Neighborhood Integration and Public School Spending *

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Abstract

There is well-documented income sorting across neighborhoods within defined administrative boundaries like school districts. Using campus level finance and demographic data for 3,500 K-12 schools in Texas, I show that income heterogeneity across neighborhoods can be mapped to per-pupil spending variation across schools within a district. I define this function as the school spending curve, and argue that the shape of the curve is vital for predicting within-school spending responses to neighborhood income shifts over time. To test this hypothesis I exploit spatial heterogeneity in the income composition of neighborhoods receiving affordable housing, and plausibly exogenous timing of construction approval to construct school enrollment and income composition shocks. I find that policy changes determining the shape of the Texas spending curve over time are soley responsible for preventing sharp declines in per-pupil spending following the construction of new affordable housing. My counterfactual exercise illustrates that benefits from increasingly progressive education policy in Texas appears to be captured by upper-middle income schools receiving new affordable housing development.

JEL Classification: H7, R31, R23

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1 Introduction

Residential income segregation is a persistent characteristic of metropolitan areas and small towns across the world (Tammaru et al. 2015, Intrator et al. 2016, Darity Jr et al. 2015, Reardon and Bischoff 2011). Cities, counties and local parishes tend to offer a vast array of public services, with subordinate precincts or zones often covering smaller neighborhood areas.[1] Core public finance theories predict sorting at the smallest geographic level in which public goods and neighborhood composition differ (Tiebout (1956), Samuelson (1954), Schelling (1971)), and economists have grown interested in the empirical relationship between residential segregation and spending for public services (Boustan and Margo 2013, Cox et al. 2022). This study overcomes public expenditure and neighborhood income data limitations to estimate public school spending curves, a function mapping within district variation in neighborhood income to per-pupil spending at the school level. In theory, an analogous curve exists for all decentralized public services with intrajurisdictional variation in per-capita spending and neighborhood income.

In particular I am interested in the predictive power of school spending curves to understand how the average school will respond to exogenous change in student income composition across time. Contemporary education policy has a growing interest in within-district variation in per-pupil spending as data advancements allow researchers to consider a more nuanced analysis of school spending progressivity (Blagg et al. 2022, Chingos and Blagg 2017). The public expenditure data in this study is a campus-level panel describing expenditures, enrollment and income composition for a sample of 3,484 K-12 schools in Texas from 2000-2020. To estimate the school spending curves, which I presume change over time, I model the within-district relationship between per-pupil expenditure and free-lunch qualifying enrollment share separately each year. I find the spending curve takes an inverse U-shaped spending curve in 2000, but per-pupil spending is strictly increasing in the share

[1] For example a county fire department may have fifteen wards, or a city police department may have 10 precincts that serve neighborhoods varying by income.

of income qualifying students by the year 2020.

I then ask if the shape of the spending curve explains the per-pupil spending response to an exogenous shock to local neighborhood income. For identification I map rental housing made available through the Low Income Housing Tax Credit (LIHTC) program during the sample period to school attendance zone boundaries in Texas. Created in 1987 and funded by the Internal Revenue Service, an estimated 3.4 million rental units across 50,567 developments have been made available under the LIHTC program umbrella. 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, Diamond and McQuade 2019), and a variety of neighborhood amenities that reshape local economies through price demographic changes (Baum-Snow and Marion 2009, Freedman and Owens 2011, Freedman and McGavock 2015). Using an event-study model that takes the timing of LIHTC project approval as the event year, I find statistically significant increases to enrollment (4% or 66 students) and the fraction of students receiving free-lunch (2.5 basis points or 33 students) peaking at 7 years following LIHTC approval.

Since the spending curve is changing over time, and the event-study estimates within-school changes over time, the LIHTC induced effect on per-pupil spending is likely to be attenuated as the unobserved policy environment is changing in the background. Indeed, in the naive event-study setup I find a null effect of LIHTC timing on per-pupil spending despite the free-lunch share increasing in an identifable way. Since LIHTC developments are built in neighborhoods across the entire income distribution, I explore heterogeneity in this result and find only moderate per-pupil spending increases following LIHTC at schools with a low pre-period share of free-lunch students.

To address the bias caused by changes to spending curves over time I ask the following counterfactual. If the shape of the spending curve remained fixed from 2000 through the duration of the panel, how would per-pupil spending respond to LIHTC induced neighborhood income shifts? My approach to this what-if question is to reconstruct a real per-pupil spending measure for each school by year data point based on the 2000 spending curve and observed school free-lunch share. This measure deflates per-pupil spending in each school by year observation by holding constant changes to the school spending curve. Further differencing reconstructed (real) spending from observed (nominal) spending yields the policy driven per-pupil spending inflation over time. Event-study estimates predict real spending to decrease by 40% in the 10 years following LIHTC had the policy environment been held constant. For context, I find that the reason nominal spending does not decrease following LIHTC is entirely accounted for by the fact that the school spending curve in Texas has become more progressive over time.

From the inverse U-shape of the 2000 spending curve I identify the threshold free-lunch share in which a marginal increase would cause per-pupil spending to predictably decline. Upper-income schools are those below the threshold, and I find that the policy effects are almost wholly contained to schools in this group. The result is partially explained by heterogeneity in the composition shock following LIHTC. It is also likely that schools on the cusp of the threshold in 2000 were likely not in danger of spending declines in future years as the spending curve became strictly increasing in free-lunch share.

Prior to a wave of state finance reforms across the US, the legacy of income segregation and public school finance was that of unequal spending and student outcomes. During this period a decentralized system of revenues and expenditures yielded inequality in spending and student outcomes. However, over half of US states have implemented reforms in the name of district finance equalization or equity. Although it has long been a point of contention, recent empirical studies point to exogenous increases in per-pupil spending as responsible better student outcomes (Hoxby 2001, Jackson et al. 2016, Lafortune et al. 2018). Further, there is robust empirical evidence that households are willing to pay for higher school spending and better quality schools (Black 1999, Barrow and Rouse 2004, Clapp et al. 2008, Cellini et al. 2010, Bayer et al. 2020a).

A second body of work attempts to disentangle household preferences for school and neighborhood composition from school spending and quality (Bayer et al. 2007, Caetano and Maheshri 2017, and Caetano and Maheshri 2020). From this literature one could surmise revealed preferences against low-income neighbors reflect either personal prejudice or sorting on unobserved amenities correlated with neighborhood income. When we consider that local governments have a portfolio of options that encourage low-income integration into high amenity neighborhoods, in practice each is met with contentious opposition. Affordable housing is no different, and while not directly deployed to integrate schools the sheer scope of most developments exceeds 150 units. The enrollment and composition results of this paper signal a material shock of LIHTC to schools.

Di and Murdoch (2013) put forth evidence that test scores and school quality do not change after the construction of LIHTC, and the naive null results of this paper superficially align with this conclusion. The nuance in how gradual shifts in the spending curve over time to produce this result broadens our understanding of the implications of local income segregation. A similar exercise of this paper can be carried out to understand local spending curves for other vital public services, and this body of knowledge can help us fully interpret welfare differences for residents of different neighborhoods. The core findings of this paper have a central theme. Absent progressive policymaking to reshape the school spending curve in Texas, affordable housing changes neighborhoods in a way would have caused per-pupil spending declines. This is despite the fact that income qualifying students require higher levels of per-pupil spending to obtain peer-equivalent educational outcomes.

The remainder of this paper builds this argument as follows. In Section 2.3 is a description of the Texas data used to estimate the main spending curves and LIHTC shocks in my analysis. In Section 3 I describe the research design in detail and estimate the shape of the spending curves for each school year. In section 4 I show the effects of LIHTC by providing visual evidence of the estimates from my event-study models. In Section 5 I outline a procedure to hold constant any changes in the spending curve that could bias my event-study results, then show how policy changes account for nearly the netire response of per-pupil spending to LIHTC shocks. I conclude the paper and summarize the policy implications in Section 6.

2 Data

2.1 School Data

The first major component of my data is a sample of K-12 schools at various grade levels in Texas from 2000-2020. The primary source of school level data is publicly available through the Texas Education Agency Academic Excellence System (2000-2012) and Academic Performance Reporting (2013-2020). The data is at the campus level, allowing me to exploit rich variation in school spending and student composition across neighborhoods within a school district. For each school I observe total spending, instructional spending, enrollment and racial demographics for annually beginning in 2000. Instructional spending is defined as activities that deal directly with the interaction between teachers and students. Salaries for teachers and classroom aides are included along with technology to deliver remote learning.[2] All expenditure values are deflated to the year 2015 and are expressed in per-pupil terms by simply dividing the the total by the enrollment each year.

The school-level data is augmented with teacher counts and counts of students receiving free or reduced lunch provided by the National Center of Education Statistics. Throughout the analysis of this paper I use the fraction of students receiving free or reduced lunch as a measure of low-income residents within the school attendance boundary. The benefit of this measure is the annual frequency which allows me to exploit the full 21 years of school data and the timing affordable housing development during that period within each school attendance boundary. While the measure is not a perfect representation of neighborhood income, it is an empirical question as to if school age-residents of LIHTC attend the geographically zoned school or bused to other schools in the same district. How LIHTC changes the student

[2] For a full classification of instructional expenses, see Appendix Figure B2.

income mix and affects school spending is the focus of this paper.

