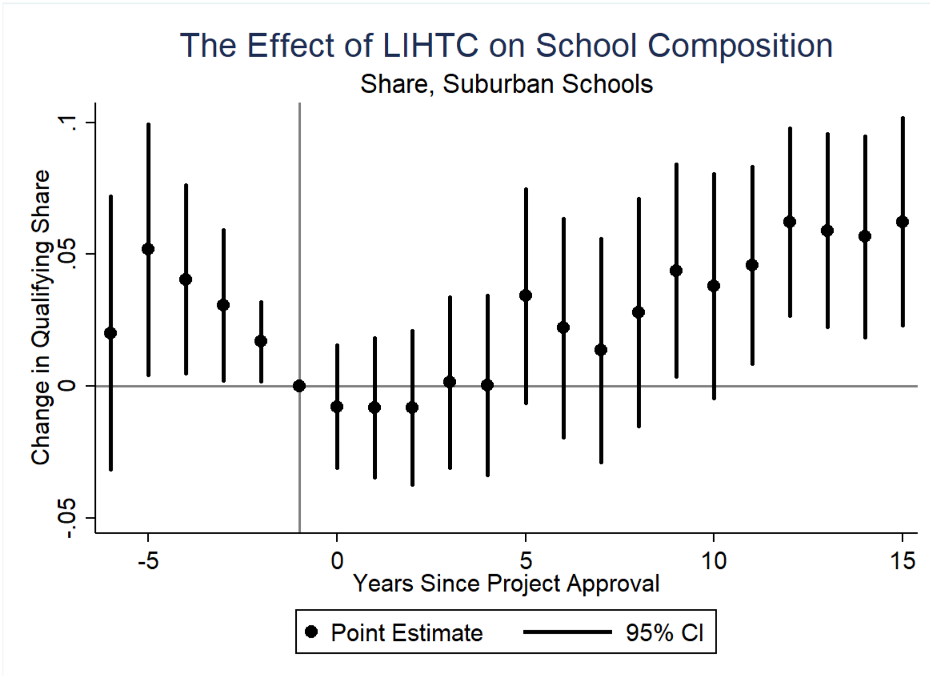
(b)



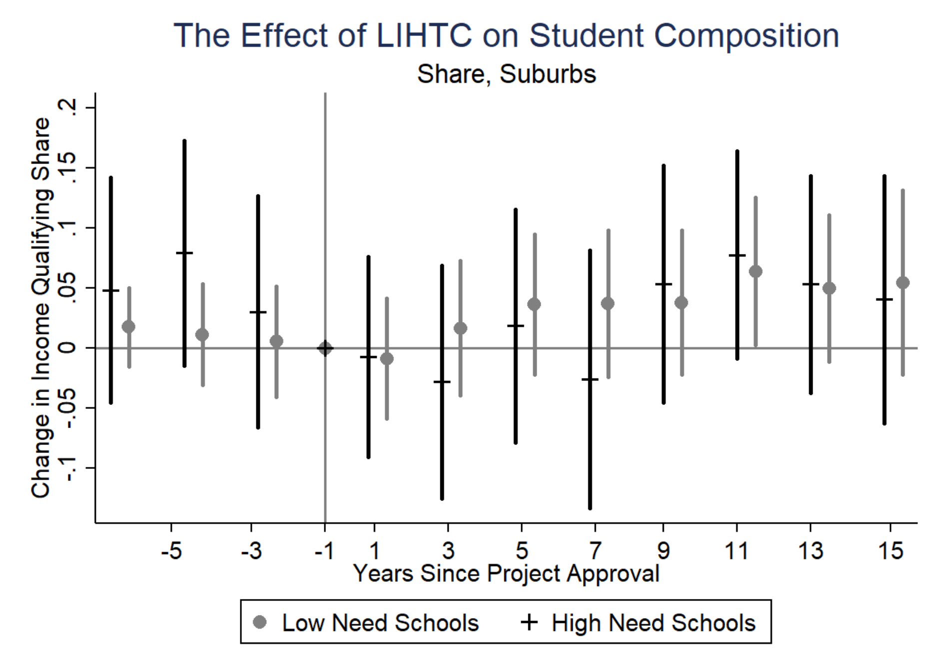
Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. High-need schools are categorized at the start of the panel and have over 50% of students that qualify for free or reduced lunch. The remainder of schools are categorized as low-need. In the upper panel the outcome is enrollment count in levels, and in the lower panel the outcome is enrollment count in logs. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city suburbs and small city suburbs 95% confidence intervals are shown, with observations clustered at the school level.

Figure A9: Suburban Composition Shocks

(a)



