Local Housing Development and Money for Neighborhood Schools*

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Abstract

Each year the Internal Revenue Service distributes over $8 billion in low-income housing tax credits (LIHTC) for rental housing development. I map LIHTC housing to school attendance zones to explore program impact on K-12 public schools, employing a rich dataset of campus level expenditures, enrollments, teacher counts, and neighborhood incomes. I estimate that LIHTC housing causes absolute school spending to increase nearly 9% and instructional spending to increase by 5%. My results imply the average LIHTC investment of $\$1,332,222$ generates a $\$452,328$ school spending spillover, equating to 35 cents for every dollar of housing tax credits. The primary mechanism is a mean enrollment increase of nearly 66 students, half of which are likely subsidized under federal lunch programs, and the whole requiring two additional teachers on average. Overall, the absolute spending increase is efficient as relative spending per-pupil does not change after LIHTC construction.

JEL Classification: H7, R31, R23

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1 Introduction

Multibillion dollar government transfers facilitate the provision of public schools and affordable housing in the United States.[1] While dollars flow from federal, state, and local sources, final decisions often rest with local agencies. Namely, when and where to build affordable housing is a decision made by state housing agencies, with testable implications for public school districts that allocate resources to schools based on enrollments and local demographics. The interaction between school districts and housing authorities that choose affordable housing locations is the focus of this paper, in the sense that new housing will change neighborhoods in a way that affects school finance. Coordination in this setting is a form of strategic interaction, a principle public finance problem rooted in the fiscal competition of neighboring jurisdictions over taxes and public goods (Tiebout 1956, Oates and Schwab 1988, Case et al. 1993, Brueckner 2003).[2]

In this paper I ask if school districts must increase spending for schools near rental housing made available through the Low Income Housing Tax Credit (LIHTC) program. 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 (HUD). 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). A central theme of the literature is a robust effect of LIHTC on a variety of neighborhood amenities that reshape local economies through price and demographic changes (Baum-Snow and Marion 2009, Freedman and Owens 2011, Freedman and McGavock 2015). I study how public school districts allocate resources to schools following a LIHTC housing shock within a school attendance zone boundary.

Expenditures changes following LIHTC are compelling along two margins of interest.

[1] According to the Hussar et al. (2020), K-12 expenditures exceed $700 billion annually, funded by state (47%), local (44.7%), and federal (8.3%) sources. Keightley and Stupak (2020) estimate the US spends close to $10 billion annually through the Low-Income Housing Tax Credit Program.

[2] See Kenyon et al. (1997) for a meta-analysis of the interjurisdictional competition literature.

First, changes to absolute spending allow me to document aggregate fiscal spillovers of affordable housing on schools. If LIHTC causes residential population change a school may require more or less teachers, and if LIHTC changes neighborhood income composition some new students may require additional support. Second, I argue that efficient school district coordination occurs when post-LIHTC spending growth matches post-LIHTC enrollment growth, and relative per-pupil spending remains unchanged. If relative per-pupil spending falls, incumbent households are made worse-off from potential decreases in school quality. Although it has long been a point of contention, recent empirical studies have found that higher per-pupil spending produces better student outcomes, and households are willing to pay for better funded schools (Jackson et al. 2016, Lafortune et al. 2018, Bayer et al. 2020a).

To assess the relationship between affordable housing development and schools, I use campus level data describing expenditures, enrollment and teacher counts for a balanced sample of 3,484 K-12 schools in Texas. Observing the finances of each school is a refinement that allows me to mitigate a core endogeneity concern in empirical urban economics. Unobserved local neighborhood factors may correlate with both LIHTC propensity and school spending, and school attendance zones are smaller geographic areas to reasonably control for fixed characteristics. With unique attendance zone boundary maps, I create a spatial assignment of LIHTC treatment to schools based on location data for LIHTC developments and the timing of new construction from 2000 to 2020. During this period, 1,205 developments and 161,573 rental units were made available in 898 school zones, or 25% of the sample.

Identification in the main model of this paper relies on a plausibly exogenous change in which schools receive LIHTC housing. In 2003, HUD released a new list of qualified census tracts for the first time in 10 years based on data from the 2000 decennial census (Hollar and Usowski 2007). Qualified census tract status is a designation that acts as a location incentive through higher LIHTC subsidies. Further, qualified census tract status remained fixed until 2013, when the next decennial census data became available. I present a robust first-stage relationship between school zones with at least one neighborhood in a qualified census tract and increases in local LIHTC development following the policy change. To interpret the results from my two stage least squares (2SLS) model I argue the exclusion restriction as follows. Conditional on observable, time-varying differences in neighborhood income, qualified census tract status only affects school spending through housing spurred by higher program incentives.

The main model predicts that affordable housing causes absolute expenditures to rise approximately 8.6% for the average school, nearly twice the magnitude of OLS estimates. Further, absolute instructional spending rises by 4.9%. The model also predicts substantial heterogeneity in the effects of LIHTC based on project scale, school grade level, neighborhood income and racial demographics. To validate the headline findings I conduct placebo tests using schools that only receive LIHTC for elderly populations, and find null effects on school spending of both types.

To quantify the absolute effect, consider that the average LIHTC development in my sample for 2020 received $1.3 million in tax credits to produce 158 units. At the average school with no prior LIHTC, my model predicts an increase in expenditures of $452,328. The implied school finance spillover from LIHTC as $2,862 per unit or 35 cents for every LIHTC dollar. Such a spillover is evidence of an important strategic complementary. In terms of magnitudes, Case et al. (1993) estimate the spillover effect from strategic competition to be 70 cents for an additional dollar of spending by a neighboring state. Internationally, Ferraresi et al. (2018) estimate every euro of current spending by a neighboring jurisdiction increases local spending by 0.65 euro (with capital spending causing a 0.10 euro spillover).

With two decades of school finance data and heterogenous timing of LIHTC events, I supplement my headline results by tracing out the dynamic effects of affordable housing along several margins. Taking the year of project approval as the event year, plots of event-study coefficients show that changes to total and instructional spending peak 5 to 6 years post project approval. I repeat this procedure for three mechanisms of interest that underscore funding formulas: enrollments, teacher counts, and the share of students receiving subsidized lunch. Enrollment and teacher counts follow a similar pattern as expenditures, meaning schools respond to the local enrollment shocks by increasing teacher counts. Spending, enrollment and teacher effects all begin to decrease after year 6.

After documenting absolute spending growth and enrollment growth patterns, I then show my dynamic model predicts a precise null effect of LIHTC on relative per-pupil spending. From this finding I conclude that districts respond efficiently to new affordable housing by maintaining the level of resources available to each student at the treated school. My results suggest that schools increase spending after LIHTC in a way that keeps school quality relatively intact, in line with Di and Murdoch (2013) who find that standardized tests at treated schools do not change after LIHTC.