2.2 LIHTC Data

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 made available in each complex, the latitude and longitude of each location, and if the development serves a specific target population.[3] 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 a map of Texas census blocks.[4] After assigning the appropriate census block to each LIHTC site, I utilize a publicly available file that matches census block to school attendance zones across the US.[5] With each housing development matched to a school zone, I aggregate annual LIHTC activity at the school level by year of project approval. The location of LIHTC development during my sample period is shown in Figure 1. To outline the variation in LIHTC size and scope, I summarize the exposure to LIHTC in Section 2.3.

2.3 Sample Data Descriptives

The final sample is restricted to non-charter, non-open enrollment schools with available attendance zone boundary information. I also exclude any schools that experienced LIHTC construction prior to the year 2000.[6] This yields a panel of 3,923 schools in Texas from 2000 to 2020. 2,938 schools in the sample (75%) are elementary or middle schools, and the remainder are high-schools.[7] 838 of the schools in the sample received at least one LIHTC

[3]Target populations include senior housing, and housing for individuals with developmental needs. I also observe the nominal dollar value of tax credits allocated for each project.

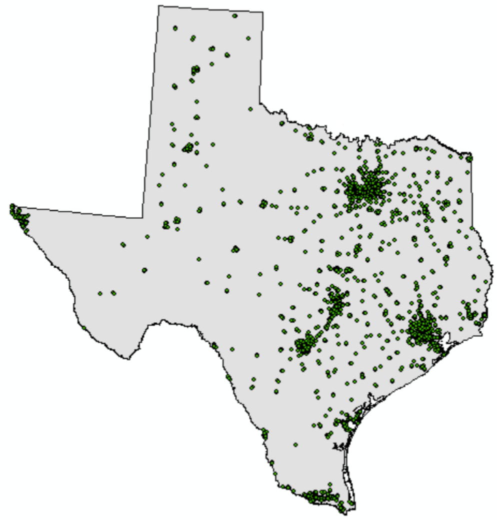
[4]The census block shapefile is provided by IPUMS National Historical Geographic Information System

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

[6]This sample restriction removes less than 40 schools.

[7]The elementary and middle school category are those where the maximum grade level is 8th grade. All others are categorized as high schools.

Figure 1: 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.

housing development within school attendance boundaries. Summary stats are reported in Table 1.

It is important to consider several facts about the sample in discussion of summary statistics. First, as a border state the Texas population is estimated to be 39% Latino in 2015, well above the national average of 17.9% in the same year. Second, over 72% of people in Texas reside in or around 6 cities, with the Dallas and Houston metro areas containing approximately half of the total population.[8] Column one of Table 1 describes all schools in the sample, column two includes schools that receive at least one LIHTC development, and column three includes the schools that never receive LIHTC housing. Given the propensity for LIHTC to be located in highly populated areas, enrollment and teacher counts at treated schools are higher than the state average. School size is the only distinguishable feature of the average treated school. Mean per-pupil spending is indistinguishable across neighborhood type. Class sizes, defined as the student to teacher ratio, are also consistent across columns 1-3.

Figure 2 lays out the variation in school spending across the distribution of school free-

[8]Source: Texas.gov. Texas Demographics 2015

Table 1: School Summary Statistics

	Full Sample	LIHTC ≥ 1	No LIHTC
Per-Pupil Spending	7,315.95	7,343.35	7,306.16
	(3445.7)	(3003.4)	(3590.6)
Free or Reduced Lunch Share	0.54	0.56	0.53
	(0.284)	(0.263)	(0.291)
Enrollment	1,032.36	1,208.69	969.31
	(781.9)	(832.9)	(753.0)
Full-time Teacher Equivalent	65.91	76.29	62.20
	(46.96)	(49.46)	(45.46)
Student-Teacher Ratio	15.30	15.56	15.20
	(3.139)	(2.077)	(3.435)
Fraction Latino Students	0.50	0.54	0.48
	(0.307)	(0.287)	(0.312)
Fraction Black Students	0.13	0.15	0.13
	(0.162)	(0.179)	(0.155)
Schools	3,926	838	3,088
Share of Total Sample		22.3%	78.7%

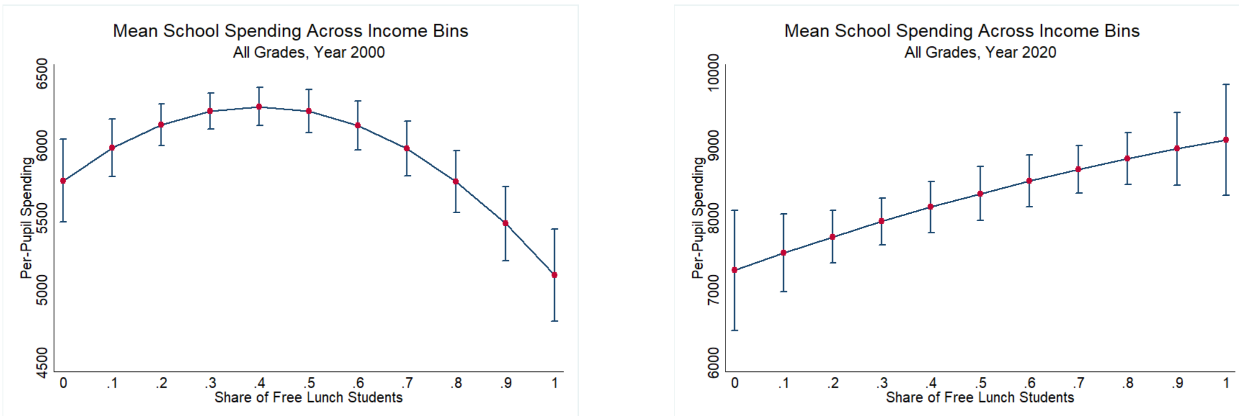
Notes: Summary statistics shown include all years of data 2000-2020 for a sample of 3,926 K-12 public schools in Texas. All dollar valued variables are inflation adjusted to the year 2015.

lunch share, with left panel displaying data for the year 2000 and the right panel displaying the year 2020. On the x-axis, schools are binned into equal-interval groups based on the continuous free-lunch share variable and mean per-pupil spending in each bin is plotted along with the standard error. The raw data plot in Figure 2 highlights distinct spending patterns across income that change over time. At the start of the sample the distribution is in concave, with per-pupil spending increasing up to about 40% free-lunch share and decreasing throughout the rest of the curve. By the end of the panel, per-pupil spending is linear and strictly increasing across the free-lunch share distribution.

If LIHTC plausibly increases the share of free-lunch students at a school, Figure 2 suggests that the school spending response will surely depend on the event year and will possibly depend on where the school lies in the free-lunch share distribution. Table 2 contains descriptive information on the variation in LIHTC timing and the free-lunch share in the year

Figure 2: Mean School Spending Across The Income Distribution

(a) (b)



Notes: Each panel plots the mean per-pupil spending level for a sample of 3,926 K-12 schools in Texas, binned into 10 equal-interval groups based on the share of students receiving free or reduced lunch. Shown with the mean for each bin is the standard error.

LITHC received project approval. The first row of Table 2 shows 2399 LIHTC developments approved in the 838 treated school zones. The approval year for the first LIHTC build in the school zone is considered the event year, and I document substantial heterogeneity in the free-lunch share at school receiving affordable housing. The bottom section of Table 2 illustrates that the majority of LIHTC development takes place in the middle of the free-lunch share distribution.

Table 2: LIHTC Treatment at Sample Schools

Year	**2003**	**2013**	**2020**
LIHTC Builds Since 2000	522	1544	2399
Free Lunch Composition 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: Row 1 reflects cumulative LIHTC developments in the sample districts from 2000-2020. The bottom pane contains counts of LIHTC builds approved in schools within each bin of the free-lunch share distribution. Descriptive statistics for the 838 schools with any LIHTC activity are presented in Table 1.

3 Research Design

In this section I outline a framework that links contemporary public school funding formulas to empirical estimation of the school spending curve. The spending curve traces out a within-district relationship between per-pupil spending and free-lunch share and school spending, and I allow for a non-linear spending curve. If the spending curve is indeed non-linear, it follows that for each year of data I can estimate the threshold level of free-lunch share in which a marginal increase in low-income students will predictably cause school spending to decrease. I use the empirical threshold to explore this hypothesis with quasi-experimental variation in based on the timing and spatial variation of LIHTC development during the sample period. Event-study results for heterogenous effects of LIHTC on school spending are presented in section 4. Lastly, I create counterfactual estimates of school spending each year holding the spending curve fixed to 2000, allowing me to explore exogenous policy changes as a mechanism for the school spending response to LIHTC shocks.