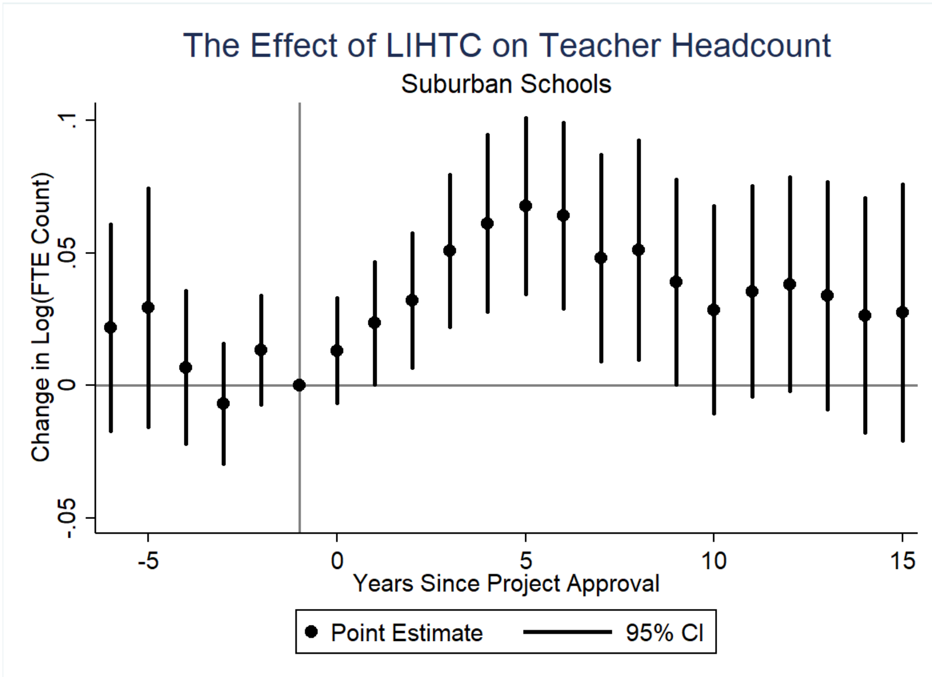
(b)



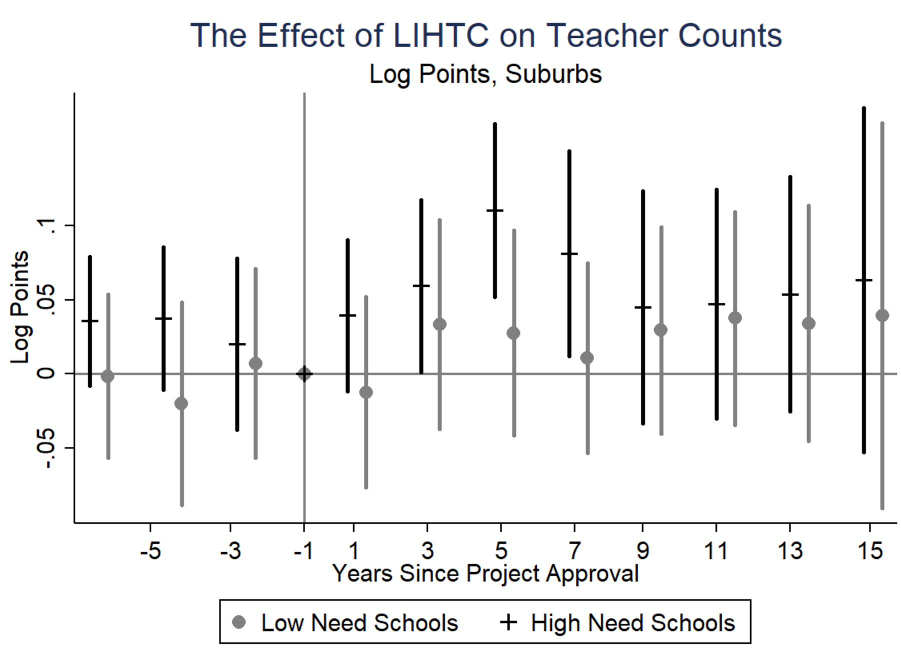
Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. High-need schools are categorized at the start of the panel and have over 50% of students that qualify for free or reduced lunch. The remainder of schools are categorized as low-need. In both panels the outcome is high-need student share. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city suburbs, and small city suburbs. 95% confidence intervals are shown, with observations clustered at the school level.

Figure A10: Suburban FTE Shocks

(a)



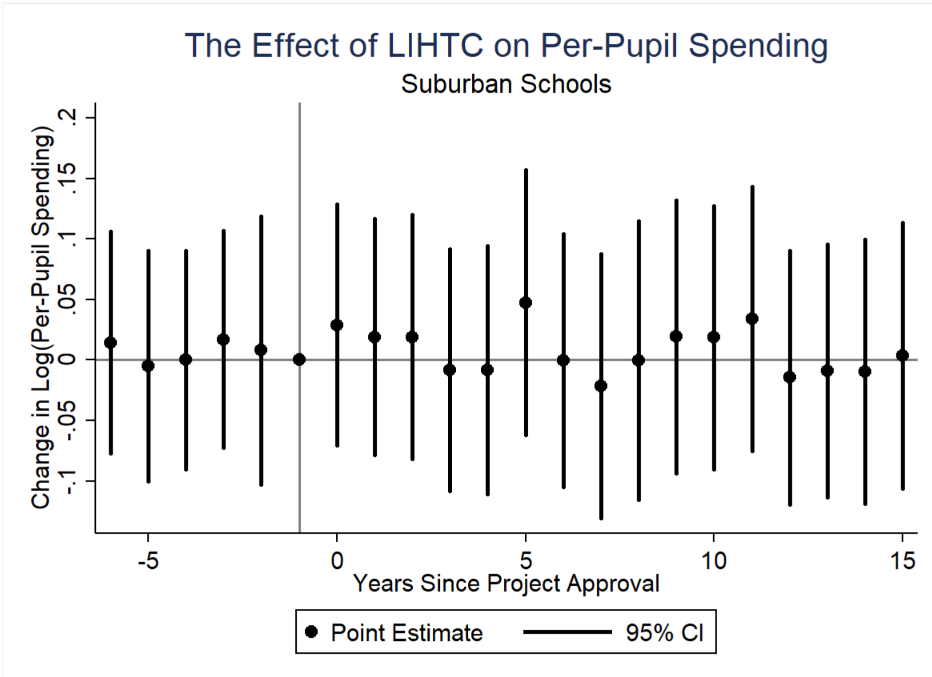
(b)