The core findings of this paper have a central theme. Federally subsidized affordable housing changes neighborhoods in a way that forces local schools to spend more, a form of crowding spillovers described by Solé-Ollé (2006). Higher enrollments from new residents require more teachers and therefore higher expenditures. The idea that affordable housing affects neighborhoods along several margins has been acknowledged in the economics literature and the policy space (Baum-Snow and Marion 2009, Ellen 2007, Ellen et al. 2007). Positioned within the literature my results suggest the LIHTC induced changes to local schools explain at least part of the equilibrium price dynamics in private markets as a response to LIHTC (Li 2022,Diamond and McQuade 2019, Davis et al. 2019). There is robust empirical evidence for the house price capitalization of school spending and school attributes (Black 1999, Barrow and Rouse 2004, Bayer et al. 2007, Clapp et al. 2008, Cellini et al. 2010, Bayer et al. 2020a). However, after documenting no effect of LIHTC on relative per-pupil spending, any house price capitalization school changes must stem from enrollment or demographic changes and not school quality.

The remainder of this paper builds this argument as follows. In Section 2 I detail the LIHTC program and describe school funding formulas that channel the demographic changes from LIHTC to school finances. Section 3 is a description of the Texas data used to estimate the main model in Section 4. Section 5 lays bare the the dynamic effects of LIHTC on school spending and presents enrollment, teacher counts, and demographic changes as mechanisms. Section 6 concludes the paper.

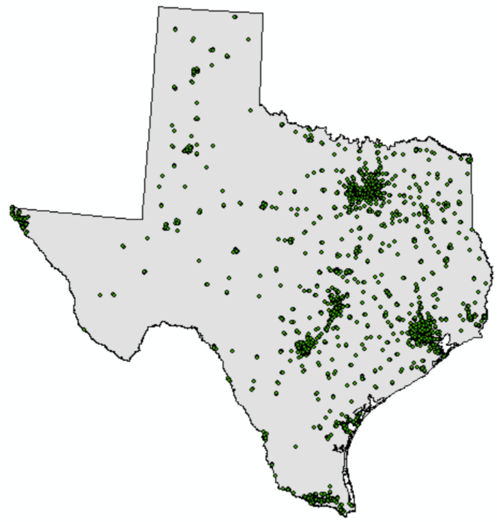
2 Background: Affordable Housing and School Finance

One-third of all US LIHTC units house at least one child under 18 (Hollar 2019). If each school aged LIHTC resident attends the geographically assigned school, this is only a starting point to understand how LIHTC affects schools. 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.

2.1 The LIHTC Program

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. The location of LIHTC development during my sample period is shown in Figure 1.

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.

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. In contrast, several papers have used QCT status as an instrument for LIHTC given a robust first-stage relationship (Baum-Snow and Marion 2009, Freedman and Owens 2011). Throughout the history of the program QCT status is updated when new census data becomes available.[3]

Who lives in LIHTC? Program guidelines require either 20% of tenants earn less than

[3]The frequency of QCT updates has increased with the frequency of census data releases. From 1987-2013 the prior decennial census data was used resulting in only four changes in 26 years. Beginning in 2015, QCT updates were released every two years with new 5-year ACS estimates.

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[4] LIHTC developments are also broadly classified by target population, with some communities explicitly reserved for residents over 62. In Texas roughly 45% of units have a resident under the age of 18, with racial shares of 34% Black, 33% Latino, and 21% white residents (Hollar 2019). In section 3 I describe in detail the variation in LIHTC timing and the units produced in my sample.

2.2 How Districts Finance Schools

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.[5] 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 (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

[4]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).

[5]2020 Texas Public School Finance Overview: Annual Report

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.[6] Once a school is in receipt of funds, the principal and school leadership have discretion over how the money is spent. Expenditure channels defined by Texas Education Agency (TEA) are presented in Figure 2.

Figure 2: Expenditure Classification for Public Schools in Texas

Function Codes

Functions are grouped according to related activities in the following major areas/classes.

- 10 – Instruction and Instructional-Related Services
- 20 – Instructional and School Leadership
- 30 – Support Services – Student (Pupil)
- 40 – Administrative Support Services
- 50 – Support Services – Non-Student Based
- 60 – Ancillary Services
- 70 – Debt Service
- 80 – Capital Outlay (School Districts); Fund Raising (Charter Schools)
- 90 – Intergovernmental Charges

Notes: Texas Education Agency accounting categories for expenditures are shown in Figure 2. Further description of instructional spending can be found in Appendix Figures B2 and B3.

The central hypothesis of this paper stems from the nature of district to campus funding formulas and the campus level decision of spending across inputs. If LIHTC rental development has a material affect on any margin of the school funding formula, there will be an identifiable change to school spending. From there, campus administrators will make a decision on whether to increase spending for instruction or non-instruction line items. I test my hypothesis with data for a panel of schools Texas to estimate how LIHTC affects school spending, instructional spending, and margins of interest in that proxy the school funding formula.

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

3 Data

3.1 Data Sources

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 (TEA), one of the few agencies that report campus level finance data. In this vein my data represents an improvement that allows me to estimate the effects of LIHTC across a more granular level than school districts. Data for total spending, instructional spending, enrollment and racial demographics for each school are reported annually beginning in 2000. Instructional spending is defined broadly by TEA 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.[7] The data is augmented with teacher counts and counts of students receiving free or reduced lunch provided from the National Center of Education Statistics.

Secondly I use a database of LIHTC activity 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.[8] 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.[9] 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.[10] With each housing development matched to a school zone, I aggregate annual LIHTC activity at the school level by year

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

[8]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.

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

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

of project approval. To outline the variation in LIHTC size and scope, I summarize the exposure to LIHTC in Table 1.

Table 1: LIHTC Treatment at Sample Schools

Year	**2003**	**2013**	**2020**
LIHTC Builds Since 2000	522	1544	2399
Units Per 100 Students, Since 2000			
25th percentile	9.04	11.46	11.88
50th percentile	16.1	20.45	21.43
75th percentile	26.83	34.96	39.65

Notes: Row 1 reflects cumulative LIHTC developments in the sample districts from 2000-2020. To characterize the exposure to LIHTC for each school in a given year, I calculate the cumulative number of LIHTC units available per 100 students. Table 1 also contains the distribution of the exposure measure. Descriptive statistics for the 898 schools with any LIHTC activity are presented in Table 2.

Identification in the first econometric model of this paper relies on two key pieces of information: the presence of a qualified census tract within school zone boundaries and rich income measures for local residents. The list of qualified census tracts are made available by HUD when new census tract data becomes available, and I use the 2003 release based on 2000 census data. To do so I create an indicator QCT equal to one if any population with a school zone matched census block resides within a qualified census tract. To measure neighborhood income I use data from the Home Mortgage Disclosure Act that describes the reported annual income of homebuyers that sign a mortgage contract in a given census tract each year. Along with the fraction of students receiving free lunch, the homebuyer income data allows me to observe and control for annual income changes within a school zone.

3.2 Sample Data

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.[11] This yields a balanced panel of 3,484 schools in Texas

[11] This sample restriction removes 3521-3484 = 37 schools.

from 2000 to 2020. 2,710 schools in the sample (78%) are elementary or middle schools, and the remainder are high-schools.[12] 898 of the schools in the sample received at least one LIHTC housing development within school attendance boundaries. Summary stats are reported in Table 2.