3.1 Institutional Details and State Funding Formulas

The headline for US public schools shows expenditures top a whopping $700 billion a year to educate over 50 million K-12 students(Hussar et al. 2020). Federal funding comprises the smallest share of revenue for a large majority of districts, and the reliance on state or local revenues for the largest share varies by state. In Texas, local property taxes provide 50% of school district revenue, 44% comes from the state, and the remaining 6% from the federal government.[9] School district reliance on property taxes has long been a point of contention, sparking a wave of state finance reforms to address disparities in potential district revenue based on property values (Hoxby 2001, Jackson et al. 2016,Lafortune et al. 2018, Bayer et al. 2020b).

Districts manage all tax revenues and allocate dollars for schools to spend. Still, there remains substantial variation in per-pupil spending and across schools in the same district

[9]2020 Texas Public School Finance Overview: Annual Report

(Roza et al. 2004, Owens et al. 2016, Chingos and Blagg 2017). The allocation process is idiosyncratic but can be described by a funding formula that considers enrollment counts, a base funding rate 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, each school receives a basic per-student allotment depending on grade level, adjusted upwards for students requiring more resources and downwards if average daily attendance decreases.[10] Once a school is in receipt of funds, the principal and school leadership have discretion over how the money is spent.

3.2 Conceptual Model of School Spending Curves

If we interpret ω as the per-pupil spending weight for the marginal free-lunch student, the weight will depend will depend on the shape of the school spending curve if the slope is not constant. The raw data plots do suggest the potential for the spending curve to be of quadratic form, which can be approximated with an OLS fixed effects model taking the form

$$Log(S_{ij}) = \alpha_0 + \alpha_1 F_{ij} + \alpha_2 F_{ij}^2 + X_{ij}\beta + \theta_j + \epsilon_{ij}, \tag{1}$$

where θ_j are district fixed effects, and X_{ij} is a vector of covariates that may explain within-district differences in S_{ij}. Conditional on X_{ij}, the weight is equivalent to the cross-sectional spending change in spending due to a marginal increase in F_{ij}, or

$$\widehat{\omega} = \widehat{\alpha}_1 + 2\widehat{\alpha}_2 F_{ij}. \tag{2}$$

I estimate equation 1 separately in each sample year. If $\widehat{\alpha}_2 \neq 0$, the slope of the spending curve is not constant, and equation 2 says the funding weight for the marginal low-income

[10] Appendix Figure B1 is an example of this process for Houston Independent School District, one of the largest school districts in Texas.

student at any school depends on the incumbent proportion of low-income students. Under the assumption that S_{ij} is either diminishing or constant in F_{ij}, the predictions for the signs are $\widehat{\alpha}_1 > 0$ and $\widehat{\alpha}_2 \leq 0$. The exogeneity condition requires unobservable school and neighborhood characteristics that may predict within-district differences in school spending are unrelated to F_{it}. That is

$$E[\epsilon_{ij}, F_{ij}|X_{ij}, \theta_j] = 0. \tag{3}$$

That $\widehat{\omega}$ depends on the existing income composition has subtle implications for the analysis of this paper. As shown in Table 2 there is substantial heterogeneity in the income composition of schools that receive new affordable housing. A qualitative prediction from the non-linear form is that per-pupil spending may rise at some LIHTC receiving schools and fall at others. Quantitatively, we can use 2 to compute the cutoff level of incumbent free-lunch share in which a marginal increase in F would cause per-pupil spending to decline, as the standard quadratic OLS response

$$\tilde{F} = -\frac{1}{4}\frac{\widehat{\alpha}_1}{\widehat{\alpha}_2} \tag{4}$$

In the case of a diminishing school spending response, ie $\widehat{\alpha}_1 > 0$ and $\widehat{\alpha}_2 < 0$, we can solve for the threshold $\tilde{F}$ in each year. That is, school spending is only predicted to increase following a marginal increase in the free-lunch share when $F_{ij} < \tilde{F}$.

I conduct the following empirical tests to test the hypothesis of this section. First, I estimate $\widehat{\alpha}_1$ and $\widehat{\alpha}_2$ of equation 1 separately for each year of the sample. This allows me to compute a threshold for each year $\tilde{F}_t$ over time and analyze the structure of the policy environment over time. I then estimate an event-study model of LIHTC construction timing, modelling changes in school spending and socioeconomic outcomes plausibly caused by by new affordable housing. If LIHTC produces identifiable increases in low-income student composition, then the model predicts the per-pupil spending response will depend of on the pre-LIHTC student composition relative to the threshold $\tilde{F}_t$. To test this hypothesis I first estimate the shape of the school spending curve each year.

3.3 Texas Funding Curves Become More Progressive Over Time

Estimates for the coefficients of interest in Equation 1 are presented in Table 3. The results in all columns include schools of all grade levels, pooling all years of data in columns 1-3 and adding fixed effects and additional controls moving left to right. In columns 4 and 5 are the results including all schools in the sample for only the years 2000 and 2020, respectively, tracing out the spending curves underlying the raw data plots of Figure 2. In each specification, standard errors are clustered at the district level.

Table 3: Cross-Section Relationship Between Income and School Spending

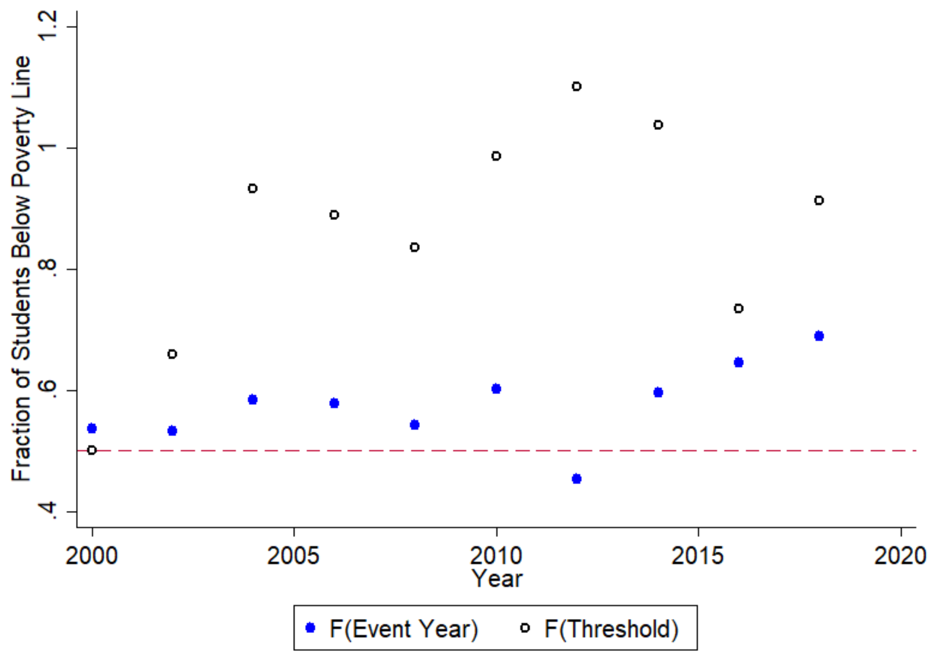
	(1) All Years	(2) All Years	(3) All Years	(4) 2000	(5) 2020
$\widehat{\alpha}_1$	0.320***	0.367***	0.383***	0.291**	0.675***
	(0.091)	(0.065)	(0.074)	(0.098)	(0.126)
$\widehat{\alpha}_2$	-0.122	-0.253***	-0.276***	-0.386***	-0.339**
	(0.091)	(0.065)	(0.062)	(0.083)	(0.116)
N	80,033	80,033	80,033	3,188	3,694
r2	0.030	0.283	0.284	0.363	0.264
District FE		×	×	×	×
Additional Controls			×	×	×

Standard errors in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

The results provide sharp evidence for the signs of $\widehat{\alpha}_1$ and $\widehat{\alpha}_2$. The economic interpretation for the direction of the signs are as follows. Beginning with a school that has no income qualifying students, a small increase in F_{it} will cause per-pupil spending to rise. However, this effect is diminishing in the incumbent free-lunch share.

Since funding requirements may differ for schools serving different grade ranges, I split the data into primary and secondary schools then estimate the within-district model on each subset. Appendix Table A1 shows that the pooled results in Table 3 reflect the funding curves for primary schools moreso than secondary schools. In fact, the results for the secondary school subset are insignificant and inconsistent in sign. Such vague results may stem from sample size in the secondary school subset resulting in a lack of power, or it could be the case that secondary school spending curves have a less-identifiable functional form. In all analysis to follow I focus on the elementary school sample for consistency sake. With estimates for $\widehat{\alpha}_1$ and $\widehat{\alpha}_2$ in tow for each year, not just 2000 and 2020, I then turn to computing $\tilde{F}_t$ for each year using Equation **??**.

Figure 3: Threshold $\tilde{F}$ Over time



Notes: The non-linear relationship between per-pupil spending and income qualifying student share yields a threshold in which a small increase in the income qualifying share would cause per-pupil spending to decline. Figure 3 shows the change in the threshold over time. Following from Table 2, Figure 3 includes the mean income-qaulifying share at schools receiving LIHTC for the first time in each year.

Figure 3 shows that $\tilde{F}_t$ increases from 0.25 in 2020 to 0.65 in 2020. There is a positive linear trend, but substantial variation around the trend during the sample period. The trend can be interpreted as the spending curve becoming more progressive over time. Economics of education scholars have claimed the US has become more progressive in school funding and this evidence corraborates that hunch.

