County Property Tax Capitalization in U.S. Cities

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Abstract

The extent to which changes in local property taxes are capitalized into housing prices is an ongoing empirical debate. Estimates of the capitalization rate for property taxes vary in magnitude and typically depend heavily on the setting, if capitalization is found to occur at all. This paper contributes to the empirical literature on property tax capitalization by generalizing the setting to large U.S. cities using novel data on county-level statutory property tax rates for three dozen counties using an event-study design to demonstrate that house prices are inversely responsive to property tax rate changes while controlling for the entire budget of local government spending. The results suggest that house prices are responsive to changes in statutory property tax rates in years of large property tax rate increases. Estimates of the property tax capitalization elasticity with respect to property tax rates is around -0.115. Using recentered-influence functions (RIFs) that analyze unconditional quantile regressions, the capitalization rate is shown to vary across the distribution of house prices. Specifically, there is no evidence that house prices are affected by changes in property tax burdens above the fourth quintile of the distribution.

Keywords: Property Tax Capitalization, Difference-in-Differences, Quantile Regressions

JEL Codes: C22, D15, H72, R31

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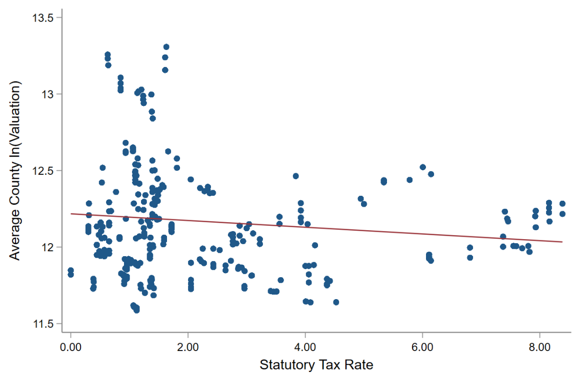
1 Introduction

As of May 2023, the Bureau of Labor Statistics (2023) (BLS) reports that homeowners' equivalent of rental expenditures for housing units is the largest single expenditure category at 25.432% of the entire representative consumption basket used to construct the BLS Consumer Price Index for urban residents (CPI-U). Property taxes represent a non-negligible annual user cost of homeownership that vary widely across time and location. At the same time, local governments often rely more heavily on taxes levied against real property than other tax revenue classes. The relationship between house prices and local public finance is a crucial component to fully understanding housing markets and house price determination, and there is a long empirical debate on the magnitude of this relationship.

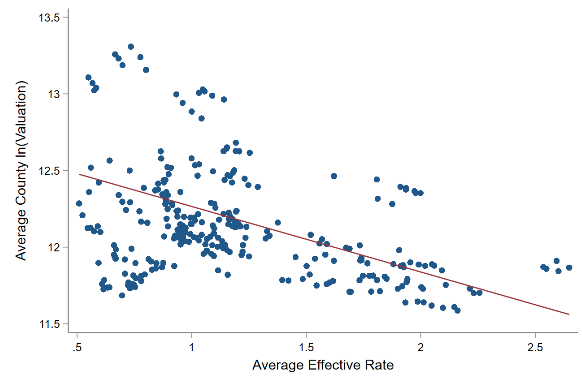
The main question in the property tax capitalization literature is, given two similar houses in otherwise comparable locations in terms of market forces and public amenities, whether differences in property tax rates affect the price of a house. Figure 1 shows the natural log of county average house prices in counties that contain large cities from 2010 to 2016 against statutory property tax rates and county average effective property tax rates that descriptively demonstrates the inverse relationship between house prices and property tax rates. County governments provide public amenities focused on education, social services, public safety, and road maintenance and rely mainly on property tax revenue to do so. County governments have substantial heterogeneity in their spending patterns so omitted variable bias may be a concern for measures of public amenities that are narrowly defined. In this paper, variation in novel county-level statutory property tax rate data are used in an event-study design to estimate the extent to which changes in property tax rates are capitalized into house prices. Categories for all county spending are included control for changes in public amenities so the capitalization estimates should be considered the differential in house prices conditional on changes in public amenities. The property tax elasticity with respect to changes in the county-level property tax rate in the preferred specification is calculated at -0.115 so a percentage increase in the property tax rate of 10% decreases house prices 1.15%. These estimates do not depend on variation from any specific location or tax change event and include full local government budgetary categories to reduce potential omitted variable bias.

Estimation models that include hedonic components are common when studying house price

Figure 1: Average Valuations by County



(a)



(b)

Note: County average natural log house prices against statutory property tax rates in Panel (a) and against county average effective property tax rates in Panel (b) pooled from 2010 to 2016. Source: American Community Survey and the Lincoln Institute of Land Policy Significant Features of the Property Tax: Property Tax Rates.

determination going back to Oates (1969), Alonso (1964), and Muth (1969) while Wales and Wiens (1974) point out that failing to account for changes in public goods can bias the estimates of the property tax capitalization rate. However, differences in house prices may not be entirely driven by observable[1] characteristics of houses or public amenities in the hedonic models, and there is no theory-driven measure of these amenities.[2] Gibbons and Machin (2008) and Sirmans et al. (2008) survey the empirical literature to show that, while spending on schools is most common[3], almost every study varies on which public amenities to include in estimation and how to measure their chosen proxies.[4]

More recent empirical studies have used boundary discontinuity designs between adjacent fiscal districts to identify causal variation in property tax rates and local amenities including Cushing (1984), Black (1999), Davidoff and Leigh (2008), Dhar and Ross (2012), Livy (2018), and Giertz

[1]Including fixed effects can reduce bias introduced by unobservables or characteristics left out of hedonic regressions, but there is little consensus as to whether observable characteristics bias hedonic regressions in the capitalization context.

[2]House prices may also be impacted by supply inelasticities of land as in Saiz (2010) that can be, at least partially, mitigated using geography-specific fixed effects.

[3]In the context of education spending, Davidoff and Leigh (2008) review and demonstrate how dramatically spending proxies can vary in a capitalization framework.

[4]In an unreported ancillary exercise, test scores in math and reading are used as controls. Importantly, these findings suggest that focusing on outcomes from school spending may under-estimate property tax capitalization estimates. Further, the findings suggest that math scores are capitalized more than reading scores.

et al. (2021). Natural experimental approaches to estimate property tax capitalization rates start with Rosen (1982) and California's Proposition 13[5] that exploit variation from specific tax change policies. Boundary discontinuity designs often rely on a control group that is not impacted by fiscal spillovers from the treated district, but inter-regional tax spillovers in property taxes have been shown to be present between neighboring fiscal districts in Germany in Merlo et al. (2023). Haughwout (1997), Elinder and Persson (2017), and Koster and Pinchbeck (2022) are among the few studies that focus on large geographic areas for estimating property tax capitalization in the United States, Sweden, and England respectively.

This paper complements the existing empirical literature on property tax capitalization in two main ways. The first contribution is producing property tax capitalization estimates that do not depend on a specific location or setting while controlling for all spending categories. This paper generalizes the setting for property tax capitalization for U.S. counties that contain large cities using novel data on statutory county-level property tax rates while controlling for the entire budget of local government spending. The estimates presented circumvent concerns about external validity and are free from potential contamination bias from fiscal policy spillovers. At the same time, including budgetary variables for each main spending category addresses potentially unobserved changes in the provisions of local public goods that may accompany changes in property tax rates. The main findings can be used to calculate an implied property tax capitalization elasticity. The second contribution is demonstrating that property tax capitalization rates vary across the distribution of house prices. Using recentered-influence functions (RIFs) in quantile analysis of the event-study design suggests that treatment effects vary along the distribution of house prices and that the highest quantile values of house prices are unaffected by changes in statutory property tax rates.

The rest of the paper is organized as follows: Section 2 explains the data sources used for estimation, Section 3 fully details and implements the event-study design, Section 4 analyzes the results along the distribution of house prices, and Section 5 briefly concludes the paper.

[5] Many other papers also study this tax change as well as other event-study designs surrounding specific tax change events that are location-specific.

2 Data

The ideal data set to study property tax capitalization into house prices in the bidding theoretical framework is household-level panel data that includes house prices for housing units with repeated sales, housing unit characteristics, local amenity characteristics, property tax rates (both effective and statutory) at each fiscal district level, and local government tax-assessed valuations. Several sources are merged at the county×year level to gather the necessary components to estimate property tax capitalization elasticities.

2.1 Sources

The American Community Survey (ACS) accessed through IPUMS Ruggles et al. (2021) includes household-level repeated cross-sectional data on self-assessed house prices, housing unit characteristics, and the availability to impute an implied overall effective tax rate. The effective tax rate is imputed using the midpoint of the property tax payment bins supplied by the ACS divided by the self-reported valuation of the house prices.[6] The benefits to using the ACS are the sample sizes and coverages that allow for the generalization of property tax capitalization to many cities. Summary statistics for housing characteristics are in Table 1.

The Lincoln Institute of Land Policy provides data sources on property tax rates and local government expenditure and revenue. First, the Significant Features of the Property Tax: Property Tax Rates[7] repository contains nearly all county property taxation reports sent to their respective state governments to be archived dating back to 1980, and statutory rates are collected from these annual records. Until now, no unified data set has been created from these annual reports so the variation provided by the statutory rates is novel. Since not every state has records for every year, the sample is limited to county×year observations for which statutory property tax rate data can be collected in at least two consecutive periods. The number of tax changes, tax increases, and tax decreases and the magnitudes of the tax changes are summarized in Table 2. The average county alters statutory property tax rates about a third of the years during the sample period,

[6]Given the magnitudes of the county statutory property tax rates and the fact that the overall effective tax rate is the sum of all statutory property tax rates, using the midpoint to impute effective tax rates from the ACS may provide underestimates. Moreover, after 2000, respondents were no longer explicitly instructed to report the full tax payment whether it was included in the mortgage payment, delinquent, or paid by another household member. It is possible that there is under-reporting due to the change in questionnaire verbiage.

[7]Access at https://www.lincolninst.edu/research-data/data-toolkits/significant-features-property-tax/ .

Table 1: Summary Statistics: Housing Characteristics

	Mean	SD	Min	Max	N
Valuation	241,408.94	172,053.47	32,000.00	1,787,203.25	237,096
ln(Valuation)	12.18	0.64	10.37	14.40	237,096
Imputed Tax Payment	2,608.81	1,743.72	74.50	8,254.45	237,096
Number of Rooms	6.51	1.72	2.00	10.00	237,096
Number of Bedrooms	4.17	0.81	2.00	6.00	237,096
Built Before 1950	0.10	0.30	0.00	1.00	237,096
Built 1950-1959	0.12	0.33	0.00	1.00	237,096
Built 1960-1969	0.12	0.32	0.00	1.00	237,096
Built 1970-1979	0.16	0.37	0.00	1.00	237,096
Built 1980-1989	0.15	0.36	0.00	1.00	237,096
Built 1990-1999	0.16	0.37	0.00	1.00	237,096
Built 2000-2009	0.17	0.38	0.00	1.00	237,096
Built 2010 or After	0.02	0.13	0.00	1.00	237,096
ln(Density)	7.89	0.80	5.05	9.64	237,096

Source: American Community Survey.

increasing once and decreasing once, and increases tax rates more frequently than decreases taxes. The average yearly percentage change in the statutory rates across all counties and all tax changes is about 0.64% but can vary substantially. About 22% of counties do not experience any statutory property tax rate changes over the sample period.

Second, the Fiscally Standardized Cities Database (FiSCs)[8] held by the Lincoln Institute of Land Policy and curated by Langley (2020) is a panel that contains revenue and expenditure data for the largest cities in each state at different fiscal levels. In the FiSCs, 'fiscally standardized' means that local government expenditures and revenues are normalized by population so these categories can be compared across districts which is especially useful in the aim to generalize the setting for property tax capitalization. Expenditure categories at the county level and in total across local fiscal districts in those counties are used to proxy for public good provisions and other local amenities that may be capitalized into house prices and are summarized in Table 3. There is substantial heterogeneity in each spending category which highlights the potential issues of focusing too narrowing on public good provision categories in the property tax capitalization framework.

While the data listed allow for estimation of property tax capitalization, there are drawbacks

[8] Access the FiSCs at https://www.lincolninst.edu/research-data/data-toolkits/fiscally-standardized-cities.