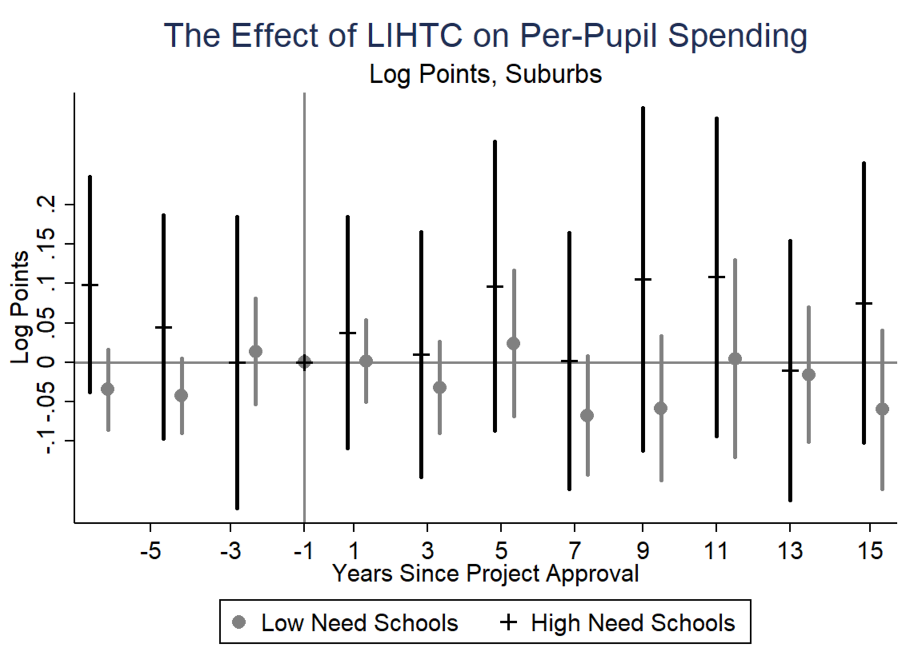
Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. High-need schools are categorized at the start of the panel and have over 50% of students that qualify for free or reduced lunch. The remainder of schools are categorized as low-need. In both panels the outcome is the count of full time equivalent (FTE) teachers in logs. Full time equivalent include full time teachers and part time teachers as a fraction of full time working hours. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city suburbs and small city suburbs. 95% confidence intervals are shown, with observations clustered at the school level.

Figure A11: Suburban Spending Shocks

(a)



(b)

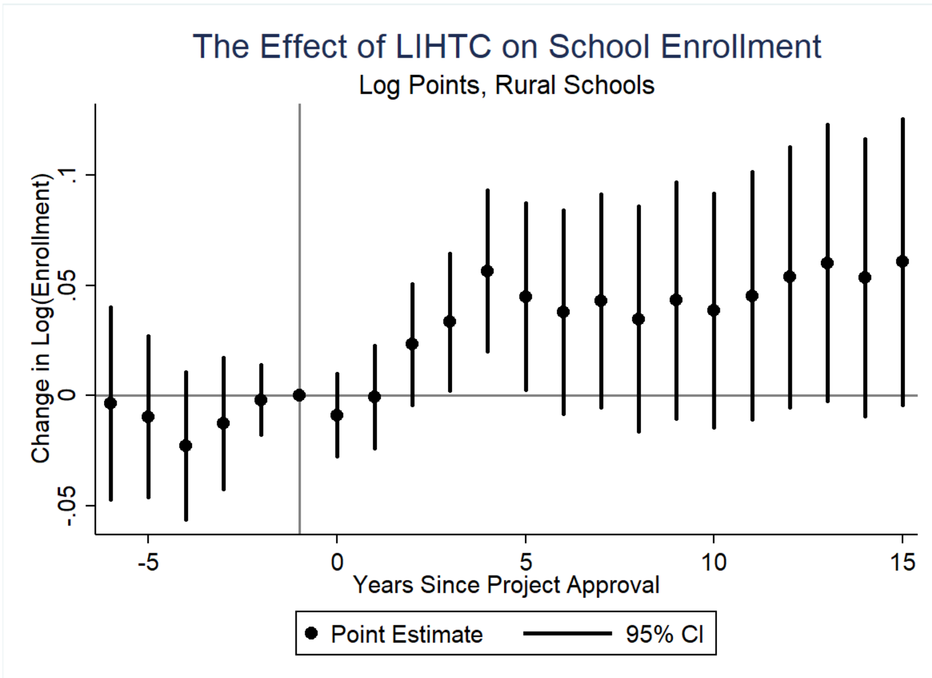


Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. High-need schools are categorized at the start of the panel and have over 50% of students that qualify for free or reduced lunch. In both panels the outcome is per-pupil spending logs. Per-pupil spending is defined as the total expenditure in a given year divided by school enrollment in the same year. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are big city suburbs and small city suburbs. 95% confidence intervals are shown, with observations clustered at the school level.