In addition to $\tilde{F}_t$, I include a second data point for estimates of the mean free-lunch share at primary schools where the first LIHTC took place in each year. In the overwhelming majority of school years, the existing free-lunch share at LIHTC receivng schools is above $\tilde{F}_t$, thus an affordable housing shock that increases the free-lunch share would be predicted to cause a per-pupil spending decrease.

In Section 4 I lay out the effects of LIHTC on student enrollment composition and per-pupil spending. While the predictions of Section 3 imply the importance of the spending curve and the incumbent neighborhood composition, the magnitude and nature of LIHTC shocks on school composition is of central importance in understanding if income integration moves the needle on per-pupil spending. I first describe institutional details and the scope of LIHTC housing developments to promote the idea that affordable housing development will affect schools on several margins. Exploiting the timing of LIHTC across years in the sample I then specify an event-study model that traces out the effect of LIHTC on enrollment, free-lunch share, and per-pupil spending for the average school receiving LIHTC. I then explore the primary margin of heterogeneity along the threshold value $\tilde{F}_t$.

Lastly, I then explore the following counterfactual idea. How might per-pupil spending responded to LIHTC had the spending curve remained fixed to the shape of the year 2000? To answer this question I put forth a procedure to estimate counterfactual per-pupil spending levels based on the spending curve, observed free-lunch share, and the district specific mean spend.

4 LIHTC Shocks to Schools

4.1 Institutional Details: LIHTC as School Demographics Shock

Models put forth by Caetano and Maheshri (2017) predict a sharp household response to any school demographic change, and empirical studies show that LIHTC changes neighborhood demographics through household sorting (Baum-Snow and Marion 2009, Dillman et al. 2017,Diamond and McQuade 2019). In this section I detail how LIHTC may predictably affect district allocation decisions through school funding formulas tied to enrollment, teacher counts, and neighborhood demographics.

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. In the simplest setup, I identify no less than five stakeholders in the development of housing through LIHTC. The federal government, which 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 tax credit, and investor tax benefits are realized over a ten-year period post investment (Eriksen 2009). Finally the renters, who 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 no include the cost of land. Secondly, building in a qualified census tract (QCT) 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 cause concentrated poverty (Ellen et al. 2007, Freedman and McGavock 2015). Lang (2012) argues that relatively lower land costs in low-income areas dominates the effect of QCT status since land costs are not subsidized.

Who lives in LIHTC? Program guidelines require either 20% of tenants earn less than 50% of the metro area median income or at least 40% of tenants 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[11] 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.

4.2 LIHTC Event-Study Shocks

To trace out the dynamic effects, I specify an event-study model that takes the form

$$Y_{ijt} = \sum_{\tau=-6}^{15} \pi_\tau (D_i \times 1[\tau_t = \tau]) + \gamma_i + \gamma_t + \epsilon_{ijt}. \tag{5}$$

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. Intuitively, 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. The interacted event study instruments approximate school $i's$ exposure to LIHTC as a function of the time since the project is approved. 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.[12] 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.

I first present the results from Equation 5 on three school inputs: enrollment counts, teacher headcounts, and free-lunch share. Recall that event time year $\tau = 0$ is the year of project approval not the year LIHTC becomes available for rent. Each image in Figure 4 includes the event-time coefficients π_τ plotted relative to the last pre-period $\tau = -1$,

[11] 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 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).

[12] Stata package eventDD is used to estimate the dynamic model and plot the coefficients. See Clarke and Tapia-Schythe (2021).

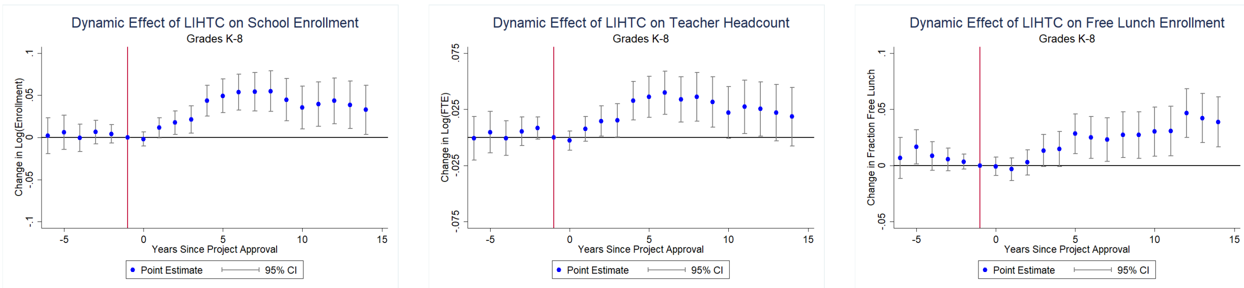
along with 95% confidence intervals for each estimate. The three outcomes in Figure 4 are indicative of first-order observable impacts of LIHTC on schools. If there are no identifiable effects on enrollment, teacher counts, or income composition, there is no motivation to expect a school spending shock.

The leftmost panel of Figure 4 portrays estimates of the LIHTC effect on the natural log of enrollment counts. Following smooth enrollment pre-trends, I document enrollment growth beginning year 2 up to a peak 5% in years 6-8 post-LIHTC. Overall the enrollment growth is gradual, however there is a small discrete jump following year 3. This possibly coincides with build/approval timing. For the average school in the treated sample that represents a net increase of 66 students. The funding formula for most school districts will predict more required spending as schools likely have class size mandates. For K-4 classes in Texas there must be no more than 22 students per teacher. For grades 5-12, districts must maintain an overall ratio of 20 to one but there is no set class size cap. The model predictions in the center panel of Figure 4 show that teacher counts increase over 3%, with the pattern of timing similar to that of enrollment. This is approximately 2 additional FTE teachers to accommodate the mean enrollment increase of 66 students.

The rightmost panel of Figure 4 illustrates the effect of LIHTC on school income composition, taking the fraction of free-lunch students as the outcome. The model predicts a gradual, persistent increase in the free-lunch share of roughly 0.025 base points. For context, if the share of free lunch students increases by 0.025 that is approximately 33 students at the mean school, or half of the peak enrollment increase.

Figure 4: Event-Study Shocks on School Characteristics

(a) (b) (c)

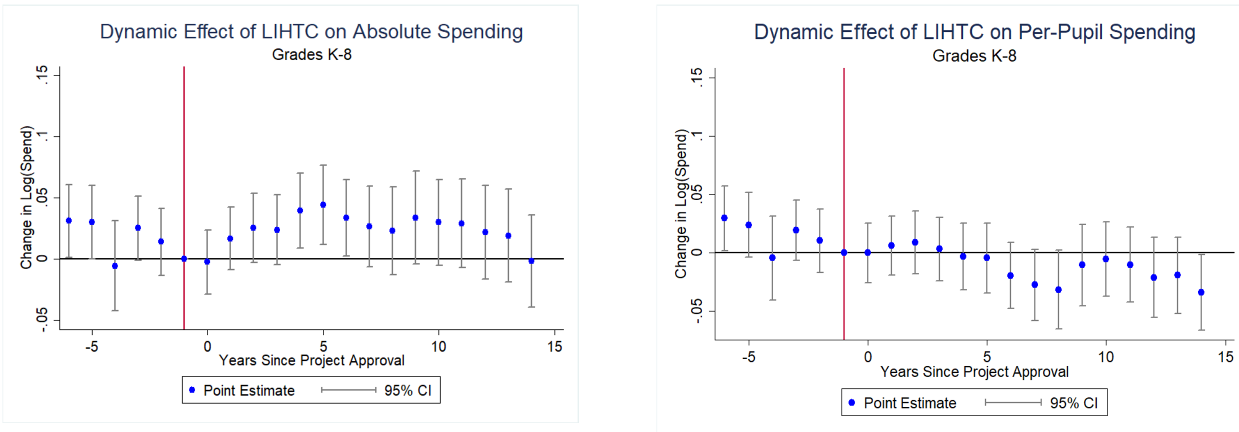


Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 5 for the outcome variable of interest. The denominator for each spending outcome is current year enrollment, thus the estimates measure relative increases in total and instructional spending for each student. Each regression includes school and year fixed effects, along with a linear time trend interacted with the intial period quartile of the homebuyer income distribution. 95% confidence intervals are shown, with observations clustered at the school level.

I next turn to the spending outcomes. In light of the enrollment increases and subsequent teacher hires, I expect absolute spending to increase following LIHTC as a result. The estimates on the left side of Figure 5 show only weak evidence for increases to absolute spending. The estimate is positive but statistically significant in only three years post-LIHTC. The estimates are noisy, possibly inferring a wide range of spending responses to the composition change from LIHTC. Further, if the percentage increase in enrollment outpaces the percentage increase in absolute spending, per-pupil spending will decrease. Quantitatively, the conceptual model predicts the small increase in free-lunch share will cause per-pupil spending to decrease at some schools. Qualitatively, to the extent that per-pupil spending is linked to school quality, education outcomes will decline as will the school.