Table 2: Summary Statistics: Tax Changes

	Mean	SD	Min	Max	N
Statutory Tax Rate	2.06	1.69	0.38	7.93	237,096
Effective Tax Rate	1.25	0.74	0.16	4.18	237,096
Change in Statutory Tax Rate	0.01	0.09	-0.53	0.49	237,096
Percentage Change in Statutory Tax Rate	0.64	3.77	-17.71	15.42	237,096
Number of Tax Changes	2.38	1.77	0.00	6.00	237,096
Number of Tax Increases	1.39	1.47	0.00	5.00	237,096
Number of Tax Cuts	0.99	0.96	0.00	4.00	237,096
Counties With No Tax Changes	0.22	0.42	0.00	1.00	237,096

Source: Significant Features of the Property Tax: Property Tax Rates.

to relying only on the ACS and FiSCs in this context. First, the implied effective property tax rate in the ACS cannot be used to isolate the effective property tax rates from different fiscal districts. As a result, only the overall level of capitalization can be measured as opposed to the capitalization rate specific to changes in county-level property taxes or other fiscal districts. Second, each yearly wave of the ACS surveys different samples of households to create repeated cross-sectional data. While natural log transformations can provide exact theoretically-derived estimation equations, panel data allow for other transformations like first differences to derive other forms for estimation equations. Lastly, self-assessments of house prices from the ACS are not necessarily an analogue for market prices.[9] Models of portfolio choice typically assume that capital stock owners know with certainty the value of their property[10] which may be an overly strong assumption for self-reported

[9]The direction and magnitude of the deviations from self-assessments and market prices is an empirical debate with little consensus where variation across studies may be driven by methodological differences or measurements of market value. Overoptimism may cause overvaluations while the sample selection bias of more valuable units in sales data may cause self-assessments to tend toward undervaluation. Kish and Lansing (1954), Ihlanfeldt and Martinez-Vazquez (1986), Goodman and Ittner (1992), and Agarwal (2007) find that self-assessments overstate actual market value while Kain and Quigley (1972), Follain and Malpezzi (1981), DiPasquale and Somerville (1995), and Kuzmenko and Timmins (2011) find that self-assessments understate actual market value. The accuracy of self-assessments can also vary over time, especially when prices are changing rapidly as shown in Anenberg (2011), and Kuzmenko and Timmins (2011). Deviations in self-reported valuations from market prices can also vary by socio-economic status, demographics, and community characteristics such as education Kain and Quigley (1972), income Agarwal (2007), access to public transportation Emrath (2002), tenure in the same housing unit Kuzmenko and Timmins (2011), and network effects within neighborhoods Bayer et al. (2016). Further, recently sold housing units may be substantively different from the typical unit in the housing stock and may have more desirable traits. Homeowners also have incentives to invest in modifications or upgrades near the time of the sale to improve resale value and recuperate more money from the investment.

[10]See Davis and Van Nieuwerburgh (2015) for a survey on the literature of portfolio choice models and housing decisions. A key implication from the Tversky and Kahneman (1979) model of loss aversion is that homeowners typically overvalue their housing units relative to market prices, especially when asset prices are falling.

house prices in the ACS.

Table 3: Summary Statistics: Population-Standardized County Fiscal Spending

	Mean	SD	Min	Max	N
County Education Services	229.11	546.82	0.00	2,989.29	237,096
County Social Services	492.74	345.84	0.01	2,464.25	237,096
County Transportation	123.32	175.18	0.04	1,011.67	237,096
County Public Safety	259.56	147.30	9.42	587.42	237,096
County Environment and Housing	124.57	107.97	10.02	410.78	237,096
County Administration	145.43	49.95	6.34	269.17	237,096
County Interest Obligations	85.39	72.79	0.03	425.52	237,096
Other County Spending	83.79	69.75	0.14	345.24	237,096
Total County Spending	1,543.92	734.98	40.56	4,651.75	237,096
County Property Tax Revenue	423.69	215.07	5.50	1,377.29	237,096

Source: Fiscally Standardized Cities (FiSCs) Database.

To augment the ACS self-assessed valuation data and ease concerns about whether ACS self-reported valuations are good representations of market prices, market data from Redfin (2022) is used in several exercises instead of the ACS self-reported valuations. Redfin[11] is a real estate brokerage that curates Multiple Listing Service (MLS) reports on actual house sale transactions in weekly intervals starting in 2012 aggregated to different geographic levels including counties. While the entire MLS reports are not in the data, market prices, listing prices, square footage, and number of sales are among the available variables. While high-frequency housing market data is useful in many contexts, this project focuses on yearly property tax policy so the weekly data are aggregated to years. Further, Redfin's database is aggregated to median sale prices by geography so desirable distributional variation is lost. However, since effective property tax rates are imputed using the ACS self-assessed valuations, using Redfin's market measures may ease the concern about endogeneity in the construction of the effective property tax rate. Both sale and list prices are analyzed so there is some sense of the actual transacted prices as well as optimism about house prices in the future.

Aggregations to geographic identifiers such as counties, CBSAs, CSAs, and cities may comprise many heterogeneous neighborhoods, communities, school districts, or towns even when the region

[11] Access the Redfin data center at https://www.redfin.com/news/data-center/.

of interest is geographically small. When regions are geographically large, the heterogeneity in localized effects may be even more pronounced so useful geographic variation is lost in aggregation. The estimates in this paper rely on county-level property taxes and county-level amenities so aggregation may mask some heterogeneity within counties, and the results are to be interpreted as being county-specific.

2.2 Sample Selection

All dollar amounts are deflated to 2016 using the CPI. House price data in the ACS is continuous after 2008, but the sample period begins in 2010 to mitigate some concern of house price volatility from macro-level factors immediately following the Great Recession as house prices recovered. In the sample data, average national house prices are lowest in 2012.[12] The sample is further narrowed to include houses where respondents reported at least one bedroom, fewer than twenty rooms overall, and each local budgetary category is non-missing which results in respondents and county data from 42 counties.

Mortgage rates for single-family homes measured by FreddieMac[13] also dropped dramatically after 2011, on average. The event-study design is at the household-level where the standardized event time is from 2012 to 2016 to guarantee that all counties have at least two pre-period years before the largest tax changes within counties. This serves the added benefit of having monotonically increasing house prices and relatively stable FreddieMac mortgage rates during the event window. Any respondent in the sample is a homeowner that is at least 18 years old, either own or are financing their current residence, are designated the primary respondents for their residence, have positive earned income, and reported a house price between the 5th and 95th percentile for their county.[14] Since the sample is limited based on the standardized event time, there are 36 counties in the event-study analysis.

[12] House price indices like the Case-Shiller Home Price Index (CSUSHPISA) at the national-level, the All-Transactions House Price Index (USSTHPI) at the national-level, and the Federal Housing Finance Agency Housing Price Index (FHFA HPI) at the county-level all indicate that house prices were lowest in 2012 in the post-Great Recession era.

[13] Access the Single-Family Loan-Level Dataset at https://www.freddiemac.com/research/datasets .

[14] Removing observations below the 5th percentile and above the 95th percentile is done after dropping observations that are coded as missing or as logical skips to reduce the potential influence of outliers.

3 Event-Study Design

3.1 Baseline Specification

To demonstrate the responsiveness of house prices to changes in statutory property taxes, consider the main estimation equation[15] for an event-study design with staggered adoption of their own respective largest tax increases which takes place in event time $t = 0$. The D_{ct} indicators are across event time. In these equations, event time is normalized to $t = -1$ so the other event time indicators are interpreted relative to $t = -1$.

$$ln(V_{ict}) = \alpha + \sum_{\substack{-t \\ t \neq -1}}^{T} \pi_t D_{ct} + H'_{ict}\lambda + B'_{ict}\gamma + \psi_c + \eta_t + \varepsilon_{ict} \quad (1)$$

Here, $ln(V_{ict})$ is the natural log of the house price reported in the ACS. The π_t coefficients measure the responses to the natural log of house prices surrounding the years of the tax change relative to the year before the tax change. Since there are never-treated counties that never experience a tax change, the never-treated counties are are assigned to the omitted group with $t = -1$. If increases in property taxes are capitalized into house prices, π_t has strong, negative coefficients for $t \geq 0$ and no discernible trends for $t < 0$ relative to the reference period. The opposite pattern is expected to emerge in counties that experience property tax cuts. There are fixed effects for county and year in ψ_c and η_t, respectively The vector H'_{ict} contains physical characteristics of a house including number of rooms, number of bedrooms, and year built.

The vector B'_{ict}[16] contains measures of local expenditure including the natural logs for expenditure categories of county general expenses[17] by the county government on public goods including

[15] While this strategy does not allow for the exact calculation of the property tax capitalization parameter in Equation (14) from Section A, the interpretation of treatment effect in the event-study design is roughly similar even though the two strategies estimate different parameters: how house prices respond to changes in property tax rates. Elasticity estimates are easily recoverable from the estimates with minimal added assumptions.

[16] To be comparable to many existing papers in property tax capitalization, an unreported ancillary exercise uses high and low standardized test scores in math and reading for all school districts in each county instead of county-level spending categories. Only including test scores introduces a significant pre-trend and finds effects about half as large as the results of this paper in the first period after the largest property tax increase. Using both test scores and spending categories does not have any pre-trends, and slightly reduces the magnitude of the coefficients relative to the main results presented in this paper. Low scores are negatively capitalized, high scores are positively capitalized, and only the math scores are statistically different than 0.

[17] "General expenditure" is defined by Langley (2020) as all spending by county governments except for transfers to other fiscal governments, utility expenditures, liquor store expenditures, and employee retirement trust expenditures. The delineation between categories listed as general expenditures and other expenditure categories helps to reduce average variation in spending and is therefore a more accurate representation of local government services. "Direct

education services, social services, transportation, public safety, environmental considerations, and housing as well as non-amenity spending such as administration expenses, interest obligations, and miscellaneous spending. The full battery of county expenditures on local public goods accounts for changes in local amenities that may arise from changes in property tax rates, so the estimates should be thought of as net capitalization given changes in public amenities. Public goods such as education, social services, transportation, public safety, and environmental and housing should intuitively add value to houses in those counties while the remaining spending categories may not provide value to homeowners living in those districts.

The natural log transformation has three benefits because per capital dollar expenditure measures tend to be right-skewed in the FiSCs, the coefficients can be interpreted as elasticities whose signs indicate which spending categories are positively or negatively capitalized into house prices, and the vector H from Equation (12) in Section A suggests that each budgetary category be in natural log terms.[18] Ancillary specifications also add macro-level controls for differences in labor market conditions across different districts and utilize test scores in math and reading as proxies for public amenities rather than the entire budget. Qualitatively, responses are smaller by around a tenth of a percent than the main specifications, but the conclusions of statistical tests remain unchanged.

Section 3.4 addresses the potential for bias from negative weights from different comparison groups in staggered designs brought up in Goodman-Bacon (2021). There is no evidence of negative weighting bias in this application. Since statutory property tax rates change frequently and with varying degrees across counties over the sample period as shown in Table 3, the event-study analysis focuses only on the largest tax changes by county to estimate a treatment effect of property tax changes on house prices. Equation (1) is meant to demonstrate that house prices are responsive to changes in property tax rates as would be consistent with property tax capitalization. The treatment is the largest statutory tax rate change for each county, and $t = 0$ is the year the new tax rate went into effect. The never-treated group contains counties whose statutory property tax rate did not change during sample period which are assigned to the reference period, and the reference

expenditures" includes all the spending categories not included in general expenditure as well as intergovernmental transfer payments to other fiscal districts.

[18]The results are robust to other common measures such as levels and budgetary shares. Different measures of spending like levels or budgetary shares do not significantly impact the signs or significance of the spending coefficients in most specifications.

period is the year before the tax change, $t = -1$. Each county in the event-study analysis has at least two years prior to the largest tax increase[19][20] which would include the reference period and one more pre-period resulting in 36 counties in the sample.

In this context, identifying an ATT requires three common assumptions. First, a never-treated group must be included as an absolute reference group. Second, there are no anticipation effects for statutory property tax rate changes so there is no strategic behavior surrounding house prices with knowledge of pending property tax rate changes. Third, parallel trends requires that the evolution of house prices in counties whose statutory property tax rates change would have been consistent had they not experienced the tax rate change. Identifying at ATE requires an added assumption that counties who experience the a magnitudinal change in statutory tax rates causes house prices to adjust on average by the same amount for any county that received the same change in statutory tax rates which is a version of parallel trends for each magnitudinal change in statutory rates. Equation (1) includes the never-treated group as an absolute control group, Figure 2 demonstrates evidence against anticipatory pre-trends, and Table 4 provides evidence of balance in pre-period outcomes of house prices consistent with parallel trends so the identifying assumptions for the ATT are satisfied.

This analysis will focus tax rate increases within counties for several reasons. First, the average county experiences more tax increase events than tax decrease events, and the magnitude of the largest tax increases are larger. Second, the marginal distribution of the largest tax increase year is much closer to uniform over the sample period than the marginal distribution of the largest tax decrease year which occur overwhelmingly more often in the last two years of the sample period. Since most counties experience their largest tax decrease so late in the sample, the post-periods are influenced heavily by the relatively few counties whose largest tax increase years were earlier. Lastly, the nature of tax increases and tax decreases may be different and be accompanied by

[19]The data is repeated-cross sectional that is not balanced so there is the potential that few counties can heavily influence certain event time periods, especially further away from the tax change event. Non-balance in this context comes from the fact that the historic statutory tax rate records are incomplete where not every county's annual reports are available for each year. The number of counties that are balanced is relatively small so the aim of generalizing the setting is lost if only a small number of counties are influencing the results. The signs of the coefficients remain negative when only focused on the balanced counties, but the magnitudes are slightly larger.