Table 2: School Summary Statistics

	Full Sample	LIHTC ≥1	No LIHTC	QCT
Enrollment	1,048.39	1,321.95	900.62	1,122.55
	(788.4)	(908.8)	(670.0)	(767.4)
Full-time Teacher Equivalent	66.89	83.99	57.66	72.06
	(47.33)	(54.47)	(40.05)	(47.56)
Student-Teacher Ratio	15.31	15.45	15.23	15.47
	(3.318)	(2.068)	(3.825)	(2.194)
School Spending	7,179.45	7,334.34	7,095.78	6,929.18
	(3126.2)	(3233.1)	(3063.7)	(2569.1)
Instructional Spending	4,908.41	4,873.75	4,927.13	4,814.67
	(1424.3)	(1330.1)	(1472.3)	(1184.1)
Median Homebuyer Income	72,035.39	65,524.71	75,552.23	60,986.95
	(33387.1)	(24986.9)	(36665.1)	(28349.2)
Free or Reduced Lunch Share	0.53	0.56	0.51	0.63
	(0.281)	(0.255)	(0.292)	(0.264)
Fraction Latino Students	0.49	0.51	0.47	0.64
	(0.307)	(0.285)	(0.317)	(0.291)
Fraction Black Students	0.14	0.17	0.12	0.17
	(0.167)	(0.191)	(0.149)	(0.218)
Schools	3,484	898	2,586	1,162
Percent Any LITHC	25.7%	100.0%	0%	36.4%
Share of Total Sample		25.7%	74.3%	33.4%

Notes: Summary statistics shown include all years of data 2000-2020 for a balanced sample of 3,484 K-12 public schools in Texas. All dollar valued variables are inflation adjusted to the year 2015. School spending and instructional spending are per-pupil measures, computed as current year expenditures divided by initial enrollment from the year 2000.

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

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

approximately half of the total population.[13] Column one of Table 2 describes all schools in the sample, column two includes the schools that never receive LIHTC housing, and column three includes schools that receive at least one LIHTC development. The rightmost column four describes schools with any amount of residents living in qualified census tracts. Since QCT status changes in 2003, then begins biannual changes in 2013, I restrict the sample in the 2SLS framework of Section 4 to 2000-2012. In the dynamic model of Section 5 I utilize the full panel of data.

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. Class sizes, defined as the student to teacher ratio, are the same across columns 1-4. Total spending per-pupil and instructional spending per-pupil all lie within +/- 2% at the mean for columns 1-4. Treated schools and schools in qualified census tracts differ from the sample mean in sociodemographic characteristics, having lower homebuyer income, a higher fraction of subsidized lunch students, and a higher Black and Latino share at the mean.

4 Estimation: School Spending With Exogenous Housing Shocks

I begin by estimating the causal effect of LIHTC development on total school spending and school spending for instruction. I am first interested in absolute spending changes, so for each of the two outcomes I hold enrollment constant and compute per-pupil expenditures for school i, in year t as

$$PPE_{it} = \frac{Spending_{it}}{Enrollment_{i,2000}}. \tag{1}$$

By fixing enrollment to initial period levels, PPE_{it} captures variation in absolute spending levels scaled by enrollment counts to ease interpretation of the estimates. I refer to PPE_{it}

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

as absolute spending throughout the paper. The baseline relationship of interest can be expressed as

$$Log(PPE_{it}) = \alpha LIHTC_{it} + X_{it}^{'}\beta + \gamma_i + \gamma_t + \epsilon_{it}, \quad (2)$$

where $LIHTC_{it}$ is a count of LIHTC builds in school zone i, year t and X_{it} are time-varying explanatory variables at the school zone level. I assume the presence of school-specific, fixed characteristics such as location or proximity to the city core may that affect absolute spending and propensity for LIHTC. As a control I include school fixed effects γ_i. Likewise I assume the presence of macroeconomic shocks that may affect spending for all schools in Texas for a given year, and include year fixed effects γ_t.

OLS estimates for $\hat{\alpha}$, the effect of one additional LIHTC complex coming online in a school zone are presented in Table 3. The effect on total spending is shown in columns 1-3, and the effect on instruction spending are shown in columns 4-6. For each of the outcomes I begin with estimates from the most naive model and incrementally add more controls that may explain changes in the school spending outcomes. In addition to school and year fixed effects I employ two groups of income-based controls. The first is a set of time trends interacted with indicators based on quartile assignment within the initial, within-county income distribution.[14] The second set of controls are school zone homebuyer income and the fraction of students receiving free lunch, both observed annually for each school.

The results in columns 1 and 4 of Table 3 show that LIHTC is positively associated with higher total spending and higher instructional spending. When school and year fixed effects are included in columns 2 and 4, the effect is no longer identified but the model predicts much more of the variation in the two outcomes as shown by the increase in R^2. This is likely explained by the majority of LIHTC developments being deployed in urban and suburban areas near large cities. Once this fixed characteristic is accounted for, OLS regression cannot distinguish LIHTC from other possible explainers of school spending.

[14] For the interacted time trends I use homebuyer incomes from the initial year 2000 multiplied by a general time trend.

Table 3: OLS Estimates: LIHTC and School Spending

	(1) Total	(2) Total	(3) Total	(4) Instruction	(5) Instruction	(6) Instruction
SZ LIHTC Builds	0.043***	0.007	0.007	0.017**	-0.001	-0.001
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Schools	3484	3484	3484	3484	3484	3484
Years	13	13	13	13	13	13
Fixed Effects		×	×		×	×
Time Trends		×	×		×	×
Income Controls			×			×
r2	0.008	0.522	0.523	0.002	0.439	0.440

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. 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.

4.1 2SLS Model

For exogenous variation in LIHTC I instrument for new development with a change in the qualified census tract designation formula in the year 2003. The formula change in 2003 was the first major update in nearly a decade, and is the first to use the 2000 decennial census data. I model LIHTC development as a function of the QCT formula change in the first-stage, expressed as

$$LIHTC_{it} = \delta QCT_i \times Post_t + X_{it}^{'}\Gamma + \gamma_i + \gamma_t + \xi_{it}. \tag{3}$$

Equation 3 is a fixed effects difference-in-differences model where QCT_i defines the treatment group as schools with at least one qualified census tract, interacted with a dummy $Post_t$ for observations in post-formula change years. QCT_i is a school fixed effect and $Post_t$ is a time fixed effect, but the interaction coefficient δ can be identified when fixed effects are employed. All other controls as the same as in the baseline model results in Table 3. Thus δ is the impact of QCT designation on new LIHTC activity, and is presumed to be positive. The IV regression uses predicted LIHTC development from the first stage and is expressed as

$$Log(PPE_{it}) = \alpha \widehat{LIHTC}_{it} + X_{it}^{'}\beta + \gamma_i + \gamma_t + \epsilon_{it}. \quad (4)$$

I will show the releveance of QCT designation on LIHTC development through sharp first-stage estimates in Table 4 and robust f-stats above 85 in the preferred specifications. I argue the IV exclusion restriction holds as follows. Conditional on contemporaneous measures of neighborhood income, QCT status only affects school spending through how the designation influences LITHC production. Prior studies of LIHTC have shown QCT designation is a strong predictor of future LIHTC independent of other local economic factors (Baum-Snow and Marion (2009), Freedman and Owens (2011)).