Figure 5: Event-Study Estimates : The Effect of LIHTC on School Spending

(a) (b)



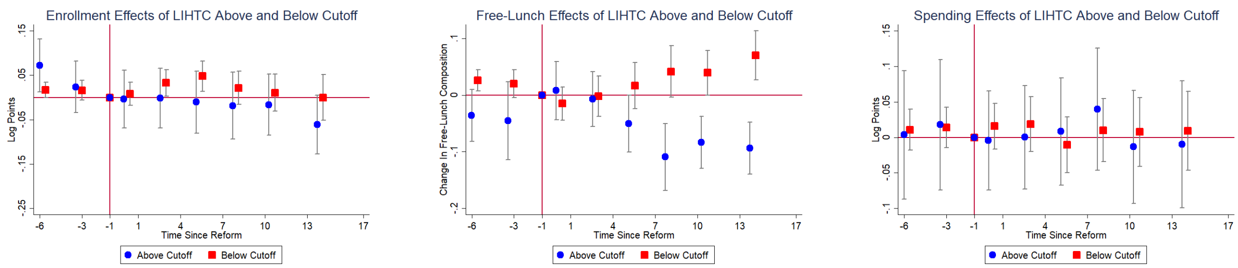
Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 5 for the outcome variable of interest. The denominator for each spending outcome is current year enrollment, thus the estimates measure relative increases in total and instructional spending for each student. Each regression includes school and year fixed effects, along with a linear time trend interacted with the intial period quartile of the homebuyer income distribution. 95% confidence intervals are shown, with observations clustered at the school level.

4.3 Heterogeneity

I now test conceptual predictions for heterogeneity in the effect of LIHTC based on the incumbent free-lunch share relative to the spending curve threshold. That the threshold changes over time adds a second dimension to the analysis here. As such, I create a categorical variable equal to one if a LIHTC receiving school is below the threshold in $\tau = -1$, and 0 otherwise. Again allowing all never treated schools to serve as the control group, I trace out interacted event-study instruments for the heterogenous effect of LIHTC on enrollment, free-lunch composition and school spending. The results are shown in the three-panel Figure 6.

Figure 6: Heterogenous Effects of LIHTC

(a) (b) (c)



Notes: Each panel plots the mean per-pupil spending level for a sample of 3,926 K-12 schools in Texas, binned into 10 equal-interval groups based on the share of students receiving free or reduced lunch. Shown with the mean for each bin is the standard error.

In the discussion of heterogeneity, I frame the results as underlying drivers of the main results in Figures 4 and 5. I document three distinct patterns in the three panels of Figure 6. For enrollment, the headline result is driven by increases at schools above the threshold. However, as the middle pane shows, the compositional effects are largest at schools below the threshold. In fact, at schools above the threshold the compositional change following LIHTC is null. The rightmost plots show the heterogenous spending effect, and as predicted school spending only rises at schools below the threshold cutoff. [WRAP UP AND TRANSITION].

5 Counterfactual and External Validity

The results in Section 4 show heterogeneous effects of LIHTC on the income composition and spending response of schools. There are indeed two margins of heterogeneity. The first is the incumbent free-lunch share explored in the heterogeneity results for Section 4. The second is the cohort effect based on the year LIHTC shocks begin to affect a neighborhood. As documented in Section 3, the spending curve is shifting over time and becoming more progressive. Take two neighborhoods, both with incumbent neighborhood composition $F_t = 0.75$. Neighborhood A gets LIHTC in 2000 and Neighborhood B gets LIHTC in 2020. The predicted spending response to a marginal increase in free-lunch share would be negative for A and positive for B, simply because of different policy environments. In this section I ask counterfactually how LIHTC would affect school spending had the spending curve be fixed to the year 2000.

To answer this question I compute adjusted per-pupil spending values by predicting school spending in each year based on observed free-lunch share, district level average spending, and the funding weight fixed to the year 2000. The procedure yields a counterfactual panel of per-pupil spending for each school in the sample. To begin, consider the data generating process for per-pupil spending at school i in district j to be a linear combination of the district specific per-pupil spending floor $\underline{\mathrm{S}}_j$ and the state-determined weight for income qualifying students, ω. The relationship between expected per-pupil spending, S_{ij}, and free-lunch qualifying share, F_{ij}, can be expressed as

$$E[S_{ijt}] = (1 - F_{ijt})\underline{\mathrm{S}}_{jt} + F_{ijt}(1 + \omega)\underline{\mathrm{S}}_{jt} + u_{ijt}. \tag{6}$$

where u_{ij} are school by year idiosyncrasies that determine S_{ij}. F_{ij} is observed in the data, while ω and naturally u_{ij} are both unobserved. Recall from Section 3 that ω is the marginal spending response to an exogenous increase in F. For the year 2000 I express this as

$$\widehat{\omega}^0 = \widehat{\alpha}_1^0 + 2\widehat{\alpha}_2^0 F_{ijt}. \tag{7}$$

$\bar{S}_{jt}$ can also be obtained from estimating equation 1 as the district fixed-effect and is year-specific, or

$$\widehat{\underline{\mathrm{S}}}_{jt} = \widehat{\alpha}_0 + \widehat{\theta}_{jt}. \tag{8}$$

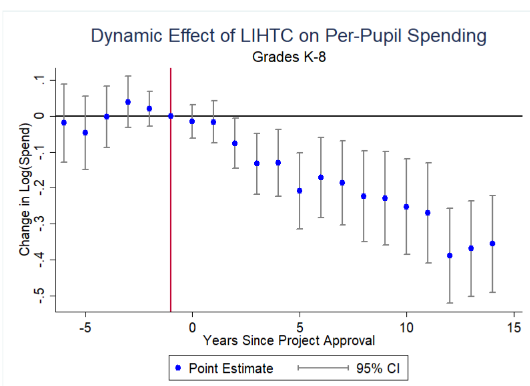
Then the prediction equation for each school by year value of per-pupil spending, deflated to the 2000 spending curve is

$$\widehat{S}_{ijt} = (1 - F_{ijt})\widehat{\underline{\mathrm{S}}}_{jt} + F_{ijt}(1 + \widehat{\omega}^0)\widehat{\underline{\mathrm{S}}}_{jt}. \tag{9}$$

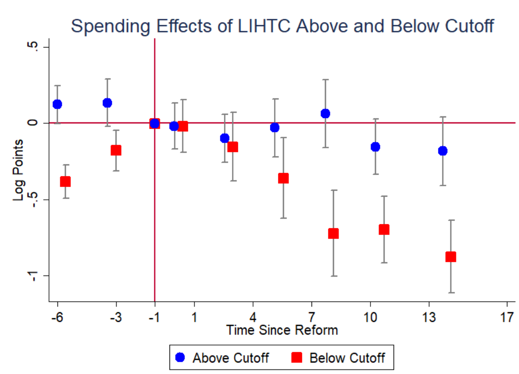
After constructing the panel of $\widehat{S}_{ijt}$ estimates, I estimate event-study Model 5 to trace out the counterfactual response to LIHTC had no policy changes taken place during the panel. Figure 7 contains plots of the LIHTC effect on counterfactual spending for elementary schools. The left panel is analogous to the right panel of Figure 5 with stark differences in the post-LIHTC pattern. Counterfactually, had the spending curve remained fixed to the year 2000, the predicted effect of LIHTC shocks would be sharp declines in per-pupil spending. This can be explained by the shape of the spending curve in 2000 and the average composition of LIHTC treated school over time. The horizontal dashed line in Figure 3 shows that for all but one year of the sample, the average school receiving LIHTC would be above the threshold in which a small increase in free-lunch share would predict a decrease in per-pupil spending.

Figure 7: Event-Study Estimates : The Effect of LIHTC on Student Composition

(a)



(b)

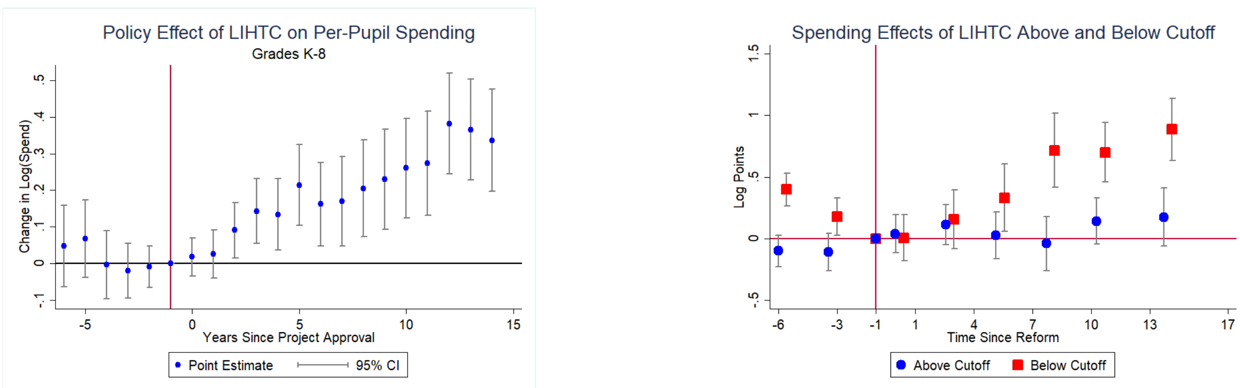


Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 5 for the outcome variable of interest. The denominator for each spending outcome is current year enrollment, thus the estimates measure relative increases in total and instructional spending for each student. Each regression includes school and year fixed effects, along with a linear time trend interacted with the intial period quartile of the homebuyer income distribution. 95% confidence intervals are shown, with observations clustered at the school level.