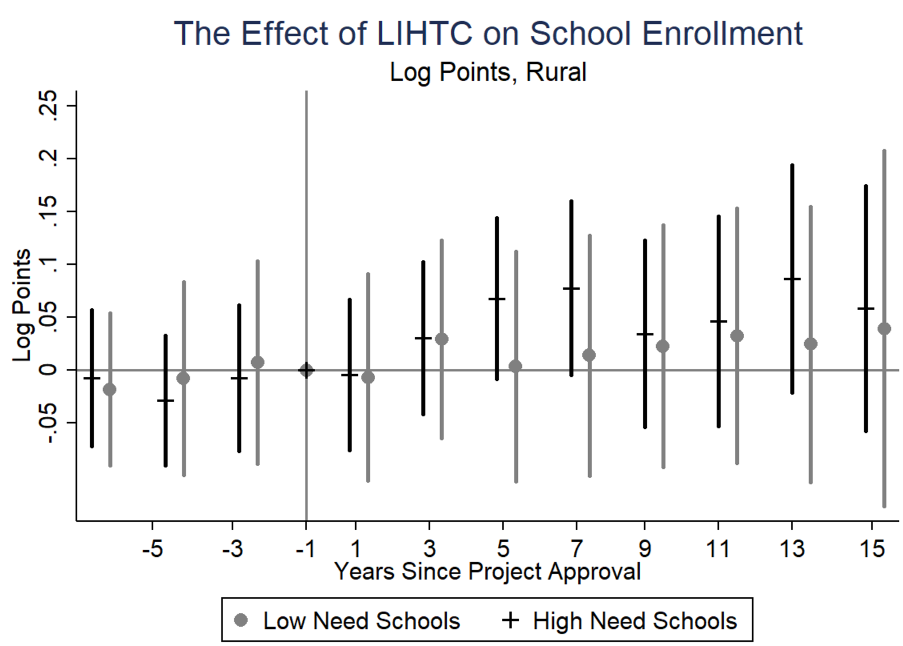
Analysis of Rural Schools

Figure A12: Rural Enrollment Shocks

(a)



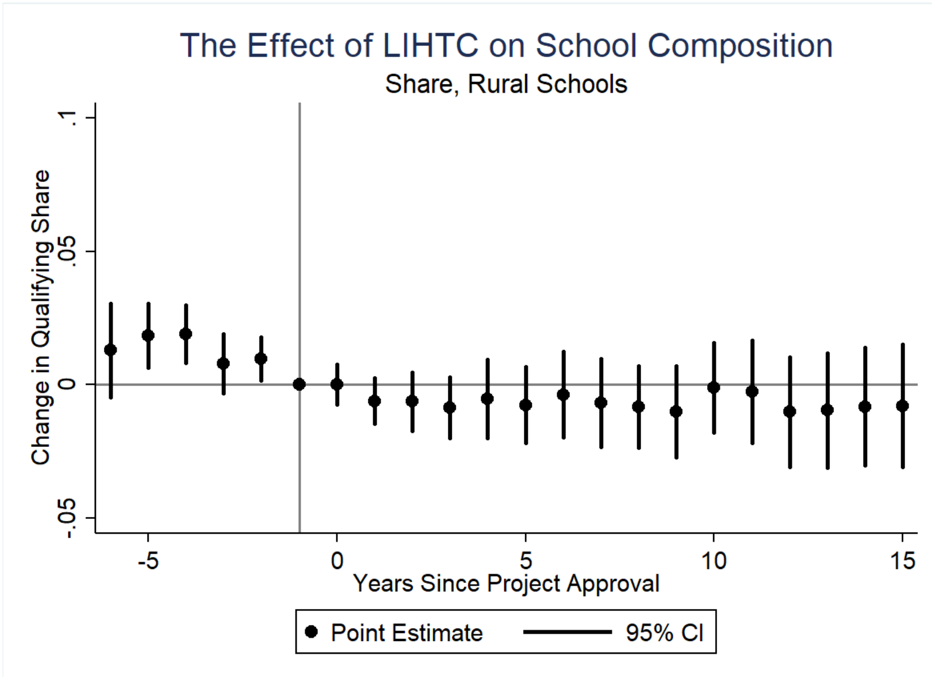
(b)



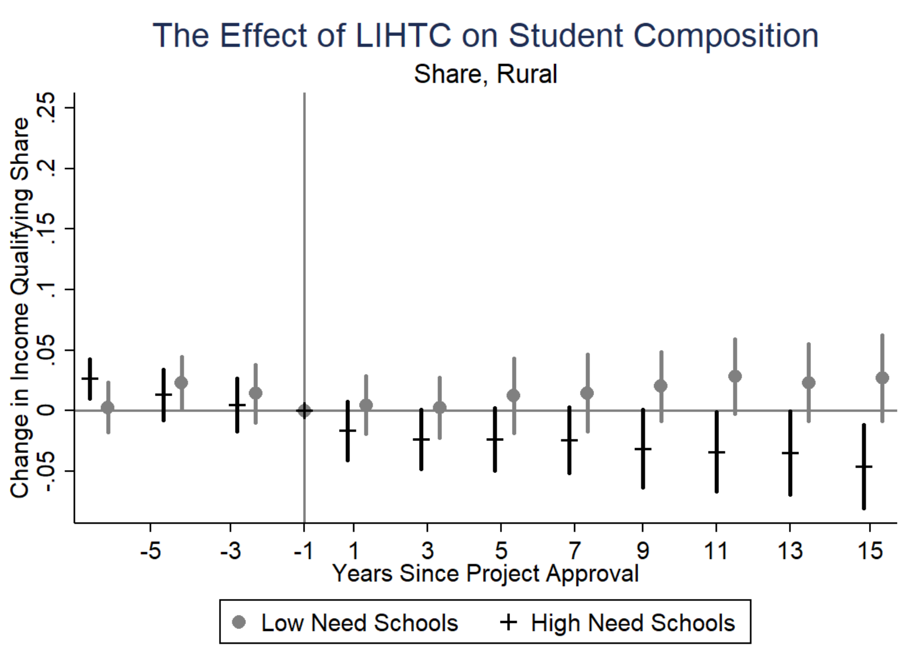
Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. High-need schools are categorized at the start of the panel and have over 50% of students that qualify for free or reduced lunch. The remainder of schools are categorized as low-need. In the upper panel the outcome is enrollment count in levels, and in the lower panel the outcome is enrollment count in logs. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are large towns, small towns, and rural remote areas. 95% confidence intervals are shown, with observations clustered at the school level.