Table 4: First Stage: QCT Designation on LIHTC Development

	(1)	(2)	(3)	(4)
$QCT_i = 1$	0.050***			
	(0.012)			
$POST_t = 1$	0.145***			
	(0.012)			
$QCT_i \times POST_t$	0.344***	0.353***	0.329***	0.331***
	(0.034)	(0.036)	(0.036)	(0.035)
Schools	3484	3484	3484	3484
Years	13	13	13	13
Fixed Effects		×	×	×
Time Trends			×	×
Income Controls				×
R2	0.088	0.746	0.748	0.748

Notes: Standard errors in parentheses. The outcome of interest is a count of 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. 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.

The results show that QCT designation increases the exposure to LIHTC in a school zone, robust to the inclusion of fixed effects, interacted time trends, and contemporaneous income controls. Evaluating column one provides insight into the relative effect of the policy on LIHTC development. Summing the coefficients infers the aggregate effect of having a QCT in the school zone after the formula change is responsible for a $0.05+0.145+0.344 = 0.54$, explaining over half of the propensity to add an additional LIHTC development. Having a QCT is the school zone at any time accounts for $0.05/0.54 = 9\%$ of this effect, the general increase in LITHC production post 2003 accounts for roughly $0.145/0.54 = 27\%$ of this effect, and the interaction effect of the policy accounts for the remaining 64% of the effect. Once the two fixed effects are captured the policy effect remains robust at this magnitude. With this exogenous variation in new rental development I turn to estimating the model in equation 4 to analyze how new LIHTC affects school spending.

4.2 2SLS Results

The main results of Model 4 are presented in Table 5. Columns 1-3 show the effects on total school spending per-pupil, and columns 4-6 show the effects on instructional spending.

Table 5: IV Estimates: LIHTC And Absolute Spending

	(1) Total	(2) Total	(3) Total	(4) Instruction	(5) Instruction	(6) Instruction
SZ LIHTC Builds	0.120***	0.0917***	0.0864***	0.0497**	0.0532*	0.0487*
	(0.0201)	(0.0217)	(0.0211)	(0.0178)	(0.0207)	(0.0203)
Schools	3484	3484	3484	3484	3484	3484
Years	13	13	13	13	13	13
Fixed Effects		×	×		×	×
Time Trends		×	×		×	×
Income Controls			×			×
Fstat	130.8	86.89	89.88	130.8	86.91	89.89

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. 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.

Moving from left to right for each of the outcomes I include additional controls in the same steps as OLS Table 3. The result of the full model in column 3 is a prediction of school spending to increase by 8.6% following new LIHTC development. Instructional spending is predicted to increase by 4.9%, and both models have a first-stage F-stat of 89.9. Taking the estimates together I can infer that the average school must increase expenditures after new affordable housing is built.

Reduced form estimates of the instrument regressed on the absolute spending outcomes are presented in Table 6. In this just-identified model, my 2SLS estimate in Table 5, column 3 is the ratio of the reduced form estimate (Table 6, column 3) and the first-stage estimate (Table 4, column 4).[15]

Table 6: Reduced Form : QCT Status and Absolute Spending

	(1) Total	(2) Total	(3) Total	(4) Instruction	(5) Instruction	(6) Instruction
$QCT_i = 1$	-0.008			-0.022**		
	(0.007)			(0.007)		
$POST_t = 1$	0.088***			0.078***		
	(0.005)			(0.005)		
$QCT_i \times POST_t$	0.035***	0.031***	0.030***	0.019**	0.018**	0.017*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Schools	3484	3484	3484	3484	3484	3484
Years	13	13	13	13	13	13
Fixed Effects		×	×		×	×
Time Trends		×	×		×	×
Income Controls			×			×
r2	0.015	0.522	0.523	0.012	0.439	0.440

Notes: Standard errors in parentheses. 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. 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. 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.

In Table 7 I show the estimated absolute spending increase equates to approximately

[15] Angrist and Pischke (2009) detail the just-identified 2SLS/IV model as one with a single endogenous regressor of interest and a single instrument.

$452,328 for the average school. My data also has information about dollar value of tax credits allocated for each project. In 2020 the average LIHTC build in Texas produced 158 units and generated a stream of tax credits valued at $1,322,222. With this information and the estimated $452,328 average spending increase, I quantify the school finance spillover for LIHTC to be $2,862 per unit or 35 cents per LIHTC dollar.

Table 7: Summarizing the Tax Cost of LIHTC

	Units per Build	**LIHTC Dollars per Build**	**School Spending**
Mean	158	$1,332,222	$5,259,634
Predicted LIHTC Shock			+8.6%
Absolute Expenditure Increase			$452,328
Expenditure Increase per LIHTC Unit			$2,862
Expenditure Increase per LIHTC Dollar			$0.35

Notes: Data used in the second row of Table 7 are from sample year 2020. The predicted LIHTC Shock is the estimate from Table 3 column 3. Mean school spending in row 2 is for schools in 2020 with no prior LIHTC treatment, and is used to calculate the expenditure dollar increase. To obtain the expenditure increase per LIHTC Unit divide the absolute expenditure increase by the mean units per build. To obtain the expenditure increase per LIHTC dollar, divide the absolute expenditure increase by the mean LIHTC dollars per build.

4.3 Heterogeneity

There is substantial heterogeneity in the size and scope of new LIHTC developments. To extend my analysis I compute the aggregate total of in-service rental units within a school zone each year, and scale the quantity by enrollment to measure the intensity of treatment for schools that receive LIHTC. The distribution of this intensity is shown in Table 1, and I denote large-scale LIHTC exposure as schools with over 26 units per 100 students. Intuitively, if there is one unit available for every four students the housing supply in the neighborhood has a material share of LIHTC housing. Estimates in Appendix Table A1 show that the school spending increase diminishes for schools with large-scale LIHTC exposure.The increase in total spending is reduced to 5.4% as shown by adding the coefficients in column 3. Likewise, summing the estimates in column 6 of Appendix Table A1 reveal an immaterial increase in instructional spending for schools with high exposure to LIHTC development. In summary, schools with a larger share of students in LIHTC housing appear to be more resource constrained, and absolute spending increases are allocated for uses other than instruction.

I next set out to estimate heterogeneity in the effect of LIHTC by differences in pre-period neighborhood income. This follows from Diamond and McQuade (2019) who document that house prices rise following LIHTC in low-income neighborhoods and fall following LIHTC in high-income neighborhoods. In this setting, however, heterogeneity in the spending response to LIHTC will reflect differences in the elasticity of school district resources. If high income neighborhoods are able to more rapidly extract more resources from the school district, expenditures will rise faster in such neighborhoods after new development. My approach to this question is to split the sample based on the pre-period, county level distribution of homebuyer income and compare the magnitude of the estimates from my main model.