The right hand side of Figure 7 shows the counterfacutal estimates classifying treated schools with a dummy equal to one if free-lunch share is above the 2000 spending curve threshold in the event year. Had policy changes never taken place, the schools below the cutoff would have observed the largest post-LIHTC spending declines. What both images speak to when compared to the results in Figure 5 is the large effects of policy changes in preventing spending declines in places receiving affordable housing. To highlight the policy effects I take the difference, $\Delta S_{ijt} = S_{ijt} - \widehat{S}_{ijt}$ estimate the event-study coefficients once again. The results are shown in Figure 8. Not only are the policy effects large, they are almost wholly contained to schools below the threshold!

Figure 8: Event-Study Estimates : The Effect of LIHTC on Student Composition

(a) (b)

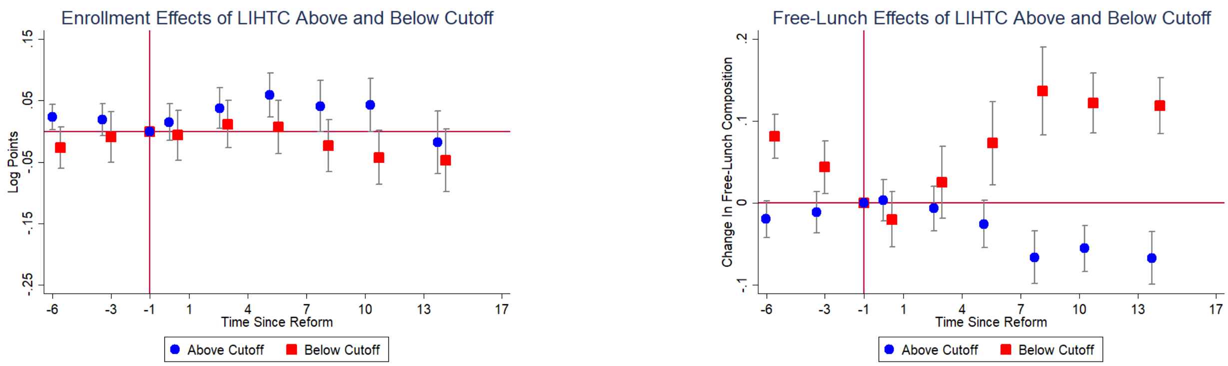


Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 5 for the outcome variable of interest. The denominator for each spending outcome is current year enrollment, thus the estimates measure relative increases in total and instructional spending for each student. Each regression includes school and year fixed effects, along with a linear time trend interacted with the intial period quartile of the homebuyer income distribution. 95% confidence intervals are shown, with observations clustered at the school level.

Theoretically, the fact that the threshold has risen over time === progressive policy changes. However, as the counterfactual results show the benefits of the policy changes in regards to LIHTC are contained at those on the lower-end of the free-lunch distribution. It is in fact because the nature of the LIHTC shock on school composition is different. In Figure 9 we see the effect of LIHTC on schools below the threshold is purely compositional, as total enrollments do not change but the free-lunch share increases markedly. Alternatively, the free-lunch share falls following LITHC at elementary schools above the threshold.

Figure 9: Event-Study Estimates : The Effect of LIHTC on Student Composition

(a) (b)



Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 5 for the outcome variable of interest. The denominator for each spending outcome is current year enrollment, thus the estimates measure relative increases in total and instructional spending for each student. Each regression includes school and year fixed effects, along with a linear time trend interacted with the intial period quartile of the homebuyer income distribution. 95% confidence intervals are shown, with observations clustered at the school level.

6 Conclusion

Urban economists typically consider neighborhood income composition as a fluid measure continuously affected by endogenous sorting. Policy that introduces low-income residents into spaces occupied by higher income households can have a wide variety of effects, and a deep literature begins with the idea that heterogenous preferences for neighborhood composition will cause continuous endogenous sorting (Schelling 1971, Bayer et al. 2007, Caetano and Maheshri (2017)). Schools are particularly interesting as the history of US public school finance is scattered with protests, violence, and government action to force school integration. However, contemporary education policy has turned to the study of school funding formulas to understand if low-income household receiving equitable resources.

In addition, the visibility of the housing debate has long sparked economists' desire to understand effects of LIHTC, the largest affordable housing program in the US. Since a substantive portion of the rental units created by the program will be leased to households with children, schools are a natural margin of interest for further study. If districts spend more following LIHTC to maintain school quality, that does not entirely eliminate schools from the menu of opposition points against affordable housing development. The exercise of this paper is limited to the study of expenditures, when concerns of free-riding could be linked to the revenues required to fund higher spending. A deeper dive into federal, state, and local revenue responses to LIHTC would be informative about who bears the financial burden of increased spending that follows affordable housing development.

The results of this paper highlight the crucial implications of progressive policy related to schools and neighborhood change. While the spending curves have become more progressive in Texas, it is plausible other states may have highly regressive funding systems that resemble Texas in the year 2000. Compositional shocks of similar magnitude to LIHTC will cause per-pupil spending to decline in such places. However, one must also as why observed per-pupil spending does not increase when free-lunch composition increases. Knowing that free-lunch programs are federally subsidized suggests those dollars may crowd-out local revenues in a sense, meaning that on an equivalent educational expenditure may have declined (Wilson et al. 2006).

References

Adkins, A., A. Sanderford, and G. Pivo (2017): "How location efficient is LIHTC? Measuring and explaining state-level achievement," *Housing Policy Debate*, 27, 335–355.

Barrow, L. and C. E. Rouse (2004): "Using market valuation to assess public school spending," *Journal of Public economics*, 88, 1747–1769.

Baum-Snow, N. and J. Marion (2009): "The effects of low income housing tax credit developments on neighborhoods," *Journal of Public Economics*, 93, 654–666.

Bayer, P., P. Q. Blair, and K. Whaley (2020a): "Are We Spending Enough on Teachers in the US?" Tech. rep., National Bureau of Economic Research.

——— (2020b): "The impact of school finance reforms on local tax revenues," in *AEA Papers and Proceedings*, vol. 110, 416–418.

Bayer, P., F. Ferreira, and R. McMillan (2007): "A unified framework for measuring preferences for schools and neighborhoods," *Journal of political economy*, 115, 588–638.

Black, S. (1999): "Do Better Schools Matters? Parental Valuation of Elementary Education," *Quarterly Journal of Economics*, 114, 577–599.

Blagg, K., J. Lafortune, and T. Monarrez (2022): "Measuring Differences in School-Level Spending for Various Student Groups. Research Report." *Urban Institute.*

Boustan, L. P. and R. A. Margo (2013): "A silver lining to white flight? White suburbanization and African–American homeownership, 1940–1980," *Journal of Urban Economics*, 78, 71–80.

Caetano, G. and V. Maheshri (2017): "School segregation and the identification of tipping behavior," *Journal of Public Economics*, 148, 115–135.

——— (2020): "Explaining recent trends in US school segregation: 1988-2014," Tech. rep., Forthcoming.

Cellini, S. R., F. Ferreira, and J. Rothstein (2010): "The value of school facility investments: Evidence from a dynamic regression discontinuity design," *The Quarterly Journal of Economics*, 125, 215–261.

Chingos, M. M. and K. Blagg (2017): "Do poor kids get their fair share of school funding?" *Washington, DC: Urban Institute.*

Clapp, J. M., A. Nanda, and S. L. Ross (2008): "Which school attributes matter? The influence of school district performance and demographic composition on property values," *Journal of urban Economics*, 63, 451–466.

Clarke, D. and K. Tapia-Schythe (2021): "Implementing the panel event study," *The Stata Journal*, 21, 853–884.

Cox, R., J. P. Cunningham, A. Ortega, and K. Whaley (2022): "Black lives: The high cost of segregation," *University of Southern California Working Paper Series.*

Cummings, J. L. and D. DiPasquale (1999): "The low-income housing tax credit an analysis of the first ten years," *Housing Policy Debate*, 10, 251–307.

Darity Jr, W. A., D. Hamilton, and J. B. Stewart (2015): "A tour de force in understanding intergroup inequality: An introduction to stratification economics," *The Review of Black Political Economy*, 42, 1–6.

Di, W. and J. C. Murdoch (2013): "The impact of the low income housing tax credit program on local schools," *Journal of Housing Economics*, 22, 308–320.

Diamond, R. and T. McQuade (2019): "Who Wants Affordable Housing in Their Backyard? An Equilibrium Analysis of Low-Income Property Development," *Journal of Political Economy*, 127, 000–000.

Dillman, K.-N., K. M. Horn, and A. Verrilli (2017): "The what, where, and when of place-based housing policy's neighborhood effects," *Housing Policy Debate*, 27, 282–305.