[20]This may also greatly affect the number of comparison groups in the decomposition for models with two-way fixed-effects (TWFE) proposed in Goodman-Bacon (2021) since there are many combinations of early treated, late treated, and untreated groups. Based on the decomposition results in Figure 3, there is evidence against the concern that a small number of counties make up the early vs late and late vs early comparison groups that could bias the estimates.

Table 4: Pre-Period Balance Table

Variable	Full	Never-Treated	Treated	Difference
Valuation	215462.6	202717.9	223221.7	-20503.79
	(142842.3)	(115297.5)	(156760.8)	(0.238)
ln(Valuation)	12.09952	12.06989	12.11756	-.0476711
	(.5970849)	(.5502687)	(.6231824)	(0.471)
Number of Rooms	6.49027	6.48397	6.49411	-.010144
	(1.70491)	(1.70282)	(1.70618)	(0.887)
Number of Bedrooms	4.16458	4.21241	4.13546	.076953**
	(.800862)	(.797618)	(.801439)	(0.015)
Statutory Tax Rate	1.841341	1.18557	2.240582	-1.055012***
	(1.544816)	(.6962255)	(1.767217)	(0.001)
Effective Tax Rate	1.213691	1.067126	1.302922	-.2357956*
	(.7146701)	(.6532372)	(.735445)	(0.058)
ln(Density)	7.877124	7.98945	7.808738	.1807127
	(.7655249)	(.7323542)	(.7771266)	(0.141)
Total County Spending	1620.502	1682.54	1582.733	99.80698
	(751.2941)	(692.7504)	(782.3988)	(0.591)
County Property Tax Revenue	430.7379	339.934	486.0203	-146.0863***
	(194.7772)	(102.1948)	(215.8732)	(0.000)
Observations	140,195	53,053	87,142	140,195

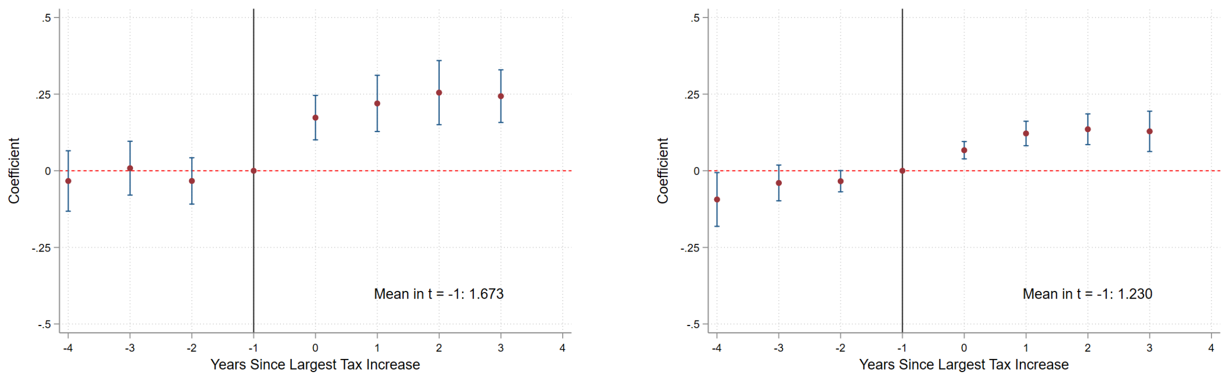
Note: *** p<0.01, ** p<0.05, * p<0.10. Balance test of pooled variable means for never-treated counties and treated counties across all pre-periods. The right-most column is the fixed-effects controlled differences with standard errors of the t-tests in parenthesis clustered at the county×year level.

different patterns of announcement beforehand that can lead to strategic behavior near the actual tax change event. Since other tax rate increases are treated as non-events and each county has at least two pre-periods, coefficients that are closer to the event are less likely to be contaminated by other tax rate increases[21] (or tax rate decreases).

Table 4 displays the results of a pre-period balance test. House prices are not statistically different between counties with tax rate increases and counties that never experience a tax rate change. Statutory property tax rates are statistically lower on average for never-treated counties which is consistent with less per capita property tax revenue. Of note, the statutory property tax rates in treated counties in the pre-period are already statistically larger than the rates of never-

[21] Varying the number of tax rate increases does not affect the magnitudes of the π_t or their significance levels in any meaningful way except in the extreme case of only one tax rate increase over the sample period. While almost a third of counties have only one tax rate increase event in the sample period and the marginal distribution of the largest tax rate increase year is relatively uniform, the interaction of these two criteria is such that too few counties have only one tax rate increase that also have sufficient coverage over the standardized event time.

Figure 2: Evolution of Tax Rate Increases



(a) County Statutory Rates

(b) Overall Effective Rates

Note: Estimates of π_t from Equation (1) with the county statutory property tax rate on the left-hand side in Panel (a) and the overall effective property tax rate on the left-hand side in Panel (b). The y-axes are the magnitudes of the coefficients relative to the omitted period, $t = -1$. The average county statutory property tax rate in the reference year is 1.673% which corresponds to 16.73 millage points. Likewise, the average overall effective property tax rate in the reference year is 1.23, or 12.3 millage points. Clustered standard errors are computed at the county×year level on both panels.

treated counties. After the largest tax increase, the differences become even more pronounced. The number of bedrooms is statistically larger in treated counties, but the difference of 0.08 bedrooms has little economic relevance. Figure 2 summarizes the magnitude of tax rate increase events by estimating Equation (1) with the statutory property tax rate on the left-hand side on Panel (a) and the overall effective property tax rate on the left-hand side in Panel (b). On average, statutory rates increase by 1.73 millage points relative to the omitted period mean of 16.73 millage points (resulting in 18.46 millage points or 1.846%[22] new average statutory rate) then remain relatively stable around the new statutory rate in subsequent periods after $t = 0$. This amounts to an average percentage increase of tax rates by 10.18% in the tax events in this design, and the largest tax change was an increase of 15.42% as seen in Table 2.

Panel (b) of Figure 2 has three main takeaways. First, overall effective rates follow the same pattern as county statutory rates which suggests that the tax rate change events are not being completely avoided through tax exemptions. However, the magnitudes for overall effective rates

[22] This is smaller in magnitude than the average statutory rate in Table 4 because the never-treated group is included in Equation (1).

are slightly smaller[23] than county statutory rates which suggests some avoidance. Second, the similar pattern between both rates suggests high correspondence from the mechanical connection between statutory and effective rates. The overall effective rate is the sum of all effective tax rates from each overlapping district[24] which are all individually highly correlated with their respective statutory rates. As such, the overall effective rate is mechanically related to county-level statutory rates. Third, the empirical design implicitly assumes that other district-level property tax rates are stable, and there is strong evidence that there is little affecting overall effective rates other than county statutory rates in this sample. At the very least, if other statutory rates are moving, they seem to be almost perfectly offsetting such that there is no observational difference in the overall rate coming from any individual district other than the county.

There is strong evidence against statistical pre-trends in tax rate changes, but periods further from the largest tax rate increase are still more likely to be affected by other tax rate changes. Figure 2 is most consistent with the average tax change being both permanent and unanticipated across counties. The most common calendar year for the largest tax rate increase is 2013 which happens in about a third of counties in the sample. By contrast, the least common largest tax rate increase year is 2015 which happens in about 5% of counties.

3.2 Flexible Specification

Now allow the changes in the statutory property tax rate to change over time in a fully-flexible event-study specification:

[23]Since the effective rates are estimated as the midpoint of the tax bins from the ACS, these are likely underestimates of true effective tax rates. Large differences between self-assessed property tax payments and actual tax payments may suggest that property taxes are not salient.

[24]The relationship between the effective tax rate for a house in county c in year t, τ^e_{ct}, and the county statutory tax rate can be expressed using the assessment ratio and the sum of all statutory tax rates, τ^s_{dt}, for each fiscal district d for a specific county:

$$\tau^e_{ct} = \frac{V^a_{ict}}{V^m_{ict}} \times \sum_d \tau^s_{dt}$$

The assessment ratio is the fraction of the assessed valuation of a housing unit to its market price which is commonly near but less than unity, but local statutes that govern reassessment vary dramatically so the ratio need not be close to unity. If any district statutory tax rate increases and the assessment ratio does not adjust immediately from a reassessment of taxable value, the overall effective tax rate increases mechanically since statutory tax rates are additively separable.

$$ln(V_{ict}) = \alpha + \sum_{\substack{-t \\ t \neq -1}}^{T} \pi_t D_{ct} \times \tau_{ct}^s + H'_{ict}\lambda + B'_{ict}\gamma + \psi_c + \eta_t + \varepsilon_{ict} \quad (2)$$

The differences between this specification[25] and the baseline specification in Equation (1) are the interactions between the event time indicator variables and the statutory property tax rates, τ_{ct}^s. This is similar to a dosage-type model whereby continuous treatments are controlled for and allowed to vary across event time. The covariates, fixed-effects, never-treated group, and reference period are similarly defined as in the baseline specification. Again, this section defines the event as the largest tax increase within counties over the sample period. Allowing the response to the statutory rate to vary across event time is an improvement over the baseline model since the latter cannot control for other changes in the statutory tax rate that are not the largest increase meaning that treatment effect estimates are likely more reliable in the flexible specification. The baseline model is meant to demonstrate the capitalization idea while the flexible model likely produces more reliable treatment effect estimates.

3.3 Threats to Identification

Regarding the main identifying assumptions for estimating an ATT, there are several main categories of how those assumptions can be violated. The added assumption to identify an ATE is likely to hold in the bidding framework if there is at least partial capitalization in multiple districts such that homeowners cannot sell their current house and buy another house in another county without bearing some of the cost of the present-discounted property tax burden in the sale or purchase of either houses.

Some local fiscal districts allow limited voting rights to constituents on specific spending projects that would require changes in property tax rates to fully finance. If constituents have voting rights on county-level property tax rates, the statutory county property tax rate is likely not exogenous

[25] An alternative specification adds fixed-effects for the standardized event time indicators, but this does not affect the signs or significance levels of the π_t or β_t coefficients where:

$$ln(V_{ict}) = \alpha + \beta\tau_{ct}^s + \sum_{\substack{-t \\ t \neq -1}}^{T} \pi_t D_{ct} + \sum_{\substack{-t \\ t \neq -1}}^{T} \pi_t D_{ct} \times \tau_{ct}^s + H'_{ict}\lambda + B'_{ict}\gamma + \psi_c + \eta_t + \varepsilon_{ict}$$

Figure 11 summarizes the results of this specification.

because homeowners have the ability to strategically vote on property tax changes that may affect the house prices which violates the assumption of no anticipation. In the bidding framework, a housing unit's price is determined by market agents' willingness-to-pay for a particular unit with particular characteristics and amenities so using sale prices from transactions would be ideal. Self-assessed valuations by current homeowners who may have voting rights on some property taxation decisions in their county may not be analogues for market prices and may introduce bias if agents are strategically choosing property tax rates. Even if homeowners do not *strategically* vote for favorable statutory property tax rate changes, these votes may affect house prices through other channels such as capital changes, permanent income, and the local government budget in the future. Whether homeowners are aware of these channels may impact how they vote on such tax changes, and the housing market response is partially determined on whether homeowners are aware these channels.

Another threat to identification in terms of anticipatory effects is announcements and overall salience of future statutory property tax rate changes even if they are determined exogenously because announcements may allow adjustments to house prices in anticipation of future tax burdens as seen in the annuity capitalization formulation from Equation (11) in Section A. The frequency that county governments reassess houses to determine their taxable value is another aspect that may increase the salience of the property tax burden, particularly if these are done on an annual basis and the homeowners are made aware of the reassessment process or the reassessed value. Homeowners who are financing through mortgage have a second potential source of information about changes in property tax burdens through their mortgage provider. If mortgage providers send notices to homeowners about forthcoming property tax burden changes before the tax rate change, homeowners may anticipate the tax shock.[26] Related to announcements is whether local governments publish their spending/revenue strategies before each new fiscal year.[27]

If homeowners perceive statutory tax rate changes as both unanticipated and permanent, the measured effects may be the largest and would have the sharpest discontinuities in the event-study

[26]Splitting the analysis into groups of homeowners who report their property tax payments as included in their mortgage payment and homeowners who pay their property taxes outright does not affect the signs or magnitudes of the responses, suggesting this mechanism may not play an role in anticipatory behavior.

[27]If, for example, the county government were to make known its intention to finance road maintenance with a temporary increase in property taxes for several years, homeowners in that district would be aware that the tax rate change would revert in the future so the impact of the tax rate change would not be as large on house prices.

designs due to the permanent and immediate change to permanent income. Figure 2 suggests that the tax rate changes are permanent on average across counties for several years and has evidence against anticipation in the pre-periods, but the data does not contain enough information to formally control or test homeowners' expectations or permanence of tax rate changes. If there are announcements or the statutory rate changes are seen as temporary, the results may tend toward no effects and may have anticipatory pre-trends. Concerns about future expectations also arise because self-assessed valuations in the ACS are not sale prices so changes in the self-assessments may come from other factors such as expectations about future prices or overall pessimism regarding housing markets. Staggered treatments and calendar year time trends may reduce some of the possible systemic bias from changing expectations across counties and time.