Figure A13: Rural Composition Shocks

(a)



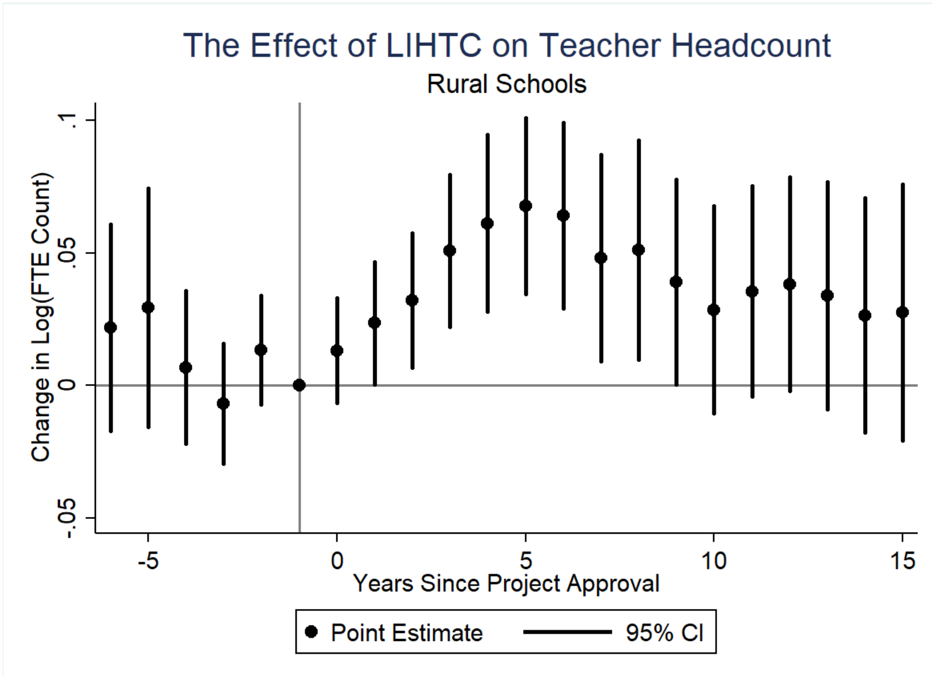
(b)



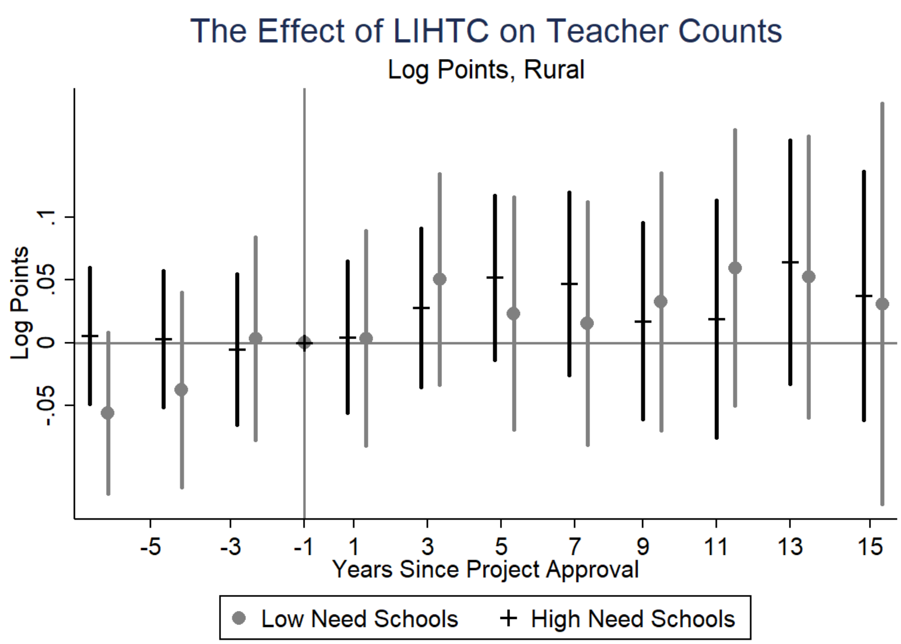
Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. High-need schools are categorized at the start of the panel and have over 50% of students that qualify for free or reduced lunch. The remainder of schools are categorized as low-need. In both panels the outcome is high-need student share. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are large towns, small towns, and remote rural areas. 95% confidence intervals are shown, with observations clustered at the school level.