Ellen, I. G., A. E. Schwartz, I. Voicu, and M. H. Schill (2007): "Does federally subsidized rental housing depress neighborhood property values?" *Journal of Policy Analysis and Management*, 26, 257–280.

Eriksen, M. D. (2009): "The market price of low-income housing tax credits," *Journal of Urban Economics*, 66, 141–149.

Eriksen, M. D. and S. S. Rosenthal (2010): "Crowd out effects of place-based subsidized rental housing: New evidence from the LIHTC program," *Journal of Public Economics*, 94, 953–966.

Freedman, M. and T. McGavock (2015): "Low-income housing development, poverty concentration, and neighborhood inequality," *Journal of Policy Analysis and Management*, 34, 805–834.

Freedman, M. and E. G. Owens (2011): "Low-income housing development and crime," *Journal of Urban Economics*, 70, 115–131.

Hollar, M. K. (2019): "Understanding whom the LIHTC program serves: Tenants in LIHTC units as of December 31, 2017," *Available at SSRN 2563151.*

Hoxby, C. (2001): "All School Finance Equalizations are Not Created Equal," *Quarterly Journal of Economics*, 116, 1189—-123.

Hussar, B., J. Zhang, S. Hein, K. Wang, A. Roberts, J. Cui, M. Smith, F. B. Mann, A. Barmer, and R. Dilig (2020): "The Condition of Education 2020. NCES 2020-144." *National Center for Education Statistics.*

Intrator, J., J. Tannen, and D. S. Massey (2016): "Segregation by race and income in the United States 1970–2010," *Social Science Research*, 60, 45–60.

Jackson, C. K., R. C. Johnson, C. Persico, et al. (2016): "The Effects of School Spending on Educational and Economic Outcomes: Evidence from School Finance Reforms," *The Quarterly Journal of Economics*, 131, 157–218.

Keightley, M. P. and J. M. Stupak (2020): "An Introduction to the Low Income Housing Tax Credit," *Library of Congress, Congressional Research Service*.

Lafortune, J., J. Rothstein, and D. W. Schanzenbach (2018): "School finance reform and the distribution of student achievement," *American Economic Journal: Applied Economics*, 10, 1–26.

Lang, B. J. (2012): "Location incentives in the low-income housing tax credit: Are qualified census tracts necessary?" *Journal of Housing Economics*, 21, 142–150.

Owens, A., S. F. Reardon, and C. Jencks (2016): "Income segregation between schools and school districts," *American Educational Research Journal*, 53, 1159–1197.

Reardon, S. F. and K. Bischoff (2011): "Income inequality and income segregation," *American journal of sociology*, 116, 1092–1153.

Roza, M., P. T. Hill, S. Sclafani, and S. Speakman (2004): "How within-district spending inequities help some schools to fail," *Brookings papers on education policy*, 201–227.

Samuelson, P. A. (1954): "The Pure Theory of Public Expenditure," *The Review of Economics and Statistics*, 36, 387–389.

Schelling, T. C. (1971): "Dynamic models of segregation," *Journal of Mathematical Sociology*, 1, 143–186.

Tammaru, T., M. Van Ham, S. Marcińczak, and S. Musterd (2015): *Socio-economic segregation in European capital cities: East meets West*, Routledge.

Tiebout, C. M. (1956): "A Pure Theory of Local Expenditures," *Journal of Political Economy*, 64, 416–424.

Wilson, K., K. Lambright, and T. M. Smeeding (2006): "School finance, equivalent educational expenditure, and the income distribution: Equal dollars or equal chances for success?" *Education Finance and Policy*, 1, 396–424.

Supplementary Appendix

Local Housing Development and Money for Neighborhood Schools

Kenneth Whaley

A Additional Analysis

A.1 Heterogeneity Results

Table A1: Cross-Section Relationship Between Income and School Spending

	Primary All Years	Primary 2000	Primary 2020	Secondary All Years	Secondary 2000	Secondary 2020
$\widehat{\alpha}_1$	0.370***	0.480***	0.466***	0.064	0.306*	0.826
	(0.078)	(0.065)	(0.082)	(0.070)	(0.114)	(0.451)
$\widehat{\alpha}_2$	-0.252***	-0.478***	-0.178*	0.081	-0.075	-0.599
	(0.074)	(0.070)	(0.076)	(0.066)	(0.140)	(0.456)
N	62684.000	2442.000	2938.000	17349.000	218.000	250.000
r2	0.312	0.445	0.443	0.509	0.784	0.552

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table A2: IV Estimates: LIHTC And School Spending By Income Sample

Income Group: Spending Outcome:	Bottom 2 Terciles Total	Upper Tercile Total	Bottom 2 Terciles Instruction	Upper Tercile Instruction
SZ LIHTC Builds	0.0586*	0.105*	0.0145	0.0810*
	(0.0229)	(0.0447)	(0.0234)	(0.0403)
Schools	2042	1442	2042	1442
Years	13	13	13	13
Fixed Effects	×	×	×	×
Time Trends	×	×	×	×
Income Controls	×	×	×	×
First-Stage Fstat	88.31	16.73	88.33	16.73

Notes: Standard errors in parentheses. Results from regression on split samples of the data based on tercile of the initial county-level income distribution. The outcome of interest is the log of per-pupil spending for school i in year t. The enrollment denominator is fixed to the intial sample year and so my outcome variable captures variation in absolute spending levels. Two-way fixed effects include school and year indicators, and time trends are specific to the initial income quartile in the county distribution of homebuyer income. Time varying income controls include the log of median homebuyer income listed on mortgages originated within the attendance zone for i in year t, and the fraction of students receiving subsidized lunch.

Table A3: IV Estimates: LIHTC And School Spending By Grade Sample

Grade Group: Spending Outcome:	K-8 Total	High School Total	K-8 Instruction	High School Instruction
SZ LIHTC Builds	0.118**	0.0595*	0.236***	0.0802***
	(0.0378)	(0.0248)	(0.0449)	(0.0203)
Schools	2710	773	2710	773
Years	13	13	13	13
Fixed Effects	×	×	×	×
Time Trends	×	×	×	×
Income Controls	×	×	×	×
First-Stage Fstat	65.32	41.28	65.34	41.28

Notes: Standard errors in parentheses. Results from regression on split samples of the data based on the highest grade-level offered. Any school offering 12th grade is included in the high school sample. The outcome of interest is the log of per-pupil spending for school i in year t. The enrollment denominator is fixed to the intial sample year and so my outcome variable captures variation in absolute spending levels. Two-way fixed effects include school and year indicators, and time trends are specific to the initial income quartile in the county distribution of homebuyer income. Time varying income controls include the log of median homebuyer income listed on mortgages originated within the attendance zone for i in year t, and the fraction of students receiving subsidized lunch.

Table A4: IV Estimates: LIHTC And School Spending

	(1) Total	(2) Total	(3) Instruction	(4) Instruction
SZ LIHTC Builds	0.0729***	0.0734***	0.0406	0.0407
	(0.0219)	(0.0220)	(0.0213)	(0.0213)
LIHTC*Maj. Latino	0.0341	0.0325	0.0251	0.0267
	(0.0221)	(0.0238)	(0.0205)	(0.0225)
Schools	3484	3484	3484	3484
Years	13	13	13	13
Fixed Effects	×	×	×	×
Time Trends	×	×	×	×
Income Controls	×	×	×	×
Interacted Controls		×		×
First-Stage Fstat	33.69	33.87	33.70	33.87

Notes: Standard errors in parentheses. The outcome of interest is the log of per-pupil spending for school i in year t. The enrollment denominator is fixed to the intial sample year and so my outcome variable captures variation in absolute spending levels. A school zone category $MajorityLatino$ is equal to one if Non-white Hispanic students make up more than half of the initial enrollment. Two-way fixed effects include school and year indicators, and time trends are specific to the initial income quartile in the county distribution of homebuyer income. Time varying income controls include the log of median homebuyer income listed on mortgages originated within the attendance zone for i in year t, and the fraction of students receiving subsidized lunch.

Table A5: IV Estimates: LIHTC And School Spending

	(1) Total	(2) Total	(3) Instruction	(4) Instruction
SZ LIHTC Builds	0.0983***	0.0979***	0.0618*	0.0622*
	(0.0260)	(0.0260)	(0.0249)	(0.0249)
LIHTC*Maj. Black	-0.0582*	-0.0584*	-0.0603*	-0.0673**
	(0.0246)	(0.0249)	(0.0243)	(0.0238)
Schools	3484	3484	3484	3484
Years	13	13	13	13
Fixed Effects	×	×	×	×
Time Trends	×	×	×	×
Income Controls	×	×	×	×
Interacted Controls		×		×
Fstat	52.84	46.97	52.85	46.97

Notes: Standard errors in parentheses. The outcome of interest is the log of per-pupil spending for school i in year t. The enrollment denominator is fixed to the intial sample year and so my outcome variable captures variation in absolute spending levels. A school zone category $MajorityBlack$ is equal to one if Black students make up more than half of the initial enrollment. Two-way fixed effects include school and year indicators, and time trends are specific to the initial income quartile in the county distribution of homebuyer income. Time varying income controls include the log of median homebuyer income listed on mortgages originated within the attendance zone for i in year t, and the fraction of students receiving subsidized lunch.