If the marginal distributions of the tax change event year are skewed toward either end of the sample window, then few counties can have substantial weight over the event time coefficients relative to the omitted year. Further, the event-study design uses only the largest tax rate increase as events and treats the other tax rate increases as non-events. While limiting the number of tax rate increases does not meaningfully affect the results, this can introduce bias if the magnitudes of the largest tax rate change events are not sufficiently larger than the next largest tax rate increases or if two large tax rate increases are in adjacent years. In any case, reducing the number of counties in any specification can make outlier counties more influential. Coefficients closer to the year of the largest tax rate increase are least likely to be influenced by other tax rate changes and are thus more reliable unless other large tax rate increases are in the year immediately before or after the largest.

Since this work aims to generalize property tax capitalization to many different fiscal districts, the natural experiment assumes that homeowners are not strategically choosing county statutory property tax rates in a way that affects house prices and that other local district-level statutory property tax rates are fixed. Figure 2 supports the assumption that other statutory property tax rates are, at least, relatively stable. While the ideal design would also limit identification threats through announcements of future budgetary plans and control for counties that offer limited voting rights, these facets are not taken into account in the empirical design.

3.4 Addressing the Potential for Negative Weighting

Negative weighting and non-ideal comparisons to observational units either already treated or yet to be treated can bias results in designs with staggered treatments. Simplifying the main design to a standard TWFE model with a binary treatment, Figure 3 and Table 5 show the decomposition exercise proposed in Goodman-Bacon (2021) of the following estimation equation:

$$ln(V_{ict}) = \alpha + \beta_{DiD} POST_{ct} + H'_{ict}\lambda + B'_{ict}\gamma + \psi_c + \eta_y + \varepsilon_{ict} \quad (3)$$

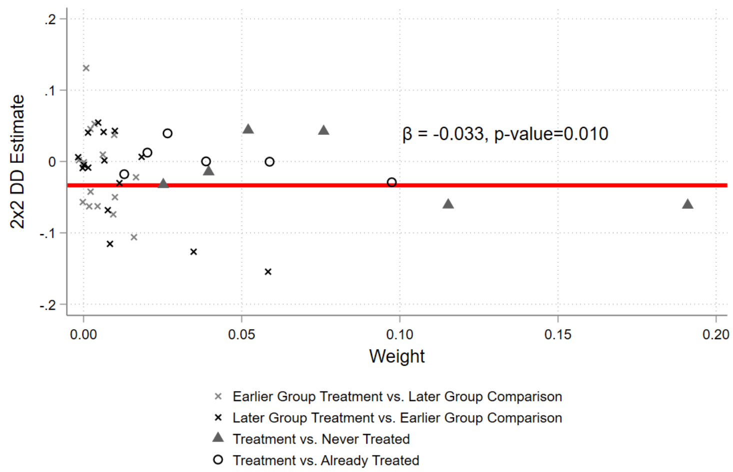
In this canonical TWFE formulation, $POST_{ct}$ is an indicator for whether a county has experienced their largest tax rate increase over the sample period. Based on the bidding framework, increases in property tax rates are expected to lower house prices. All the groups from the decomposition are negative in sign, there is no evidence of negative weighting, and nearly half of the influence of the TWFE DiD coefficient comes from comparisons to the never-treated group. Based on these results, no correction is necessary in this application.

Table 5: Goodman-Bacon Decomposition: Binary Treatment Assignment

	Mean β_{DiD}	Weight
Early-Treated vs. Late-Control	-0.036	0.080
Late-Treated vs. Early-Control	-0.085	0.166
Treated vs. Never-treated	-0.029	0.499
Treated vs. Already-treated	-0.007	0.255

Note: Allow the continuous treatment variable to be simplified into a simple binary indicator. This table decomposes the TWFE DiD estimate into different comparison groups based on the procedure in Goodman-Bacon (2021).

Figure 3: Goodman-Bacon Decomposition: Binary Treatment Assignment



Note: Allow the continuous treatment variable to be simplified into a simple binary indicator. This figure decomposes the TWFE DiD estimate into different comparison groups based on the procedure in Goodman-Bacon (2021) and is the graphical representation of Table 5.

3.5 Baseline Results

The main results[28] from the event-study design from Equation (1) are in Table 10, and Column (4) is summarized in Figure 4 where the tax event is the largest tax rate increases[29][30] within counties. Estimates closer to the event year are less likely to be contaminated with other tax change events, so most of the discussion will focus on the first year of the new statutory tax rate change. All standard errors reported are clustered at the county×year level. Clustering at the county level may deal with potential autocorrelation, but doing so does not affect the significance of the main results.

With full controls, there is an average 3.62% drop in house prices in the first year after the

[28] All results are clustered at the county×year level. Dealing with autocorrelation by clustering at the county level slighly widens the standard errors but does not affect the conclusions of significance tests at conventional levels.

[29] The largest tax decreases exhibit the opposite pattern as tax increases but only in counties with only one tax decrease event which is likely attributed to the reasons mentioned for only analyzing tax increases. While a similar pattern emerges when analyzing the larger sample of counties that have multiple tax rate decreases, there are significant pre-trends with the larger sample where house prices are statistically lower and rising in the pre-period and stabilize after the tax rate decrease. While not reliable for producing estimates due to anticipation, the reverse pattern does suggest the empirical design is useful variation for analyzing the property tax capitalization mechanism.

[30] To further demonstrate the capitalization effect for tax rate increases, Figure 6 summarizes the results of estimating Equation (1) on the smallest statutory tax rate increase. The most common year for the smallest tax increase is 2015. Overall, the trend in the signs of the coefficients are consistent with property tax capitalization following a tax rate increase, but there is no statistical evidence that the smallest tax increase changes house prices.

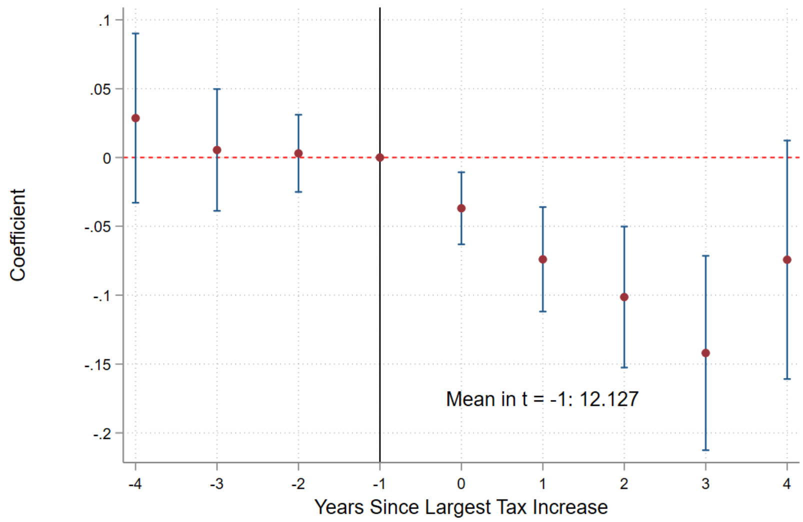
county's largest tax increase relative to the mean house price in the reference period of $184,795 which corresponds to about a $6,692 decrease in dollar terms relative to the average 0.173% level increase in the statutory tax rate from Figure 2. This implies an elasticity of -0.341. Though this estimate seems large in response to the magnitude of the treatment, the bidding framework for house price determination suggests that the present-discounted value of all future property tax payments are reflected in the house price, not just the change in the first year. The effect in the first year is slightly larger in specifications with fewer controls up to a 4.04% implied decrease in house prices in Column (1) of Table 10. The π_t coefficients become larger in negative magnitude with subsequently larger standard errors in the years following the tax increase suggesting that house prices are tending not to revert to the same levels as before the tax change until five years after the reference year. The post-period estimates of π_t are statistically significant and economically relevant in each specification with little evidence of pre-trends as more controls are added. Given that this specification cannot control for other tax change events, the fact that the event is related only to county-level statutory tax rate changes not overall tax rate changes, and the magnitudes of the coefficients, the treatment effects in the post-periods for the baseline specification are likely overestimates that are contaminated by other tax changes.

Figure 5[31] is the summary of results of estimating Equation (1)[32] for the county-level median sale price and county-level median list price. While the first period after the largest tax increase is not different than 0, the coefficients imply a drop in median sale prices of 2.52% and a drop of 1.55% for list prices relative to the year before the tax increase became effective. The coefficients in the second and third years after the shock imply even larger drops in prices that are statistically different than 0, and both prices revert to insignificant in the fourth year after the reference year. The treatment effects of the sale and list prices are slightly smaller than the ACS self-assessed valuations, but the three measures follow the same pattern surrounding the largest tax increase.

[31] Similar patterns emerge with each measure of house prices around the largest tax rate increase where house prices are stable then fall after the tax rate change.

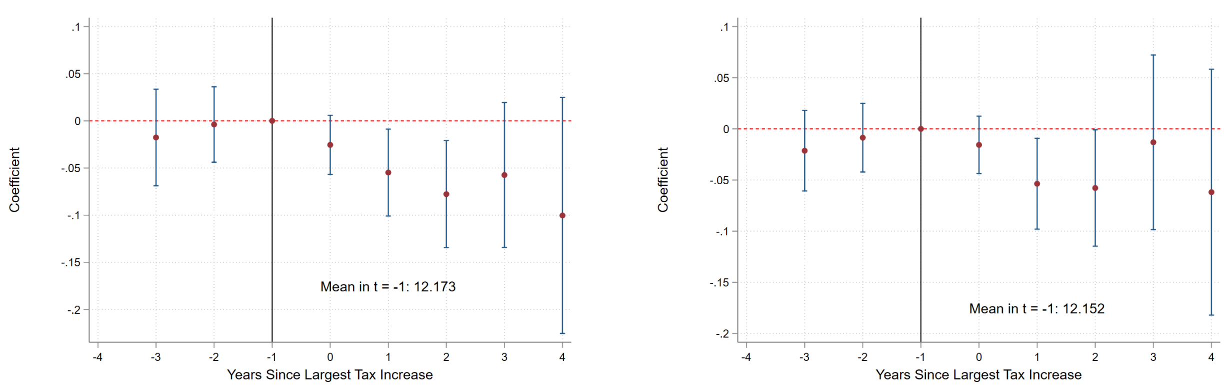
[32] The Redfin data is only available starting in 2012 and the FiSCs are only available up to 2016. At the same time, the most common event year for the largest tax increase is 2013 so the budget variables are left out of the specification for the Redfin outcomes to guarantee enough counties have at least two pre-period years before the largest tax increase. However, the budgetary variables account only for small differences in the magnitudes of the coefficients closer to the year of the largest tax rate increase in Table 10 when self-assessed valuations are the outcome variable.

Figure 4: Baseline π_t Estimates: ln(Valuation)



Note: Estimates of π_t from Equation (1) where the y-axis is the magnitude of the coefficient relative to the omitted period, $t = -1$. The average natural log self-assessed valuation in the reference year is 12.127 which corresponds to about $184,795. Clustered standard errors are computed at the county×year level.

Figure 5: Baseline π_t Estimates: Redfin Median Sale and Median List Prices

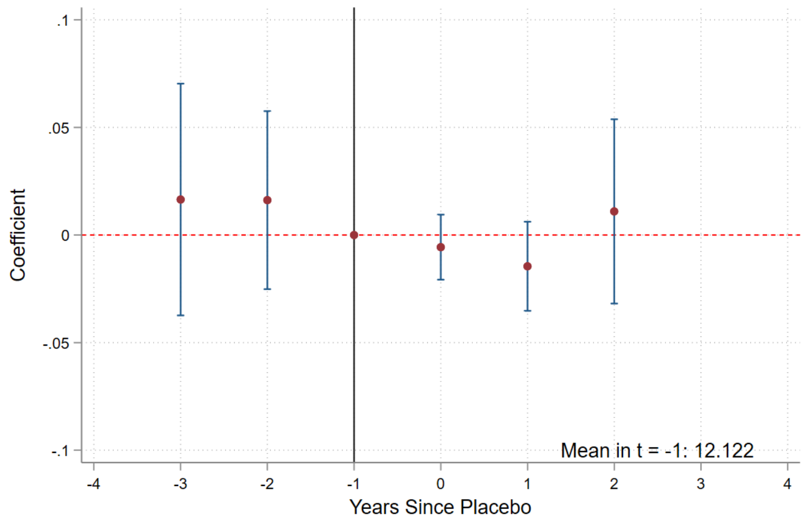


(a) Median Sale Price

(b) Median List Price

Note: County median natural log sale prices are in Panel (a) and county median natural log list prices are in Panel (b). Their means in the reference period are annotated in their respective panels. Clustered standard errors are computed at the county×year level. Source: Redfin.