Appendix Table A2 presents estimates in column 1 and 3 from a subset of schools at all grade levels in the bottom two-thirds of the income distribution, and columns 2 and 4 contain schools in the upper tercile. I find that the magnitude increase of total school spending in high income neighborhoods is nearly twice the size of low income neighborhoods. Moreover, the results in Appendix Table A2 show that schools in the high-income group increase instructional spending by nearly 8% following LIHTC. In stark contrast to the high-income group, I find no evidence that LIHTC causes schools in the bottom terciles of the distribution to increase instructional spending.

To this point my analysis uses a pooled sample schools irrespective of grade level. Given that school resources are organized differently based on the grade levels served, a sensible presumption is the effect of LIHTC will vary by grade as well. In Appendix Table A3, I report heterogeneity in the estimated effect of LIHTC by again splitting the sample into two groups. The first group consists of elementary and middle schools and the second group consists of high schools.[16] In column 1 and 2 my model predicts the LIHTC induced total spending increase for high schools is about half the magnitude of the increase for elementary and middle schools. Comparing columns 3 and 4 I find that the instructional spending increase for high schools is about one third the increase in elementary and middle schools.

4.4 Robustness : 2SLS Placebo Test

My headline results rest on the argument that qualified census tract status only affects schools through the production of new housing. To ensure that my results are not an artifact of policy timing I conduct the following placebo test following Di and Murdoch (2013). New LIHTC developments earmarked for elderly populations should not affect the schools through the QCT to LIHTC channel. As such, I estimate my 2SLS model taking only elderly LIHTC developments as the treatment and excluding LIHTC with no population target from the sample. I find no evidence for the effect of elderly LIHTC on school spending as shown in

Table 8: IV Estimates: LIHTC Senior Housing And Absolute Spending

	(1) Total	(2) Total	(3) Total	(4) Instruction	(5) Instruction	(6) Instruction
SZ Senior Housing	1.700 (1.247)	2.796 (3.233)	1.955 (3.451)	0.489 (0.573)	1.727 (2.056)	1.548 (1.835)
Schools	2439	2439	2439	2439	2439	2439
Fixed Effects		×	×		×	×
Time Trends		×	×		×	×
Income Controls			×			×
Fstat	2.021	0.762	0.326	2.022	0.762	0.790

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. 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 8. The weak f-stat reflects the lack of a robust first-stage relationship. The results

[16] Eighth grade is the maximum grade level offered for schools in group 1. The remainder are in group 2.

from my first-stage are presented and Table A6. In the case of elderly targeted LIHTC, qualified census tract status is not linked to higher housing development.

5 The Dynamic Effects of LIHTC On Schools

The full panel of 21 years of data along with the staggered arrival of LIHTC throughout this period allows for further analysis of dynamic effects based on the timing of new LIHTC. The goal is to identify the role of sorting in producing the average treatment effect from section 4. The central idea is as follows. In the year of project approval, $\tau = 0$, public announcement is made of the forthcoming development and construction begins. Households simultaneously update beliefs about relative neighborhood quality as an impetus for sorting. In the results of this section I put forth LIHTC induced sorting as a plausible mechanism role for changes to schools following new affordable housing.

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

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

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 school outcomes Y_{it}[17].

I first present the results from equation 5 on the absolute spending outcomes of interest.

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

Then, I put forth three mechanisms that could explain why school spending increases following LIHTC: enrollment, teacher counts, and the fraction of students receiving free or reduced price lunch. Last, I study the efficiency of absolute spending increases through analysis of the per-pupil spending when allowing enrollment to change. The event-time coefficients π_τ are plotted to show the dynamic effects of LIHTC visually, along with 95% confidence intervals at each coefficient. All estimates are plotted relative to period $\tau = -1$.

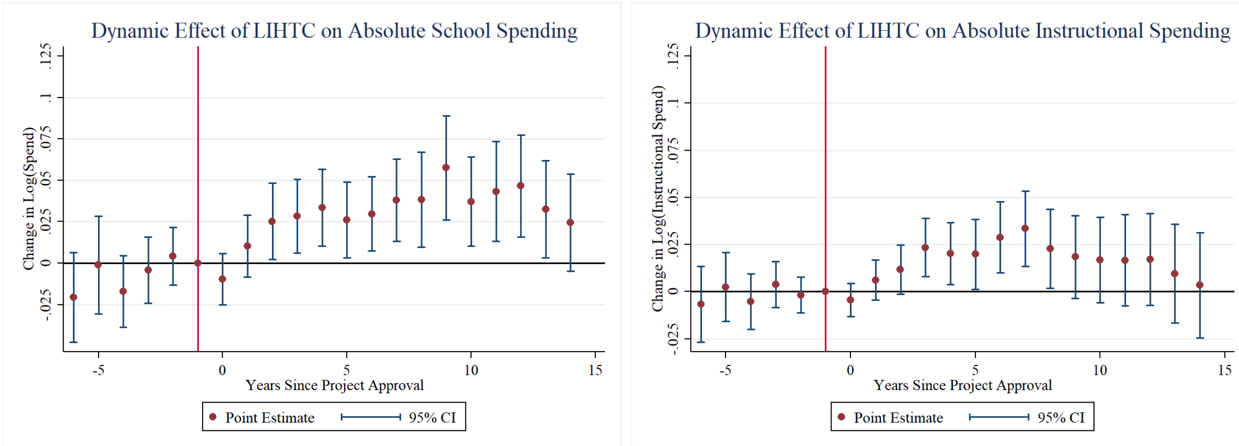
5.1 Absolute Spending

I estimate Model 5 first setting Y_{it} to Log(PPE_{it}) as in the analysis of Section 4. The left and right panel of Figure A1 show a gradual increase in spending beginning the year after project approval, becoming statistically distinguishable from the pre-period after years 2 and 3. It also takes over 5 years for the increases to peak. The total spending increases appear to be more durable than spending on instruction, remaining significant through year 14 while the affect of LIHTC on instructional spending declines after year 7. Even with stable pre-trends there are no discrete jumps in either outcome of Figure A1.

In terms of magnitude the event-study point estimates are smaller than those of the 2SLS model. If the assumptions of my 2SLS model hold, the event-study estimates appear to understate the effect of LIHTC on both total and instructional spending. Taken together I can infer that local economic conditions that are structurally related to the timing of LIHTC on average represent a downward bias of the effect of LIHTC on school spending. Further, my IV estimates may represent an upper-bound of the effect of LIHTC on school spending. For robustness I test for a Placebo effect of elderly designated LIHTC and plot the results in Appendix Figure A2. Similar to the 2SLS results I find no dynamic effect of elderly LIHTC on schools.

Figure 3: Event-Study Estimates : The Effect of LIHTC on Absolute 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 fixed to initial school enrollment, thus the estimates measure absolute increases in total and instructional spending. 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.