A.2 IV Robustness

Table A6: First Stage: QCT Designation on Elderly LIHTC Units

	(1)	(2)	(3)	(4)
$QCT_i = 1$	0.005			
	(0.006)			
$POST_t = 1$	0.051***			
	(0.008)			
$QCT_i \times POST_t$	0.004	0.008	0.014	0.014
	(0.016)	(0.016)	(0.017)	(0.016)
Schools	2439	2439	2439	2439
Years	13	13	13	13
Fixed Effects		×	×	×
Time Trends			×	×
Income Controls				×
R2	0.001	0.653	0.655	0.655

Notes: Standard errors in parentheses. The outcome of interest is a count of elderly designated LIHTC developments within the attendance boundary of school i in year t. QCT is an indicator equal to one if the school has any neighborhood that lies within a qualified census tract. $POST$ is an indicator equal to one for all years after the new list of qualified census tracts was released in 2003.

Figure A1: Event-Study Estimates : Placebo Effect of LIHTC on School Spending

(a) images/tx_spending_placebo.png

(b) images/tx_ins

Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 5 with T=0 when a new LIHTC complex is approved and reserved for older populations. Other LIHTC builds are omitted from the sample, and schools never receiving any LIHTC are the control group. Each regression includes school and year fixed effects, along with a linear time trend interacted with the intial period quartile of the homebuyer income distribution. 95% confidence intervals are shown, with observations clustered at the school level.

Figure A2: Event-Study Estimates : Placebo Effect of LIHTC on Free-Lunch Enrollment

images/tx_free_placebo.png

Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 5 with T=0 when a new LIHTC complex is approved and reserved for older populations. Other LIHTC builds are omitted from the sample, and schools never receiving any LIHTC are the control group. Each regression includes school and year fixed effects, along with a linear time trend interacted with the intial period quartile of the homebuyer income distribution. 95% confidence intervals are shown, with observations clustered at the school level.

B Data Appendix

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).[13] 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 receiving lunch subsidies are provided by the 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 provided 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. With the two restrictions I have 3,484 of 5,562 schools available for a balanced panel from 2000-2020.

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

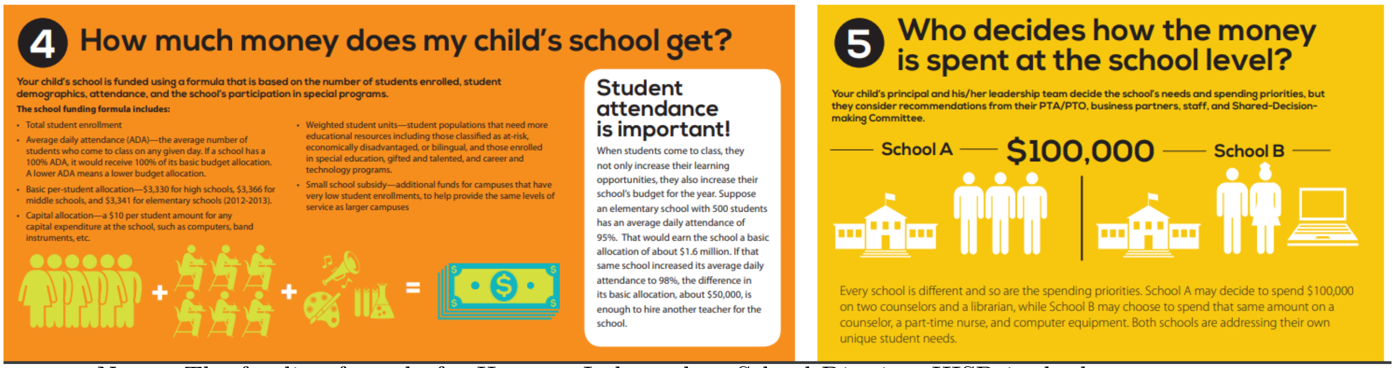
[13] The TEA managed *Texas Academic Performance Reporting* system has public databases available back to the 2013 school year. The *Academic Excellence Indicator System* housed the data prior to 2013. The data prior to 2004 is not listed on the Academic Excellence Indicator System website but remains 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.

zone crosswalk publicly available through NHGIS. Of the 2901 observations matched to a census block, 783 are classified as targeting senior aged population groups and used for placebo tests. 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. The last piece of data from the LIHTC sample is the dollar values of tax credits in for each project, to be sold by the developer to passive investors in exchange for operational cash flow. The real dollar value of each tax credits allocated is ambiguous in the sense that the market value for each credit can change based on prospective alternative investments. I only use a snapshot of the tax credit dollars in 2020 to conceptualize the total spillover costs of the program. Analyzing the dollar values over the entire sample period will be biased by unobserved changes to market conditions over time.

The IV model in Section **??** rests on exogenous LIHTC development created by qualified census tract (QCT) status. By centering my analysis on the 2003 QCT release, I restrict my post period to observations prior to 2013 when the new set of QCTs were released. After the 2013 release, the list would then be updated every two years based on changes to census 5-year estimates of census tract poverty and income levels. The 13 years of data from 2000 to 2012 give a clean policy break prior to more frequent changes that would limit the pre and post design. The event-study models utilize the full panel of data from 2000 to 2020 to maximize the identification window for lags and leads relative to LIHTC announcement.

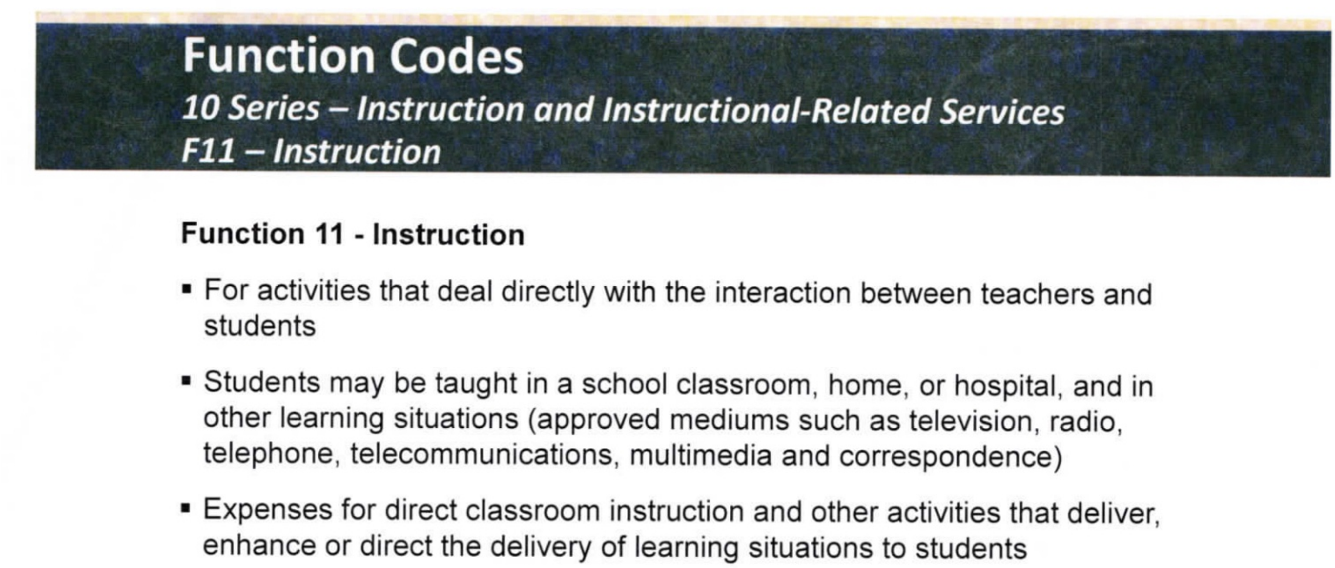
B.2 School Spending Details

Figure B1: 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

Figure B2: TEA Definition of Instruction Spending



Notes: TEA details for the Instructional Expenditures. Source: TEA financial coding presentation. https://resources.finalsite.net/images/v1584825879/lacklandisdnet/qzosmiohb1gfl3mtwijq/TEAFinancialCodingPresentation2019.pdf

Figure B3: TEA Instruction Spending Examples

Function Codes

10 Series – Instruction and Instructional-Related Services

F11 – Instruction

Examples

Salaries and related expenses associated with:

- Classroom teachers
- Teacher aides and classroom assistants
- Substitute teachers
- Teachers that deliver instruction by television, satellite, etc.
- Managers and coordinators for instructional networks
- Special education instructional services
- School bus aides for special education
- Field trips
- Upkeep and repairs to instructional materials and equipment in the classroom
- Band instruments (purchased by school or donated)
- Testing materials for tests developed and administered by teachers
- Instructional supplies
- Graduation expenditures
- Vehicles and insurance for instructional purposes, including driver education

Notes: TEA details for the Instructional Expenditures. Source: TEA financial coding presentation. https://resources.finalsite.net/images/v1584825879/lacklandisdnet/qzosmiohb1gfl3mtwijq/TEAFinancialCodingPresentation2019.pdf