Figure 6: Baseline π_t Estimates: Smallest Property Tax Rate Increase



Note: Estimates of π_t from Equation (1) with the natural log of ACS self-assessed valuations as the dependent variable where the tax event is the smallest tax increase over the sample period, and the y-axis is the magnitude of the coefficient relative to the omitted period, $t = -1$. Clustered standard errors are computed at the county×year level.

3.6 Flexible Results

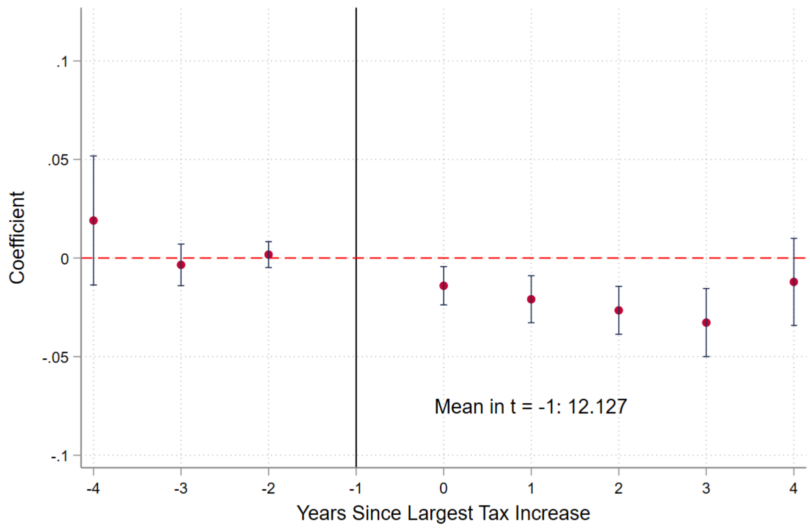
The results from the fully flexible event-study specification in Equation (2) are in Table 11, and Column (4) is summarized in Figure 7 where the tax event is the largest tax rate increase[33] by county. Again, estimates nearer to the event are less likely to have spillovers from tax change events other than the largest tax rate increase. The marginal distribution of the largest tax rate increase year is the same as in the baseline analysis as are the average statutory property tax rate level changes from the largest tax increases of 0.173% amounting to a 10.18% percentage increase over the previous year, on average. The pre-period coefficients are all jointly, statistically indistinguishable from 0 while the magnitudes and signs of the coefficients exhibit no discernible pattern.[34]

With full controls, there is an average 1.168% drop in house prices in the first year of the new statutory tax rate, $t = 0$, which amounts to a 2,158$ decrease from the reference period mean of

[33] The largest tax decreases exhibit the opposite pattern as tax increases in this section but only in counties with only one tax decrease event, as with the baseline specification. However, there are again significant pre-trends where house prices are statistically lower and rising in the pre-period and stabilize after the tax rate decrease with positive, insignificant π_t coefficients in all $t \geq 0$ periods.

[34] While the $t = -4$ coefficient as nearly as large as the largest $t \geq 0$ coefficient, the coefficients furthest from the event are most likely to be influenced by other tax change events so coefficients closer to the event are more reliable.

Figure 7: Flexible π_t Estimates



Note: Estimates of π_t from Equation (2) where the y-axis is the magnitude of the coefficient relative to the omitted period, $t = -1$. The average natural log ACS self-assessed valuation in the reference year is 12.127 which corresponds to about $184,795. Clustered standard errors are computed at the county×year level.

$184,795. Treatment effects range between a 0.46% decrease and a 1.19% decrease in $t = 0$ with various combinations of covariates, but the overall magnitudes in each specification are relatively stable to each other across event time reaching only a 2.98% decrease in $t = 3$ but still revert in $t = 4$.[35] The treatment effects are still economically large, and are likely more reliable estimates of the treatment effect than the baseline specification whose estimates are upwards of three times larger in $t = 0$ and become larger in subsequent periods. On average, a 10.18% increase in the property tax rate lowers house prices by 1.168% in the first year of the new statutory property tax rate in the most reliable specification which is evidence that property taxes are partially capitalized into house prices. This implies a property tax capitalization elasticity with respect to the property tax rate of -0.115.[36]

[35] This pattern remains consistent in flexible model specifications that include event time fixed-effects, although the coefficients are slightly smaller in negative magnitude than Equation (2), and reversion to statistical insignificance occurs in $t = 3$.

[36] For reference, OLS estimation with the natural log of ACS house prices as the outcome and the natural log of the implied effective property tax rate is -0.167. OLS has theoretical endogeneity as in Section A, so the OLS estimate should be seen as a point of comparison only. Least-squares IV estimates using the natural log of the statutory rate as an instrument for the log of the effective rate are much larger, around -0.766 for this sample. IV should, again, only be considered for comparison to the design presented in the paper.

3.7 Treatment Effects and Capitalization Parameters

Using an event-study to estimate treatment effects does not provide direct information on the theoretical property tax capitalization parameter, but these two parameters can be roughly compared with some assertions. The property tax capitalization parameters are interpreted as the portion of every $1 change in the tax burden that is reflected in house prices. In dollar terms, the average treatment of a 0.173% level increase in the county-level statutory tax rate corresponds to about $320 per year increase in the yearly property tax burden for the average house in the first year after statutory tax change. Since the bidding model dictates that house prices will reflect the present-discounted value of *all future* tax payments as well as the current year, the change in the present-discounted tax burden depends further on the discount rate and the number of years the current homeowners expect to own that house.

Tax payments are made in perpetuity so changes in the tax burden today can be treated as an annuity. If the time horizon on the stream of present-discounted future tax payments is the same as the typical mortgage term of 30 years and the urban discount rate estimated by Koster and Pinchbeck (2022) of 3.5%, the increase in the present-discounted future tax payment burden is $6,091 from a $320 increase in the annual property tax payment. Paired with the estimated treatment effect from the flexible event-study specification of a $2,158 decrease in the first year relative to the reference period, the implied capitalization rate is 0.354. To estimate an elasticity, use the percentage decrease in the first post-period, 1.168%, and the percentage increase in the property tax rate, 10.18%, to calculate -0.115. The elasticity calculation is more reliable due to not relying on assumptions about the discount rate or the time horizon.

Different measures of the discount rate that are higher and shorter time horizons will lower the present-value calculation leading to even higher implied capitalization rates. The average homeowner in the sample has lived in their current house between 10 and 19 years already, and only 5.19% moved in the year before their ACS sample wave. Taking the midpoint of the average tenure of homeowners in the sample and using the urban discount rate from Koster and Pinchbeck (2022) of 3.5% would mean that the increase in the present-discounted future tax payment burden is $3,717 from the $320 increase in the annual property tax payment, and the implied capitalization rate is 0.581. Further, $320 may not be the effective change in the property tax burden if reassessments of taxable house values occur around the statutory change.[37]

Full-capitalization implies that increases in the property tax burdens are perfectly offset by decreases in house prices, and there is evidence that tax increases are being less-than-fully capitalized immediately following a tax increase using treatment effect in event-study designs. Using the estimates from the work in this paper, the implied capitalization rate falls somewhere between 0.354 and 0.581 using event-study treatment responses while the elasticity is -0.115.

4 Quantile Analysis

This section allows responses to changes in property tax rates may vary along the distribution of house prices[38] as well as across event time in the event-study design. Using unconditional quantile methods proposed in Firpo et al. (2009) that rely on the marginal distribution of house prices, this section investigates whether the capitalization parameter, δ, and responses to tax change events vary along the distribution of house prices. Unconditional quantiles are the preferred approach since the quantiles of the house price distribution are determined a priori and are therefore agnostic to the distributions of the covariates or fixed-effects, even though these factors are important when interpretation of the resulting coefficients. The essential component of estimating unconditional quantiles is first estimating the recentered-influence function (RIF). Define Y as the outcome of interest, F_Y as the associated CDF, f_Y as the PDF, then the RIF quantile value, q_θ at any quantile θ is defined as:

$$RIF(Y; q_\theta, F_Y) = q_\theta + \frac{\theta - \mathbb{I}[Y \leq q_\theta]}{f_Y(q_\theta)} \tag{4}$$

The unconditional quantile regression is then accomplished by replacing house prices with their RIF[39] quantile values, assuming linearity in the parameters. This section will use similar spec-

[37]It may be the case that reassessments are more likely to occur shortly preceding statutory tax rate increases so that the local governments can determine with more accuracy the expected impacts on their property tax revenues before the new statutory rates are enacted. But counties vary in their reassessment strategies so there may be some lag in reassessments.

[38]Since the median sale price and median list price from Redfin are already collapsed to the median by county, this section focuses mainly on the ACS self-assessed valuations.

[39]For example, consider $\theta = 0.8$ at the 80th percentile of the house price distribution. The RIF function creates a new outcome variable that takes on values of $q_{0.8} + (0.80/f_Y(q_{0.8}))$ for house prices above the 80th percentile and values of $q_{0.8} - (0.20/f_Y(q_{0.8}))$ for house prices at or below the 80th percentile. The unconditional quantile regression uses the new outcome variable with the two possible values on the left-hand side. The linear combination in Equation (4) of the distributional statistic, q_θ, and the influence function (IF) is called the recentered-influence function (RIF).

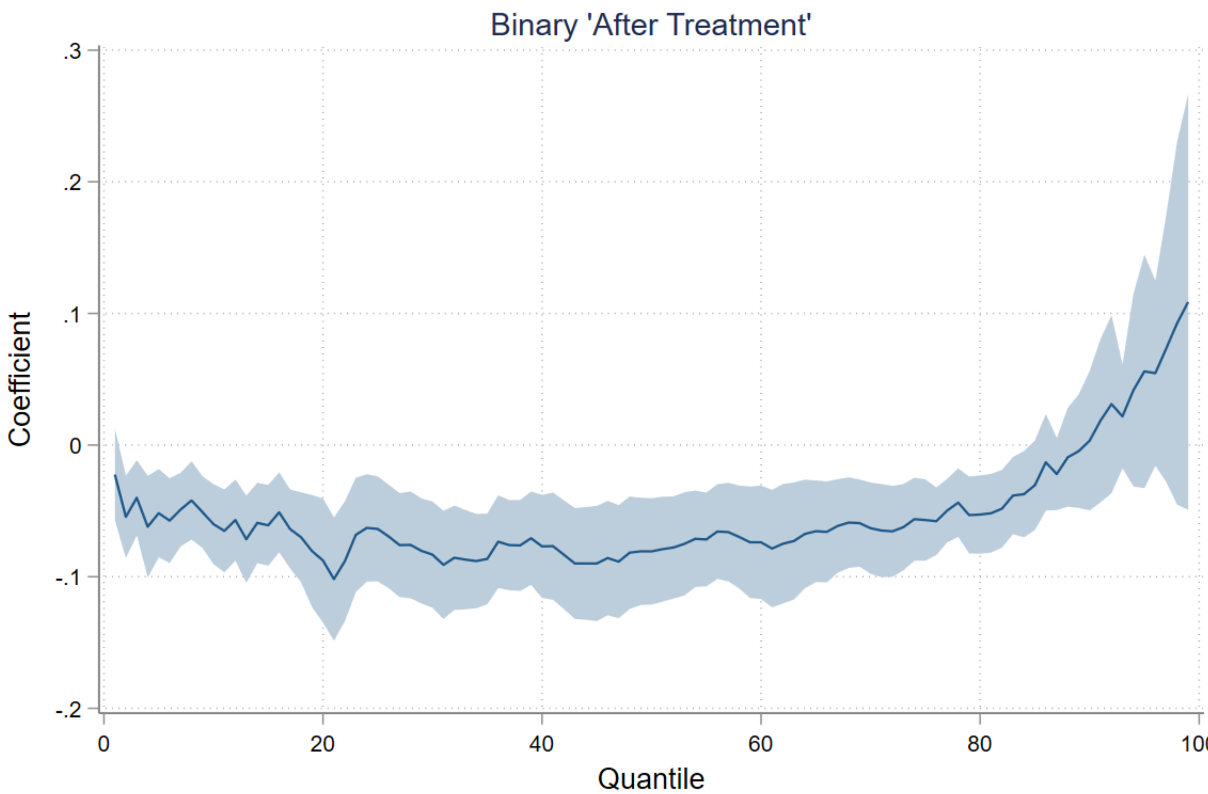
ifications as Equation (1) looking at the baseline event-study and Equation (2) for the flexible event-study with the resulting RIF on the left-hand side to examine responses along the distribution of house prices. The regression coefficients of unconditional quantile regressions are interpreted as the marginal effect on the unconditional quantile outcome value due to a one unit change in the unconditional averages of the covariates. Put differently, if the mean of a covariate changes by one unit, the RIF quantile values will change by the quantile regression coefficient. This interpretation lends itself well to changes in statutory property tax rates that affect all homeowners in a county, but analyzing quantiles of house prices allows homeowners to respond differently across the distribution of house prices. While the distribution of house prices is unconditional, the regressions are still conditional on house characteristics and county-level spending as in Equation (1).