Figure A14: Rural FTE Shocks

(a)



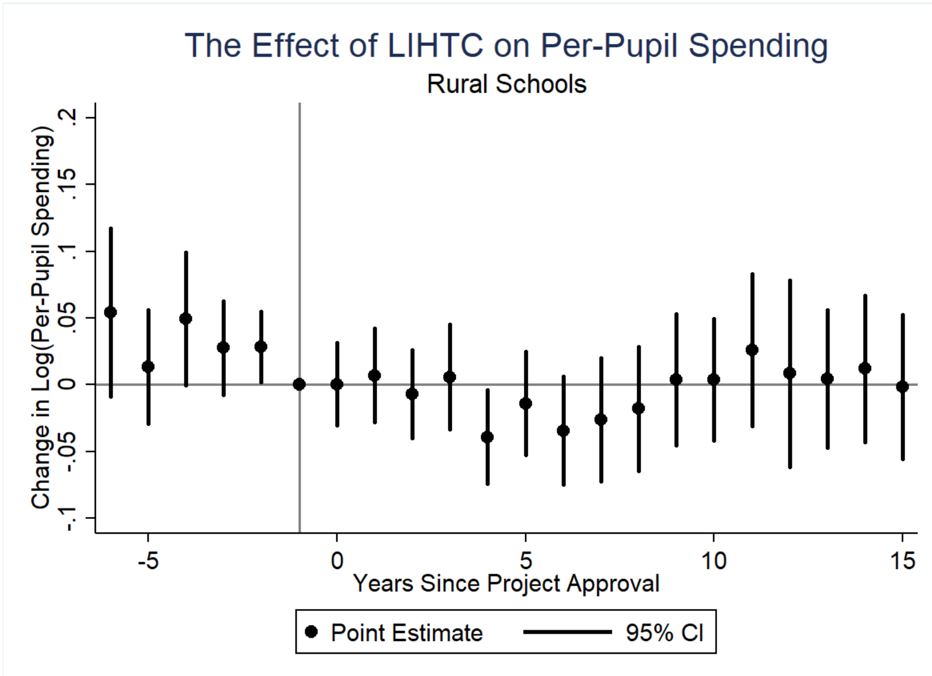
(b)



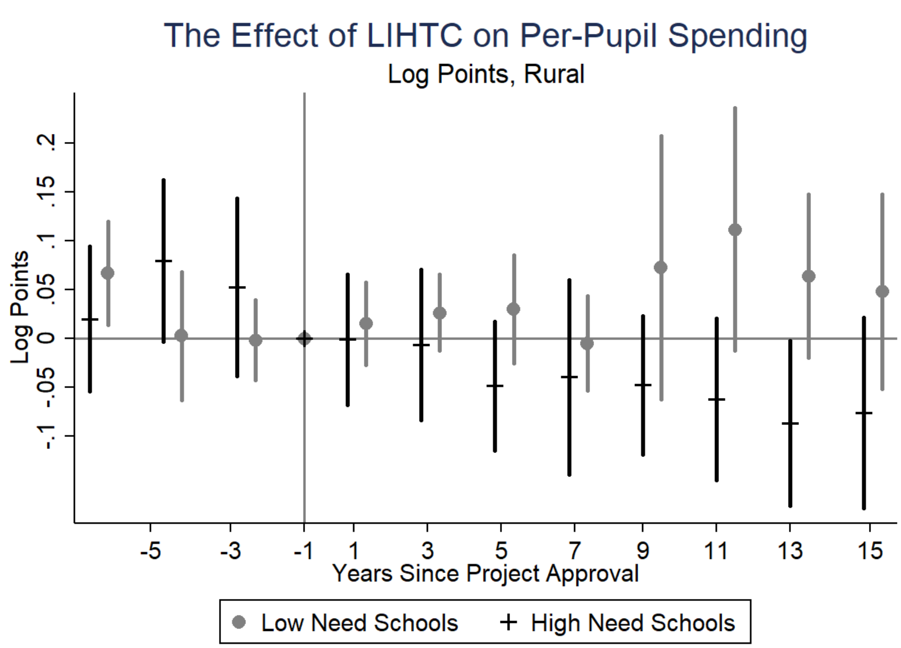
Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. High-need schools are categorized at the start of the panel and have over 50% of students that qualify for free or reduced lunch. The remainder of schools are categorized as low-need. In both panels the outcome is the count of full time equivalent (FTE) teachers in logs. Full time equivalent include full time teachers and part time teachers as a fraction of full time working hours. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are large towns, small towns, and rural remote areas. 95% confidence intervals are shown, with observations clustered at the school level.

Figure A15: Rural Spending Shocks

(a)



(b)



Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 1 for the outcome variable of interest. High-need schools are categorized at the start of the panel and have over 50% of students that qualify for free or reduced lunch. In both panels the outcome is per-pupil spending logs. Per-pupil spending is defined as the total expenditure in a given year divided by school enrollment in the same year. Each regression includes school and year fixed effects along with linear time trends interacted with fixed indicators for refined category of locale. The locales are large towns, small towns, and rural remote areas. 95% confidence intervals are shown, with observations clustered at the school level.

Table A1: Within District Regression: City Center Schools

	(1) logspend	(2) logspend	(3) logspend	(4) logspend	(5) logspend	(6) logspend
$\widehat{\alpha}_1$	0.326**	0.504***	0.320	0.555***	0.380*	0.294*
	(0.110)	(0.079)	(0.160)	(0.146)	(0.165)	(0.141)
$\widehat{\alpha}_2$	-0.213*	-0.481***	-0.058	-0.265	-0.186	-0.053
	(0.092)	(0.080)	(0.121)	(0.136)	(0.119)	(0.108)
N	28741.000	1225.000	1325.000	1411.000	1411.000	1411.000
r2	0.341	0.364	0.163	0.425	0.358	0.338

Notes: Estimates from the non-linear regression Model 3 are presented for the policy parameters. The dependent variable is log(per-pupil spending) and the independent variable is the share of high-need students. $\widehat{alpha}_1$ is the marginal increase and $\widehat{alpha}_2$ models the non-linear effect. As standard in the OLS case where the non-linear effect is negative, the turning point $\tilde{F}_t$ is indicative of the threshold high-need student share in which a marginal increase would cause per-pupil spending to decline. Each model includes district fixed effects and controls for the share of Latino students and the school enrollment size.