5.2 Enrollments, Teacher Counts and Demographics

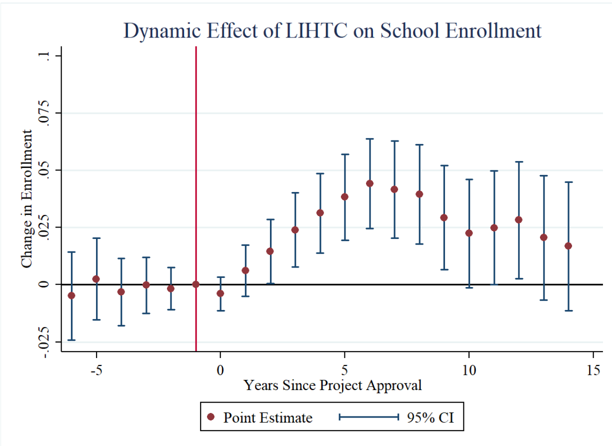
Why do schools need to spend more following the creation of new rental housing? In Texas, schools are funded a base amount for each student then additional dollars for school and neighborhood specific factors.[18] If LIHTC increases enrollments, and schools must hire more teachers to maintain reasonable class sizes, expenditures will rise after LIHTC. Demographic changes can also affect the cost to support each student. In this section I estimate the event-study model with enrollment, teacher counts, and the fraction of students receiving free-lunch as outcomes. I document statistically significant effects for three margins of interest following LIHTC approval, and the timing is consistent with changes to absolute spending as shown in Figure A1.

The first outcome of interest is student enrollment, for which I plot the event-study coefficients in the left side of Figure 4. The model predicts a gradual increase in enrollments to nearly 5% at the post-LIHTC peak in year 7. For the average school in the treated sample

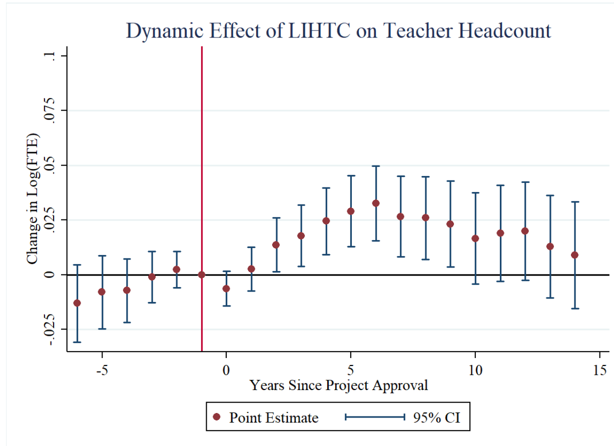
[18]School specific factors include high cost of living adjustments, the share of non-native English speakers, the share of students living below the poverty line, and the share of students receiving subsidized lunch.

Figure 4: Event-Study Estimates : The Effect of LIHTC on Enrollment and Teacher Counts

(a)



(b)

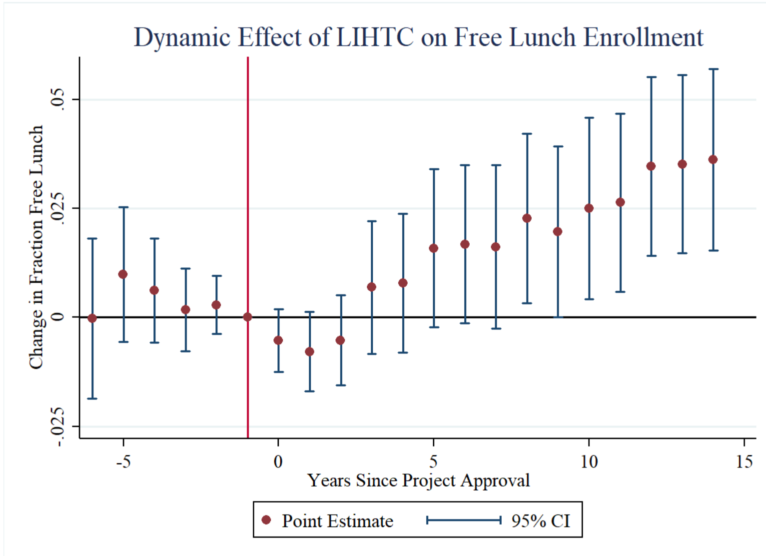


Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 5 for the outcome variable of interest. Each regression includes school and year fixed effects, along with a linear time trend interacted with the intial period quartile of the homebuyer income distribution. 95% confidence intervals are shown, with observations clustered at the school level.

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 event-study model predicts that teacher counts increase over 2.5%, 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.

Changes in neighborhood socioeconomics will affect school spending primarily through federal dollars allocated to the school for Title 1 Grants and Nutritional Programs. Title 1 Grants are paid to each district based on federal estimates of poverty within the student population (Gordon 2004). Likewise, nutritional programs are funded by the Department of Agriculture to subsidize breakfast and lunch during the school year and in some cases, the summer (Hussar et al. 2020). In my data I do not observe spending for either of the two largest federal programs, but I do observe the fraction of students receiving either free or reduced price lunch.

Figure 5



Notes: Event-study estimates of the $\hat{\pi}_t$ coefficients from Equation 5 for the outcome variable of interest. 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 5 shows the event-study estimates taking the fraction of free-lunch students as the outcome of interest as a proxy for overall federal program participation. The results show a gradual, persistent increase in spending on programs backed by federal dollars based on demographic changes to enrollments. Unlike the headline enrollment growth in Figure 4 the subsidized lunch share increases throughout the duration of the post period. For context, if the share of free lunch students increases by 0.025 that is approximately 33 students, or half of the peak enrollment increase.

The timing traced out by the event-study estimates indicate that LIHTC effects on school spending are likely associatied with enrollment increases requiring more teachers. After LIHTC development I find that spending, enrollment, and teacher counts increase then peak and decline beginning six years post-approval. This pattern holds for both total spending and instructional spending. Further, the timing appears less related to socioeconomic changes proxied by the fraction of students receiving free-lunch subsidies, which is predicted to rise steadily in the years following LIHTC. This set of results show that spending changes are driven by changes to student headcount, and not socioeconomic composition.

5.3 Relative Spending Per-Pupil and School Quality

To this point in Section 5, I am able to show that local LIHTC investment will require more resources for schools in absolute terms. What about the resources devoted to each student following LIHTC? To understand the overall dynamic effect on relative spending per-pupil, I allow enrollment to change in the denominator of the outcome for school i in year t:

$$PPE'_{it} = \frac{Spending_{it}}{Enrollment_{it}}. \tag{6}$$

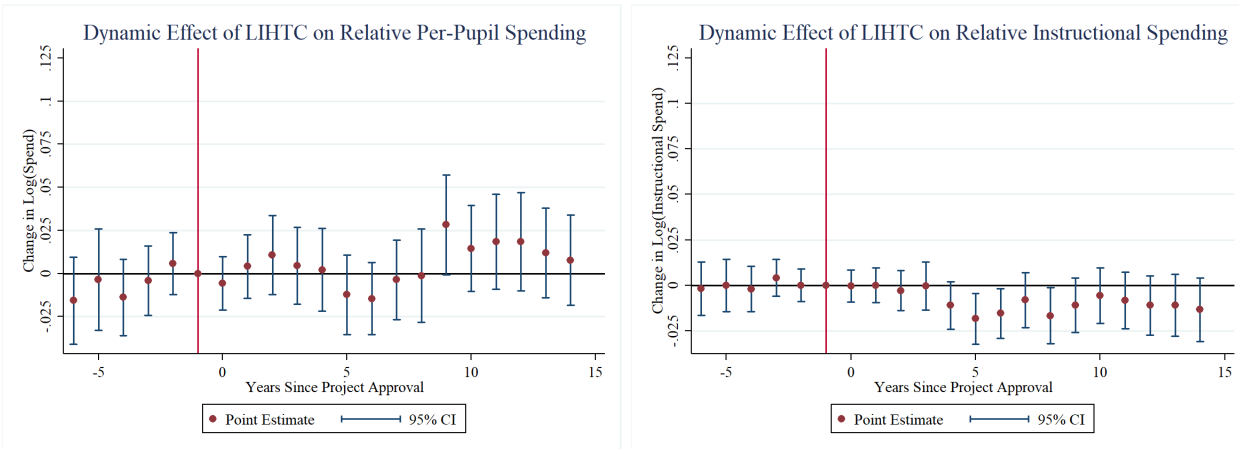
The goal of estimating Model 5 with PPE'_{it} as the outcome is to evaluate the efficiency of school district budgeting during an affordable housing shock. Affordable housing produces a negative spillover if enrollment growth exceeds expenditure growth at a school, and relative spending per-pupil declines. The absolute spending increase is considered efficient if relative spending per-pupil does not fall after LIHTC. I plot the dynamic event-study coefficients in Figure 6.

The estimates on the left side of Figure 6 show a null effect of LIHTC on relative spending per-pupil, inferring that districts increase overall spending at treated schools to meet enrollment growth. In terms of how the money is spent, the right side of Figure 6 are estimates for the effect of LIHTC on relative spending for instruction. From the estimates I gather that enrollment growth outpaces instructional spending growth causing instructional resources to decline on a per-pupil basis, and by year 5 the decrease is statistically significant.

The results paint an interesting picture in regards to the allocative efficiency of school district funding for schools experiencing an affordable housing shock. If there is no change in total relative spending per-pupil as Figure 6 suggests, the absolute spending increase districts allot for schools would be deemed efficient. Incumbent students would not experience a decrease in dedicated resources for each student, and new students would on average receive

Figure 6: 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.

the same level of real spending. When combined with the findings of Di and Murdoch (2013), this efficient spending increase is responsible for test scores for the average student to remain unchanged following LIHTC development. It does appear that relative spending for instruction declines, but the magnitude and confidence interval suggest the decrease may not have a measurable effect on school quality and student outcomes.

6 Conclusion

The results of this study highlight increased financial obligations of schools zoned to new affordable housing development, reflecting fiscal spillovers from the decisions of state housing authorities. The average school increases total spending by 8.6% and instructional spending by 4.9% for each new LIHTC development built. What explains the absolute spending increases at treated schools? I find gradual enrollment increases that peak 5 to 6 years after new housing has been approved. Teacher counts increase in a similar fashion, and the timing of both coincide with the timing of absolute changes in total and instructional spending after

LIHTC. Inference from the dynamic model results imply that school districts are responding to the aggregate local population changes caused by both LIHTC take-up and sorting.

I evaluate the efficiency of the school district response to LIHTC through the ratio of absolute spending growth to enrollment growth. The response is considered inefficient if absolute spending growth is lower than enrollment growth post-LIHTC, as the relative spending per-pupil will decline in this case. I find that absolute spending growth coincides efficiently with enrollment growth such that average student resources at a treated school do not change. This is a crucial point when positioned within the literature that claims test scores do not change following LIHTC. The absence of measureable declines in school quality speaks to the coordination of districts and state housing agencies to limit spillovers of LIHTC on schools to financial statements and not student outcomes.

Further research is required to understand if affordable housing produces material changes to school racial demographics (Dizon-Ross 2020), given parental preferences for school racial composition (Caetano and Maheshri 2017). I do attempt to explore heterogeneity in the effect of LIHTC on school spending based on pre-existing neighborhood racial demographics, with mixed results presented in Appendix Tables A4 and A5. The lack of power suggests my model is likely not well-suited to explore this topic at length.

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.

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Supplementary Appendix

Local Housing Development and Money for Neighborhood Schools

Kenneth Whaley

A Additional Analysis

A.1 Heterogeneity Results

Table A1: IV Estimates: LIHTC And School Spending

	(1) Total	(2) Total	(3) Total	(4) Instruction	(5) Instruction	(6) Instruction
SZ LIHTC Builds	0.145***	0.136***	0.133***	0.0954**	0.0868*	0.0847*
	(0.0399)	(0.0387)	(0.0383)	(0.0369)	(0.0360)	(0.0357)
LIHTC*Large Build	-0.0874**	-0.0801**	-0.0792*	-0.0629*	-0.0562*	-0.0842*
	(0.0299)	(0.0289)	(0.0373)	(0.0271)	(0.0264)	(0.0340)
Schools	3484	3484	3484	3484	3484	3484
Years	13	13	13	13	13	13
Fixed Effects	×	×	×	×	×	×
Time Trends	×	×	×	×	×	×
Income Controls		×	×		×	×
Interacted Controls			×			×
First-Stage Fstat	209.8	209.1	24.08	209.8	209.1	24.08

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 $LargeBuild$ is equal to one once a school has more than 25 LIHTC units per 100 students (75th percentile.) 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 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

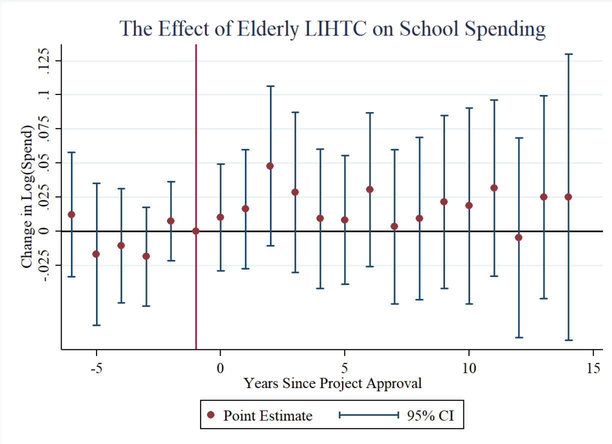
Table A6: First Stage: QCT Designation on Elderly LIHTC Units

	(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

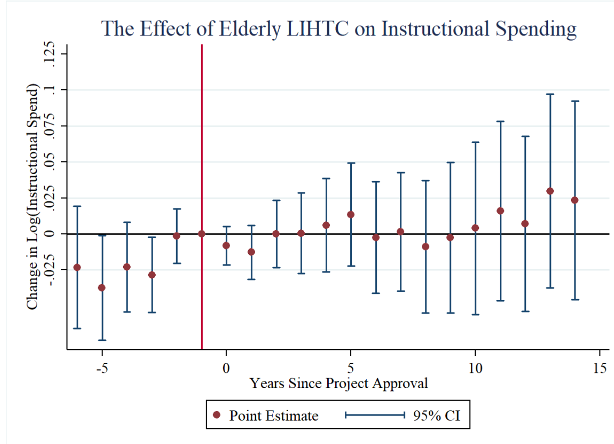
Notes: Standard errors in parentheses. The outcome of interest is a count of elderly designated LIHTC developments within the attendance boundary of school i in year t. QCT is an indicator equal to one if the school has any neighborhood that lies within a qualified census tract. $POST$ is an indicator 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)