Tests of the coefficients of interquantile ranges will be use to evaluate whether quantile regression coefficients are statistically different from each other along the distribution at decile values relative the median. Insignificant results relative to the median do not necessarily indicate that there is not heterogeneity along the distribution. Interquantile ranges are differences in the RIF values at those quantiles which amount to testing the differences in the estimated coefficients. For notational ease, let the quantile θ be denoted as the Q-th percentile for the remainder of the section where the median, $\theta = 0.5$, can be notated as Q50. Further, let $\pi_{t,\theta}$ be estimates of the coefficients at quantile θ.

4.1 Binary Treatment Results

In the simplest case, allow the event study design to be a simple TWFE model with an indicator for whether a county has experience the largest tax rate increase as in Equation (3). Figure 8 displays results from the entire distribution of each $\pi_{t,\theta}$ from Q1 to Q99. There is evidence that the highest-priced houses do not respond to changes in property tax rate increases, and the differences begin to emerge around the 9th decile. To investigate whether tax rate increases are different on the high end of the distribution, Table 6 contains information on the highest decile against the rest of the distribution. While high-value houses tend to be in low-tax counties, there is no evidence that the largest tax rate increase is of a smaller magnitude than the rest of the distribution in percentage terms. The counties with the highest prices have statistically smaller level tax rate increases, but that is most likely attributable to being in lower tax rate counties. Percentage terms

Figure 8: Binary Treatment Event-Study Quantile π_t Estimates



Note: Estimates of indicator variables from quantile regressions of Equation (3.4) from Q1 to Q99 at every quantile where the y-axis is the magnitude of the $\pi_{t,\theta}$ coefficient on the event time indicator dummy relative to the omitted period, $t = -1$. Clustered standard errors are computed at the county×year level.

allow for the best comparisons across counties and can be easily used for calculating property tax capitalization elasticities.

4.2 Baseline Event-Study Quantile Results

To measure differences in treatment effects in years following the largest statutory tax rate increases, quantile analysis is performed on the $\pi_{t,\theta}$ coefficients from Equation (1) using the RIF as the dependent variable. Table 7 contains $\pi_{t,\theta}$ coefficients at each decile along the distribution of self-assessed house valuations. For comparison, Column (4) of Table 10 is the mean regressions of Equation (1), and Figure 9 characterizes the entire distributions of each $\pi_{t,\theta}$ from Q1 to Q99 for completeness. There is evidence against pre-trends in the estimated coefficients for $t < 0$ periods which are mostly flat and the confidence intervals contain 0 almost universally except on the extreme

Table 6: Distributional Tax Shocks

Variable	Full	Top 10	Lower 90	Difference
ln(Valuation)	12.17834	13.3238	12.05253	1.271275***
	(.6423829)	(.2300089)	(.5405772)	(0.000)
Statutory Tax Rate	2.165486	1.580319	2.22976	-.6494415***
	(1.951275)	(1.586495)	(1.976737)	(0.000)
Change in Statutory Rate	.1075478	.0856916	.1099484	-.0242568
	(.9791301)	(.8345426)	(.9937018)	(0.788)
Percentage Change in Statutory Rate	.0053474	.005533	.0053268	.0002062
	(.0399381)	(.0446339)	(.0393835)	(0.974)
Max(Change in Statutory Rate)	.9897464	.7209407	1.019272	-.298331**
	(1.390758)	(1.109854)	(1.415117)	(0.015)
Max(Percentage Change in Statutory Rate)	.0398623	.039735	.0398764	-.0001414
	(.0455296)	(.0470919)	(.0453533)	(0.981)
Observations	386,649	38,266	348,383	386,649

Note: *** p<0.01, ** p<0.05, * p<0.10. Balance test of pooled variable means for the top decile of house values against the lower deciles. The right-most column is the fixed-effects controlled differences with standard errors of the t-tests in parenthesis clustered at the county×year level.

low end of the pre-period furthest from the event.

Across deciles, the only pre-period coefficient that is statistically different from 0 is the fourth pre-period before the tax increase at Q10. In the mean regression from Section 3.5, the coefficient in the first year of the tax change, $t = 0$, is -0.0369 which corresponds to a 3.62% decrease in house prices. The coefficients along the first eight deciles follow the same overall pattern from $t = 0$ to $t = 3$ where there is a response to the tax change that persists for several years with increasingly larger coefficients in the second and third year of the higher tax rate. Focusing closer to the event, the coefficients from Q10 to Q80 at $t = 0$ are mostly larger than the mean estimated coefficient and range in effect size from 3.31% at Q80 to 6.91% at Q20. The ninth decile is the only coefficient that is either positive or statistically indistinguishable from 0 in the first period of the higher statutory tax rate.

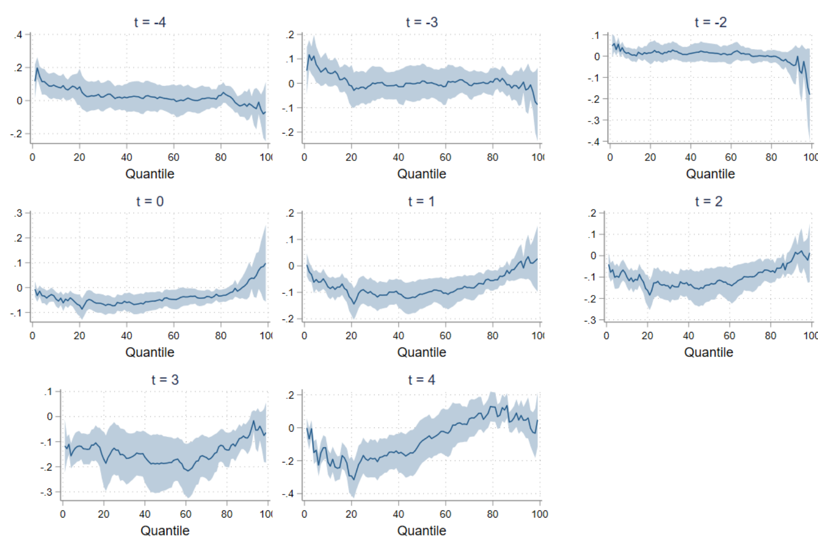
To investigate whether of the estimates are statistically different across deciles, Table 12 contains the results of statistical tests of the interquantile range of the $\pi_{t,\theta}$ coefficients relative to the median where the Median column has the same coefficients from Table 7. Each column is the coefficient of the larger decile minus the coefficient of the smaller decile. While the effect sizes vary, there is no statistical evidence that the estimates at $t = 0$ are different from the median across deciles

Table 7: Baseline Event-Study Quantile Regressions

	Q10	Q20	Q30	Q40	Median	Q60	Q70	Q80	Q90
t = -4	0.0860**	0.0829	0.0216	0.0168	0.0240	0.0074	0.0005	0.0315	-0.0199
	(0.038)	(0.055)	(0.044)	(0.043)	(0.045)	(0.045)	(0.040)	(0.032)	(0.040)
t = -3	0.0445	-0.0105	-0.0021	-0.0144	0.0093	-0.0124	-0.0079	0.0045	-0.0097
	(0.028)	(0.043)	(0.035)	(0.035)	(0.036)	(0.038)	(0.028)	(0.029)	(0.031)
t = -2	0.0089	0.0148	0.0204	0.0128	0.0151	0.0082	0.0008	-0.0028	-0.0385
	(0.015)	(0.027)	(0.021)	(0.021)	(0.022)	(0.023)	(0.016)	(0.015)	(0.035)
t = 0	-0.0468***	-0.0716***	-0.0667***	-0.0601***	-0.0555***	-0.0474**	-0.0411**	-0.0336***	0.0064
	(0.015)	(0.022)	(0.019)	(0.019)	(0.019)	(0.020)	(0.016)	(0.013)	(0.027)
t = 1	-0.0794***	-0.1265***	-0.1092***	-0.1055***	-0.1072***	-0.1026***	-0.0815***	-0.0557***	-0.0018
	(0.019)	(0.030)	(0.027)	(0.027)	(0.028)	(0.028)	(0.023)	(0.019)	(0.026)
t = 2	-0.1012***	-0.1624***	-0.1409***	-0.1385***	-0.1370***	-0.1346***	-0.0980***	-0.0754***	-0.0266
	(0.024)	(0.037)	(0.034)	(0.035)	(0.039)	(0.040)	(0.034)	(0.027)	(0.033)
t = 3	-0.1285***	-0.1708***	-0.1556***	-0.1615***	-0.1860***	-0.2112***	-0.1632***	-0.1331***	-0.0854***
	(0.031)	(0.055)	(0.053)	(0.052)	(0.054)	(0.052)	(0.043)	(0.035)	(0.033)
t = 4	-0.2091***	-0.2931***	-0.1859***	-0.1553**	-0.0797	-0.0292	0.0542	0.1261***	0.0899**
	(0.038)	(0.060)	(0.058)	(0.060)	(0.067)	(0.071)	(0.056)	(0.045)	(0.042)
Observations	237096	237096	237096	237096	237096	237096	237096	237096	237096
RIF(Q)	11.356	11.614	11.827	11.984	12.146	12.307	12.497	12.711	13.024
R-squared	0.137	0.210	0.257	0.300	0.330	0.355	0.370	0.391	0.440
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimated Effect in t=0 (%)	-4.568	-6.912	-6.449	-5.836	-5.400	-4.631	-4.027	-3.306	0.638

Note: *** p<0.01, ** p<0.05, * p<0.10. Dependent variable is the natural log of the ACS self-reported valuations of their house in 2016 dollars from Equation (1). The rows are estimates of the $\pi_{t,\theta}$ coefficients on the event time indicator dummy variables relative to the omitted period, $t = -1$. The RIF(Q) row is the unconditional mean in that decile. Clustered standard errors are computed at the county×year level.

Figure 9: Baseline Event-Study Quantile π_t Estimates



Note: Estimates of indicator variables from quantile regressions of Equation (1) from Q1 to Q99 at every quantile where the y-axis is the magnitude of the $\pi_{t,\theta}$ coefficient on the event time indicator dummy relative to the omitted period, $t = -1$. Clustered standard errors are computed at the county×year level.

except at Q90 where the coefficient in Table 7 is not statistically different from 0. In the second and third year of the new statutory tax rate, there is evidence that the seventh and eight decile are statistically smaller in negative magnitude than the median so the effects of the statutory tax rate increase are still significant but waning toward the high end of the distribution relative to the median. Tests of statistical differences from the median do not necessarily preclude heterogeneous effects along the distribution, and there are clear visual patterns in Figure 9 that demonstrate these differences. The $\pi_{t,\theta}$ coefficients are U-shaped in the $t \geq 0$ periods indicating that the center of the distribution is most effected by changes in property tax rates.

4.3 Flexible Event-Study Quantile Results

Consider now quantile regressions of the flexible event-study design to estimate $\pi_{t,\theta}$ coefficients from Equation (2). Table 8 contains the $\pi_{t,\theta}$ estimates at each decile, Column (4) of Table 11 is the mean regression results, and Figure 10 characterizes the entire distribution of $\pi_{t,\theta}$ from Q1 to Q99. The last row of Table 8 is the percentage change in house prices in the first year after the tax rate increase relative the the mean in the omitted year. As with the baseline quantile estimates, the coefficients in the $t < 0$ periods are mostly flat except in the lowest quantiles and in the years furthest from the event which is suggestive evidence against pre-trends. Figure 9 and Figure 10 basically follow similar patterns along the distribution of house prices including the U-shape in the $t \geq 0$ periods, though the magnitudes are smaller in absolute value in the flexible specification.

The mean regression estimate of π_t in $t = 0$ is -0.0117 which corresponds to a 1.168% decrease in house prices, and each decile estimate of $\pi_{t,\theta}$ is larger than the mean except for the eighth and ninth deciles. There is evidence that homeowners in the higher end of the distribution are responding differently to changes in property tax rates than the rest of the distribution in the flexible specification as well. Reversion to no effects takes place only between the median and the eighth decile and only in the furthest post-period year from the tax increase event. For homeowners below the median, the impacts of the property tax increase persist throughout the sample period.

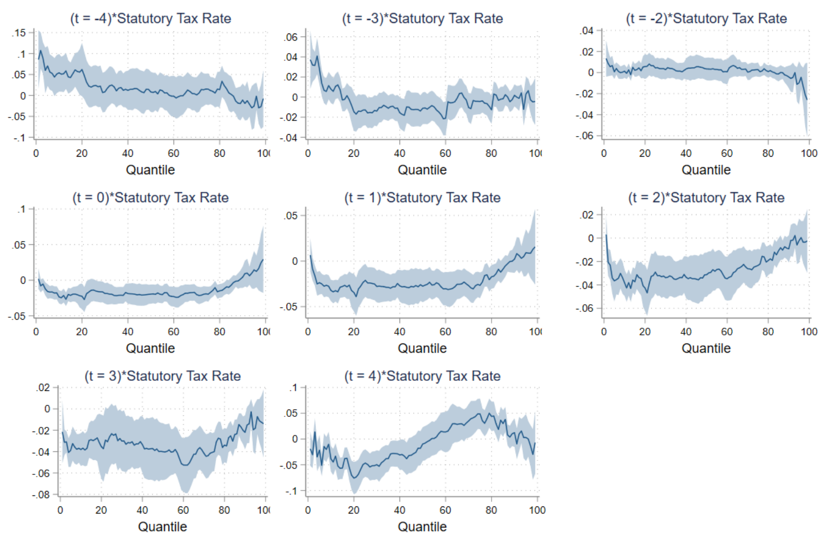
Investigating whether the treatment effect vary across the distribution is done using statistical tests of the interquantile ranges at each decile relative to the median. As with the baseline specification results, the Median column of Table 9 displays the same $\pi_{t,\theta}$ coefficients from Table 8 for comparison, and the signs are always interpreted as the larger decile minus the smaller decile.