Table A2: Within District Regression: Suburban Schools

	(1) logspend	(2) logspend	(3) logspend	(4) logspend	(5) logspend	(6) logspend
$\widehat{\alpha}_1$	0.310***	0.524***	0.939**	0.470***	0.473***	0.461***
	(0.064)	(0.126)	(0.310)	(0.130)	(0.111)	(0.113)
$\widehat{\alpha}_2$	-0.211**	-0.559***	-0.553*	-0.191	-0.333**	-0.175
	(0.078)	(0.146)	(0.265)	(0.100)	(0.104)	(0.130)
N	17856.000	681.000	806.000	880.000	880.000	880.000
r2	0.264	0.482	0.125	0.438	0.374	0.498

Notes: Estimates from the non-linear regression Model 3 are presented for the policy parameters. The dependent variable is log(per-pupil spending) and the independent variable is the share of high-need students. $\widehat{alpha}_1$ is the marginal increase and $\widehat{alpha}_2$ models the non-linear effect. As standard in the OLS case where the non-linear effect is negative, the turning point $\tilde{F}_t$ is indicative of the threshold high-need student share in which a marginal increase would cause per-pupil spending to decline. Each model includes district fixed effects and controls for the share of Latino students and the school enrollment size.

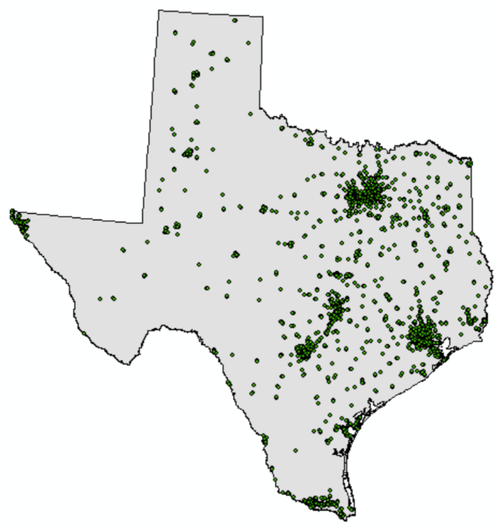
Table A3: Within District Regression: Rural Schools

	(1) logspend	(2) logspend	(3) logspend	(4) logspend	(5) logspend	(6) logspend
$\widehat{\alpha}_1$	0.464	0.100	1.024***	1.343***	1.138**	1.184***
	(0.256)	(0.250)	(0.284)	(0.272)	(0.352)	(0.262)
$\widehat{\alpha}_2$	-0.487*	-0.706**	-0.816**	-1.316***	-1.059**	-0.987***
	(0.236)	(0.242)	(0.308)	(0.262)	(0.332)	(0.253)
N	14526.000	487.000	549.000	579.000	579.000	579.000
r2	0.363	0.781	0.700	0.683	0.674	0.623

Notes: Estimates from the non-linear regression Model 3 are presented for the policy parameters. The dependent variable is log(per-pupil spending) and the independent variable is the share of high-need students. $\widehat{alpha}_1$ is the marginal increase and $\widehat{alpha}_2$ models the non-linear effect. As standard in the OLS case where the non-linear effect is negative, the turning point $\tilde{F}_t$ is indicative of the threshold high-need student share in which a marginal increase would cause per-pupil spending to decline. Each model includes district fixed effects and controls for the share of Latino students and the school enrollment size.

B Data Appendix

Figure B1: LIHTC in Texas



Notes: Each dot marks the location of a rental housing development under LIHTC program oversight. Source: Texas Department of Housing and Community Affairs.

B.1 Assembling the Panel

In this section I provide detail of the data sources behind the school and housing panel data. The first piece of the data is the school level finance data provided publicly by the Texas Education Agency (TEA).[14] TEA provides total expenditure data and total spending for instruction dating back to 2000, along with enrollment counts and the racial composition of each school. I balance the panel for schools in 2000-2020 based on the TEA finance data.

Additional data describing teacher counts and the count of students income qualifying for lunch subsidies are provided by National Center for Education Statistics table generator for the years 2000-2020 at the campus level. The two sources have different school identifiers, so the additional data is merged to the finance data using a crosswalk of school IDs pro-