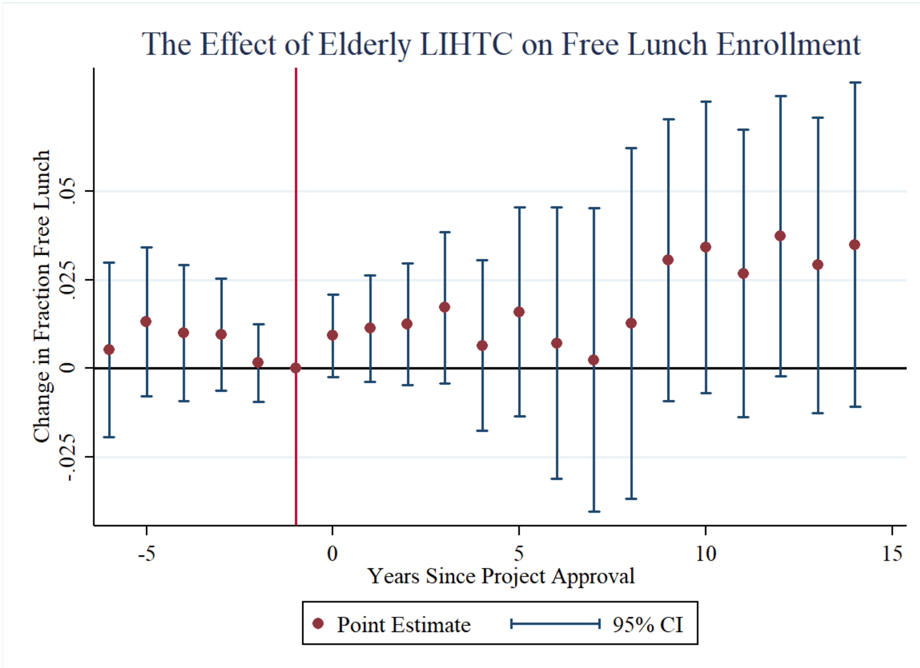


(b)



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



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).[19] 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

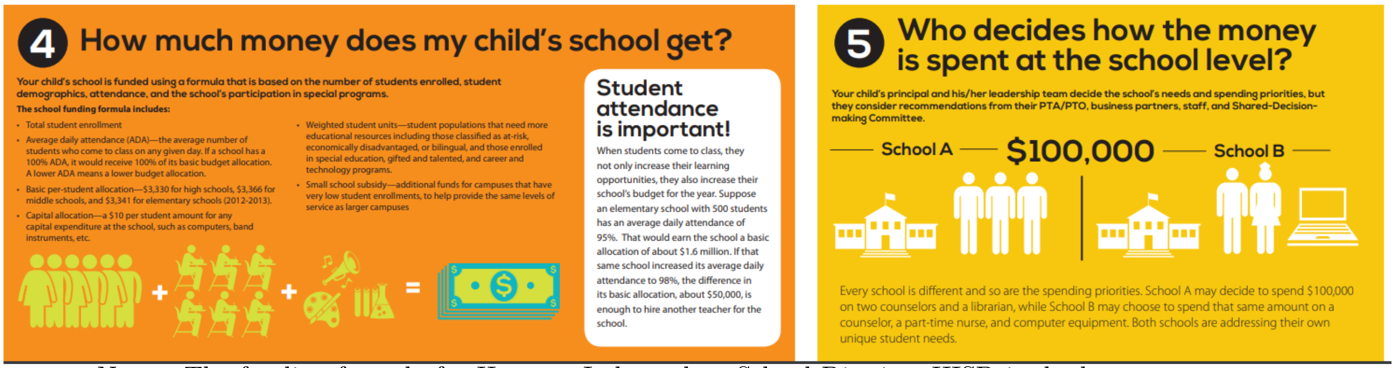
[19] The TEA managed *Texas Academic Performance Reporting* system has public databases available back to the 2013 school year. The *Academic Excellence Indicator System* housed the data prior to 2013. The data prior to 2004 is not listed on the Academic Excellence Indicator System website but remains 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 4 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.

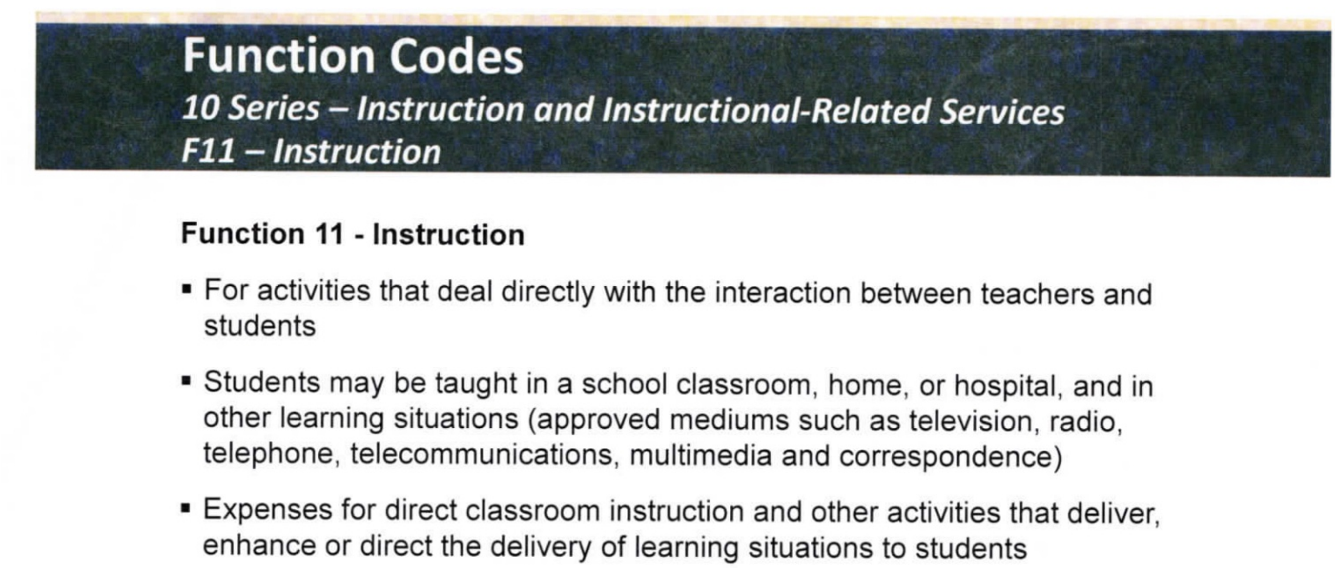
B.2 School Spending Details

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