Table 8: Flexible Event-Study Quantile Regressions

	Q10	Q20	Q30	Q40	Median	Q60	Q70	Q80	Q90
Statutory Tax Rate	0.1186**	0.0117	-0.0094	0.0313	0.0398	0.0985	0.1027	0.0583	-0.0417
	(0.047)	(0.067)	(0.052)	(0.056)	(0.064)	(0.075)	(0.065)	(0.059)	(0.064)
(t = -4)*Statutory Tax Rate	0.0540**	0.0620*	0.0086	0.0123	0.0083	-0.0017	0.0014	0.0139	-0.0111
	(0.023)	(0.032)	(0.024)	(0.024)	(0.024)	(0.025)	(0.021)	(0.022)	(0.020)
(t = -3)*Statutory Tax Rate	0.0079	-0.0145	-0.0139*	-0.0156**	-0.0112	-0.0211**	-0.0103	-0.0126*	0.0017
	(0.007)	(0.010)	(0.008)	(0.008)	(0.008)	(0.008)	(0.007)	(0.007)	(0.006)
(t = -2)*Statutory Tax Rate	0.0013	0.0057	0.0028	0.0035	0.0034	0.0007	0.0004	0.0010	-0.0041
	(0.003)	(0.006)	(0.005)	(0.005)	(0.005)	(0.006)	(0.004)	(0.003)	(0.005)
(t = 0)*Statutory Tax Rate	-0.0235***	-0.0225**	-0.0186**	-0.0188***	-0.0195***	-0.0230***	-0.0202***	-0.0149***	0.0042
	(0.005)	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.005)	(0.008)
(t = 1)*Statutory Tax Rate	-0.0323***	-0.0345***	-0.0279***	-0.0272***	-0.0276***	-0.0303***	-0.0270***	-0.0173***	0.0021
	(0.006)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.008)	(0.007)	(0.008)
(t = 2)*Statutory Tax Rate	-0.0382***	-0.0427***	-0.0338***	-0.0336***	-0.0313***	-0.0347***	-0.0262***	-0.0191***	-0.0092
	(0.006)	(0.010)	(0.009)	(0.009)	(0.010)	(0.009)	(0.008)	(0.006)	(0.006)
(t = 3)*Statutory Tax Rate	-0.0380***	-0.0354**	-0.0302**	-0.0334**	-0.0401***	-0.0525***	-0.0417***	-0.0339***	-0.0219***
	(0.008)	(0.015)	(0.014)	(0.013)	(0.013)	(0.013)	(0.010)	(0.008)	(0.008)
(t = 4)*Statutory Tax Rate	-0.0386***	-0.0759***	-0.0498***	-0.0309**	-0.0097	0.0137	0.0349**	0.0439***	0.0123
	(0.013)	(0.016)	(0.014)	(0.015)	(0.017)	(0.020)	(0.016)	(0.014)	(0.014)
Observations	237096	237096	237096	237096	237096	237096	237096	237096	237096
RIF(Q)	11.356	11.614	11.827	11.984	12.146	12.307	12.497	12.711	13.024
R-squared	0.137	0.210	0.257	0.300	0.329	0.354	0.370	0.391	0.440
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimated Effect in t=0 (%)	-2.324	-2.227	-1.840	-1.860	-1.934	-2.272	-2.004	-1.477	0.418

Note: *** p<0.01, ** p<0.05, * p<0.10. Dependent variable is the RIF of the natural log of the ACS self-reported valuations of their house in 2016 dollars from Equation (2). The rows are estimates of the π_t coefficients on the event time indicator dummy variables interacted with the statutory property tax rate relative to the omitted period, $t = -1$. The RIF(Q) row is the unconditional mean in that decile. The final row is the percentage response in the outcome variable in the first year after the tax increase event. Clustered standard errors are computed at the county×year level.

Figure 10: Flexible Event-Study Quantile π_t Estimates



Note: Estimates of indicator variables from quantile regressions of Equation (2) from Q1 to Q99 where the y-axis is the magnitude of the $\pi_{t,\theta}$ coefficient on the event time indicator dummy relative to the omitted period, $t = -1$. Clustered standard errors are computed at the county×year level.

There is no statistical differences in the differences between decile estimates in $t = 0$ except at the ninth decile which does not have a statistically significantly negative coefficient. Though the coefficients are not statistically different from the median, there is suggestive evidence in Figure 10 that responses to property tax changes is heterogeneous along the distribution of house prices.

5 Conclusion

This paper uses uses a bidding framework model of house price determination to estimate property tax capitalization parameters and treatment effects relative to changes in property tax rates in order to generalize the capitalization framework to counties across the United States that contain large cities that do not rely on specific locations or settings. Using novel data on statutory county-level property tax rates, several strategies are used to provide both descriptive and causal estimates of capitalization rates and treatment effects in response to tax rate changes.

This is the first work on property tax capitalization to use a staggered-treatment event-study that does not depend on a specific tax change event in a specific location which is made possible through exploiting variation in novel statutory property tax rate data. Using an event-study design

Table 9: Flexible Event-Study Quantile Regressions Relative to the Median

	IQR(50-10)	IQR(50-20)	IQR(50-30)	IQR(50-40)	Median	IQR(60-50)	IQR(70-50)	IQR(80-50)	IQR(90-50)
Statutory Tax Rate	-0.0787	0.0282	0.0492	0.0085	0.0398	0.0586*	0.0629*	0.0185	-0.0816
	(0.053)	(0.051)	(0.035)	(0.023)	(0.064)	(0.030)	(0.035)	(0.046)	(0.079)
(t = -4)*Statutory Tax Rate	-0.0458**	-0.0537**	-0.0004	-0.0040	0.0083	-0.0099	-0.0069	0.0056	-0.0194
	(0.020)	(0.026)	(0.013)	(0.007)	(0.024)	(0.007)	(0.015)	(0.021)	(0.025)
(t = -3)*Statutory Tax Rate	-0.0191**	0.0034	0.0028	0.0044	-0.0112	-0.0099***	0.0008	-0.0015	0.0129
	(0.007)	(0.008)	(0.004)	(0.003)	(0.008)	(0.003)	(0.005)	(0.006)	(0.008)
(t = -2)*Statutory Tax Rate	0.0021	-0.0023	0.0006	-0.0001	0.0034	-0.0027	-0.0030	-0.0024	-0.0075
	(0.004)	(0.003)	(0.002)	(0.001)	(0.005)	(0.002)	(0.003)	(0.005)	(0.008)
(t = 0)*Statutory Tax Rate	0.0040	0.0030	-0.0010	-0.0008	-0.0195***	-0.0034	-0.0007	0.0047	0.0237**
	(0.005)	(0.005)	(0.003)	(0.002)	(0.007)	(0.002)	(0.003)	(0.005)	(0.010)
(t = 1)*Statutory Tax Rate	0.0047	0.0069	0.0003	-0.0003	-0.0276***	-0.0028	0.0006	0.0103	0.0296***
	(0.006)	(0.006)	(0.004)	(0.003)	(0.009)	(0.003)	(0.004)	(0.006)	(0.011)
(t = 2)*Statutory Tax Rate	0.0069	0.0114*	0.0025	0.0023	-0.0313***	-0.0034	0.0051	0.0122*	0.0221**
	(0.007)	(0.006)	(0.004)	(0.003)	(0.010)	(0.003)	(0.004)	(0.006)	(0.010)
(t = 3)*Statutory Tax Rate	-0.0020	-0.0047	-0.0099*	-0.0066**	-0.0401***	-0.0125***	-0.0016	0.0062	0.0181
	(0.009)	(0.008)	(0.006)	(0.003)	(0.013)	(0.004)	(0.006)	(0.009)	(0.013)
(t = 4)*Statutory Tax Rate	0.0288**	0.0662***	0.0401***	0.0212***	-0.0097	0.0235***	0.0447***	0.0536***	0.0221
	(0.014)	(0.013)	(0.010)	(0.006)	(0.017)	(0.007)	(0.008)	(0.011)	(0.018)
Observations	237096	237096	237096	237096	237096	237096	237096	237096	237096
R-squared	0.057	0.035	0.028	0.028	0.329	0.040	0.049	0.106	0.210
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: *** p<0.01, ** p<0.05, * p<0.10. Dependent variable is the difference in the RIF of natural log of the ACS self-reported valuations of their house in 2016 dollars from Equation (2) at the two deciles listed. The center column is the Median column from Table 8 and each column is the interquantile range of the given decile and the median where the signs are always the larger decile minus the smaller decile Clustered standard errors are computed at the county×year level.

and focusing on the largest statutory tax rate increases in the novel county-level statutory tax rate data, house prices measured with three different variables respond to changes in statutory tax rates in the first three years following the event and revert by the fourth year after the tax change goes into effect. Using several measures of house prices, the treatment effect in the baseline model is statistically significant and economically large between a 1.168% and 3.62% decline in the first year following the tax rate increase. Using quantile analysis, these treatment effects do not statistically vary from the median across the distribution in the first year of the new statutory tax rate of house prices except above the ninth decile. The most expensive houses whose homeowners do not seem to respond to statutory property tax rate changes by adjusting their self-assessed valuations despite receiving the same percentage increase to property tax rates. There is evidence that there is heterogeneity across the distribution in responses to property tax rate changes.

While the capitalization parameter and treatment effects are two different parameters, the implied capitalization rate from the event-study analysis is less than 1 suggesting that the largest statutory property tax rate changes are less-than-capitalized into house prices (less than a dollar-for-dollar response). The county-level property tax capitalization elasticity calculation is -0.115 suggesting than every 10% percentage increase in statutory property tax rates reduces house prices by 1.15%. Calculating capitalization rates implies partial capitalization between 0.354 and 0.581, depending on the discount rate and time horizon in the present-discounting formula.

Taken together, there is strong evidence that property tax capitalization occurs in counties that contain large cities across the United States which is congruent with more convincing work in property tax capitalization. The degree of capitalization has heterogeneity along the distribution of house prices where the treatment effects are non-existent for the high-priced houses. These estimates do not depend on specific qualities of any of the 36 counties in the sample so the effects can be generalized to counties that contain large cities in the United States.

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A Theory - Household Bidding Model

Canonical bidding models to determine house prices with property tax capitalization go back to Brueckner (1979) and are given full theoretical treatment in Yinger (1982) and Yinger et al. (1988). There are aspects from utility maximization models and asset pricing models in this framework, and each can be used to derive similar conclusions as the bidding model.[40] The bidding framework for house prices relies on several assumptions. First, household utility depends on housing consumption, public good provision and quality, and consumption of a composite good. Second, households differ in their demographic characteristics but have well-defined preferences based on their income. Third, households do not face moving costs. Fourth, all households receive the same level of public goods as any other household in their fiscal district. Lastly, cities have many local fiscal districts with well-defined boundaries that finance different levels/qualities of public goods with different effective property tax rates. Households are not concerned with how the effective property tax rate or levels/qualities of public goods are determined by the fiscal district. Rather, households only care about the resulting parameters that are determined by the fiscal district so the fiscal district's budget constraint does not factor into household utility.

Let H be units of housing services and public amenities, P be the after-tax price of those services, and Y be household income. Define S as the quality of public goods and services and Z be a numeraire composite consumption good. The households derives utility from the numeraire, housing services and public amenities, and the quality of those housing services and amenities: $U(Z, H, S)$. The after-tax prices of housing services are an implicit function of the quality of public goods and the effective property tax rate, $P(S, \tau^e)$, that will simply be denoted as P for notational ease. Allow τ^e to be the effective property tax rate and r to be the discount rate in percentage terms across time t. The household's budget constraint[41] is then:

$$Y = Z + PH(1 + \tau^e/r) \tag{5}$$

Rearrange Equation (5) by solving for P to set up the the main question for housing bidding models which is how much a household would bid for a specific housing unit in a particular market

[40] Epple et al. (1984) is one such example that uses an indirect utility derivation as a form of user cost.