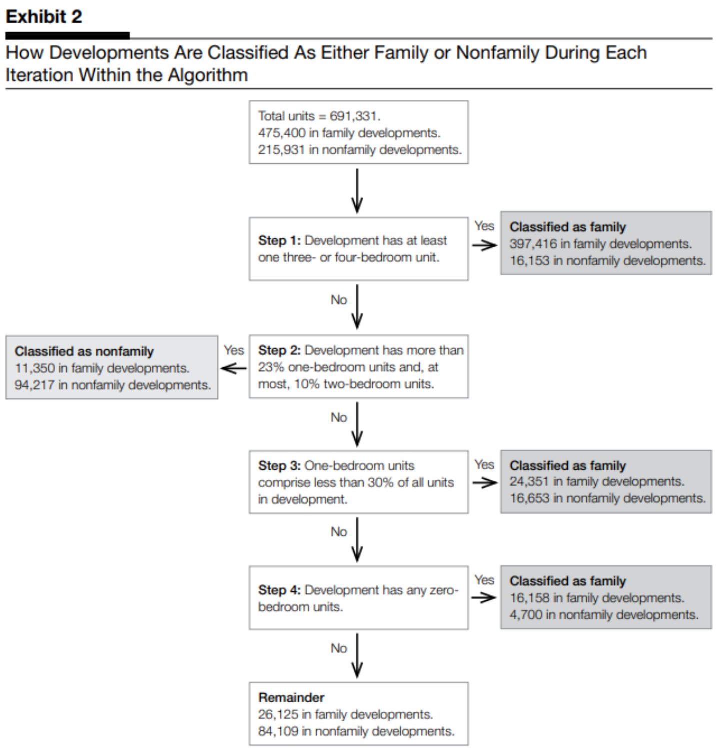
[14]The TEA managed *Texas Academic Performance Reporting* system has public databases available back to the 2013 school year. The *Academic Excellence Indicator System* housed the data prior to 2013. The data prior to 2004 is not listed on the Academic Excellence Indicator System website but remains available via the archive. Navigating to the 2004 webpage then adjusting the url with the desired year will take you to the pre-2004 data. A unique campus identifier is consistent for schools across both systems.

vided by TEA via email request. The sample is restricted to non-charter schools and those without open attendance boundaries. My analysis is limited to schools with available spatial data for the school attendance zones, which comes from The School Attendance Boundary Information System (SABINS) project for the 2009-2010 school year. The SABINS project was carried out by researchers at University of Minnesota, William and Mary, and Census IPUMS and was discontinued after the 2009-2010 school year.

I aggregate LIHTC data to school zones by first mapping each individual LIHTC complex to a census block using shapefiles loaded to ArcGIS. The LIHTC data from Texas Department of Housing and Community Affairs (TDHCA) is coded with latitude and longitude data that I use to map each LIHTC complex to a census block. Each housing observation is then merged to a school zone to be aggregated by year, using a SABINS census block to school attendance zone crosswalk publicly available through NHGIS. To facilitate identification in my event study design, I limit the sample to those schools in which no LIHTC was assigned prior to the start of the sample. This restriction, combined with the non-charter non-open boundaries restriction leaves me with 3,925 schools across 688 districts.

Of the 2901 LIHTCevents in the sample, I must classify each as family, senior, or other LIHTC types. To do this I follow the procedure below, obtain from Atkins and O'Regan (2014). 297 LIHTC observations are missing data for the quantity of units in the complex. For those observations I fill the data using the zip-code median for the entire sample. From the algorithm, 783 are classified as targeting senior aged population groups and used for placebo tests. The remainder are taken as family targeted LIHTC.

Figure B2: Denoting LIHTC as Family or Senior Housing

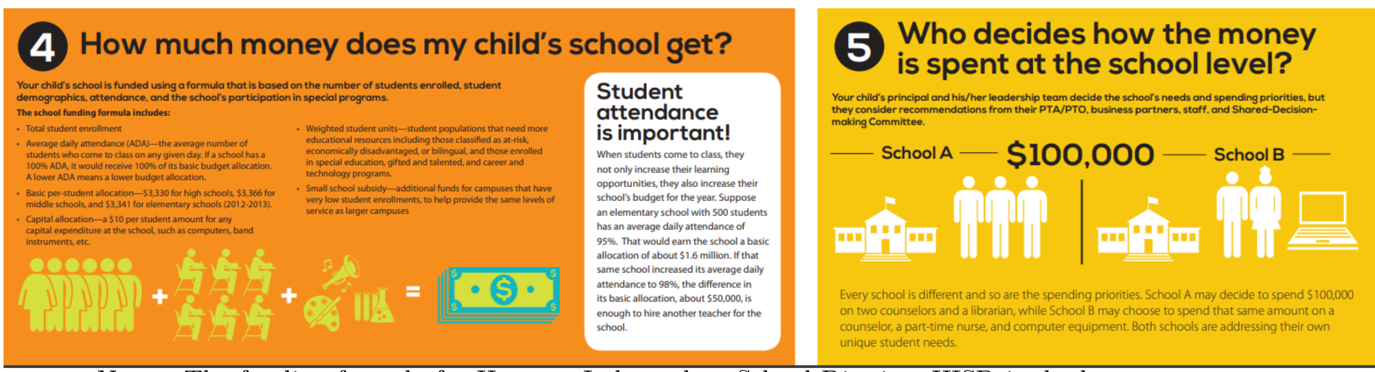


Notes: Classification of LIHTC units by type. Source: Atkins and O'Regan (2014)

B.2 Texas Funding Formulas

As with many states, although property tax rates are school district specific, the revenues themselves are "rolled" to the state level for redistribution in the name of base funding equalization. States themselves have funding formulas that assign dollar amounts to districts based on a complex funding formula. School districts in Texas themselves have a great deal of fiscal authority, charged with allocative decisions across schools in the district. District funding formulas are often presented to be much simpler in nature, and the majority of districts in Texas are transparent about underlying school funding formulas. An example of the district funding formula for Houstin ISD, the largest in Texas, is shown in Figure B3.

Figure B3: An Example of the District to School Allocation Process



Notes: The funding formula for Houston Independent School District. HISD is the largest public school system in Texas and one of the ten largest in the United States. Source: HISD Budget Basics. https://www.houstonisd.org/cms/lib2/TX01001591/Centricity/Domain/22921/Budget_BasicsRd2_rev022113b.pdf