[41] Ross and Yinger (1999) use alternative notation for τ^* in place of τ^e/r where $T = \tau^e V = PH\frac{\tau^e}{r} = \tau^* PH$.

with access to certain public goods and services provided by the fiscal authority for that market.

$$\begin{aligned} \max_{H,Z} \quad & P = \frac{Y - Z}{H(1 + \tau^e / r)} \\ \text{s.t.} \quad & U(H, Z, S) = U^0(Y) \end{aligned} \tag{6}$$

Households treat S and τ^e as given parameters, and applying the envelope theorem to the rearranged budget constraint with respect to the quality of public services and the effective property tax rate yields:

$$P_S = \frac{U_S / U_Z}{H(1 + \tau^e / r)} \tag{7}$$

$$P_{\tau^e} = -\frac{P/r}{1 + \tau^e / r} \tag{8}$$

Equation (7) highlights the marginal rate of substitution between the quality of local public goods and the consumption numeraire good which can be interpreted as the dollar benefits of local public goods to households in those fiscal districts. Solving the Equation (8) with the initial condition that after-tax and pre-tax prices are the same when $\tau^e = 0$ yields the basic capitalization formulation in Equation (9) which is a form of hedonic price equation. The intuition is that the willingness to pay for any housing unit is equal to the real present-discounted sum of all future housing services, H, times their after-tax prices, P, using the real discount rate, r. The present-discounted annual cost of housing services is approximately equal to the rental rate for a given year so $r = \frac{R}{V}$. The total value of a house is the numerator number of dollars added from each period for the useful life of the housing unit. In this formulation, H is a vector of all housing services or attributes that give a housing unit value and each characteristic has its own price in the price vector, P. Given enough periods the expression can be simplified algebraically[42] to a multiplicative

[42]To do this, multiply each side of $V = \sum_{t=1}^{T} \frac{PH}{(1+r)^t}$ by $(1 + r)$, subtract the resulting expression from V, combine terms, and allow $T \to \infty$:

$$V(1 + r) = PH + \sum_{t=1}^{T-1} \frac{PH}{(1 + r)^t}$$

$$V - V(1 + r) = \sum_{t=1}^{T} \frac{PH}{(1 + r)^t} - \left(PH + \sum_{t=1}^{T-1} \frac{PH}{(1 + r)^t} \right) = -PH + \frac{PH}{(1 + r)^T}$$

$$V[1 - (1 + r)] = PH[(1 + r)^{-T} - 1]$$

formulation:

$$V = \sum_{t=1}^{T} \frac{PH}{(1+r)^t} \Rightarrow V = \frac{PH}{r} \tag{9}$$

The imposition of a property tax is reflected as the present-discounted value of all future tax payments and is subtracted from the present-discounted values of housing services[43] while substituting the after-tax price vector, P, for the pre-tax price vector, $\hat{P}$, which is a function of public good quality only. The tax payment is calculated by the local fiscal authority as the market value of a house times the effective tax rate, τ, so a substitution can be made where $T = \tau V$:

$$V = \frac{\hat{P}H}{r} - \frac{T}{r} \Rightarrow V = \frac{\hat{P}H}{r} - \frac{\tau V}{r} \tag{10}$$

Equation (10) assumes that property taxes are fully capitalized into house prices. Put differently, any changes to property tax payments or property tax rates are present discounted and fully reflected in the price of a house as well as changes in housing services, the prices of housing services, and the quality of local public goods. To be more flexible and allow for less-than-full capitalization (or over-capitalization), let δ represent the degree of property tax capitalization. Solving for V then yields the well-known property tax capitalization equation:

$$V = \frac{\hat{P}H}{r} - \delta\frac{\tau V}{r} \Rightarrow V = \frac{\hat{P}H}{r + \delta\tau} \tag{11}$$

Under full capitalization[44] of property taxes, $\delta = 1$ and current homeowners bear all the burden of present and future discounted property tax payments. When there is no capitalization, $\delta = 0$ and house prices do not reflect any changes in present or future property tax obligations. Over-capitalization can occur when public good provision is below the optimal level because willingness

$$V = PH\left(\frac{1-(1+r)^{-T}}{r}\right) \Rightarrow V = \frac{PH}{r}$$

[43]Ross and Yinger (1999) allow this to be expressed either with after-tax prices P or pre-tax prices $\hat{P}$ and with the τ^* notation where $V = \frac{PH}{r} = \frac{\hat{P}H}{r+\tau^e} = \frac{\hat{P}H/r}{1+\tau^*}$.

[44]In a series of works, Brueckner (1979) theoretically allows for an imperfect Tiebout (1956) equilibrium but assumes that all tax revenues are spent on improving or providing new public goods so there are no intergovernmental transfer payments. In this framework, local fiscal districts choose tax rates that are 'efficient' in the sense of Samuelson (1954) where net benefits of the public goods enjoyed by residents in that district equal the net costs of providing those public goods. Full capitalization occurs if property tax rates are efficiently set by local fiscal districts.

to pay for local public goods exceeds the necessary tax revenue to provide the goods. This type of sub-optimal tax policy can occur as a result of political processes or statutory property tax rate limitations that prevent taxes from being high enough to fully finance public goods demanded by constituents.[45] Similarly, under-capitalization can occur if the supply of local public goods exceeds the demand for those public goods. No capitalization occurs if homeowners sell their houses in the fiscal district where property taxes are increasing such that the buyers in those markets would pay a higher sale price and also bear all the burden of the property tax increase.

To derive an estimation equation, use a natural log transformation[46] of Equation (11) to recover a general form for empirical analysis:

$$ln(V) = ln(\hat{P}) + ln(H) - ln(r + \delta\tau) \tag{12}$$

Since $\hat{P}$ is not a function of the effective property tax rate, the (non-linear) effect of the property tax rate on house prices is only in the final term of Equation (12). As noted in Palmon and Smith (1998) and Ross and Yinger (1999), there are broadly four major hurdles to causal identification in empirical capitalization in estimation equations similar to Equation (12): the entanglement of the discount rate and the capitalization rate, exact functional form, endogeneity of the effective property tax rate, and which hedonic housing services to include. Sirmans et al. (2008) survey decades of property tax capitalization studies and show that many studies either use endogenous OLS functional forms or use estimation equations that are not derived from theory that often ignore the entangled discount and capitalization rates.

The first issue with an estimation equation of this form with the effective rate included is that the semi-elasticity estimation coefficient is an expression of both r and δ that cannot be algebraically separated:

$$\frac{\partial ln(V)}{\partial \tau} = \beta = -\frac{\delta}{r + \delta\tau} \tag{13}$$

[45] Work by Ross and Yinger (1999) and Hilber (2017) summarizing the theoretical and empirical literature on house price capitalization and implications of local public good provisions demonstrate that small deviations to theoretical assumptions drastically reduce the value of interpreting such deviations as efficiency gains or losses. The way house prices across districts reflect differences in underlying public goods provision is an empirical debate that is closely related to the property tax capitalization debate.

[46] Another common way to derive an estimation equation using panel data is to take first-differences of Equation (11) before the substitution of τV for T, say during a reassessment, and assume constant tax rates after reassessment. The resulting estimation equation is: $\Delta V = \frac{-\delta}{r}\Delta T$.

Algebraically rearranging Equation (13) by solving for δ[47] yields:

$$\delta = \frac{-\beta r}{\tau\beta + 1} \tag{14}$$

If the real discount rate is strictly positive, then estimates of $\hat{\beta}$ should be sufficient statistics to determine if δ is statistically different than 0 to demonstrate at least partial property tax capitalization. Since r and δ cannot be estimated directly in this form, the usual approach to make assumptions about either r or δ to back out the other after estimation. Do and Sirmans (1994) and Koster and Pinchbeck (2022) are among the only studies to estimate the discount rate in a property tax capitalization setting finding between 3% and 4%. A theoretically-driven approximation of the real discount rate is the inverse of the price-to-rent ratio, $r \approx \frac{R}{V}$. The remaining three common issues are addressed in this paper by using estimation equations derived from the theoretical model, using two empirical strategies to circumvent the endogeneity of the effective property tax rate, and including a full battery of fiscal spending categories to control for changes in local public goods across counties.

The basic bidding theoretical model has many extensions that include inter-jurisdictional sorting based on differential local public good provision and quality, expectations about future house prices within fiscal districts, different discount rates for the various housing services, the imposition of other tax instruments, property tax deductions to taxable income, and zoning. Each of these has its own set of difficulties in empirical estimation in addition to the four previously mentioned, but panel data is usually required for these extensions in order to track individuals or households as they move or update their beliefs about the housing market.

[47]Since theory suggests that $\beta < 0$, the capitalization parameter δ will be positive so long as the sign of the denominator is positive which occurs when $\tau < -1/\beta$.

B Tables and Figures

Table 10: Baseline π_t Results: ACS Valuations

	(1)	(2)	(3)	(4)
t = -4	0.0889***	0.0846***	0.0355	0.0286
	(0.019)	(0.019)	(0.031)	(0.031)
t = -3	0.0264	0.0280	0.0089	0.0055
	(0.020)	(0.020)	(0.022)	(0.022)
t = -2	0.0132	0.0088	0.0105	0.0030
	(0.011)	(0.012)	(0.013)	(0.014)
t = 0	-0.0412***	-0.0413***	-0.0376***	-0.0369***
	(0.013)	(0.013)	(0.013)	(0.013)
t = 1	-0.0757***	-0.0763***	-0.0715***	-0.0739***
	(0.019)	(0.019)	(0.019)	(0.019)
t = 2	-0.1077***	-0.1125***	-0.0957***	-0.1013***
	(0.027)	(0.027)	(0.026)	(0.026)
t = 3	-0.1280***	-0.1356***	-0.1353***	-0.1420***
	(0.039)	(0.039)	(0.035)	(0.036)
t = 4	-0.0711	-0.0652	-0.0784*	-0.0743*
	(0.044)	(0.043)	(0.043)	(0.044)
Observations	237096	237096	237096	237096
R-squared	0.374	0.527	0.374	0.527
Physical Characteristics	No	Yes	No	Yes
Budget Controls	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Estimated Effect in t=0 (%)	-4.035	-4.043	-3.692	-3.621

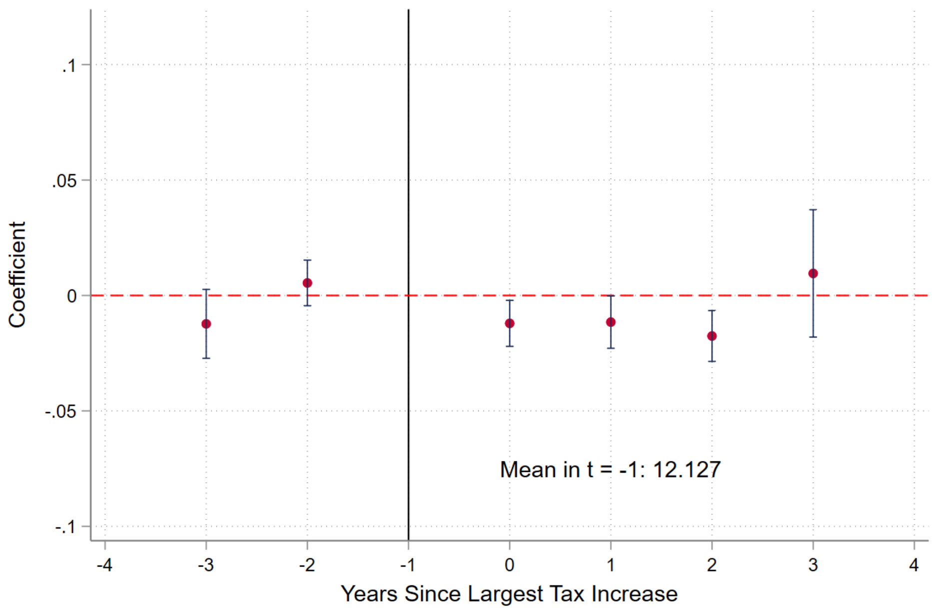
Note: *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Dependent variable is the natural log of the ACS self-reported valuations of their house in 2016 dollars from Equation (1). The final row is the percentage response in the outcome variable in the first year after the tax increase event. Clustered standard errors are computed at the county×year level.

Table 11: Flexible π_t Results: ACS Valuations

	(1)	(2)	(3)	(4)
(t = -4)*Statutory Tax Rate	-0.0043*	-0.0027	0.0205	0.0178
	(0.002)	(0.002)	(0.016)	(0.017)
(t = -3)*Statutory Tax Rate	-0.0058**	-0.0045*	-0.0036	-0.0035
	(0.002)	(0.002)	(0.005)	(0.005)
(t = -2)*Statutory Tax Rate	-0.0026	-0.0018	0.0021	0.0015
	(0.002)	(0.002)	(0.003)	(0.003)
(t = 0)*Statutory Tax Rate	-0.0046**	-0.0045**	-0.0120***	-0.0117***
	(0.002)	(0.002)	(0.004)	(0.004)
(t = 1)*Statutory Tax Rate	-0.0059**	-0.0063***	-0.0172***	-0.0179***
	(0.002)	(0.002)	(0.004)	(0.004)
(t = 2)*Statutory Tax Rate	-0.0072**	-0.0087***	-0.0222***	-0.0240***
	(0.003)	(0.003)	(0.006)	(0.005)
(t = 3)*Statutory Tax Rate	-0.0103**	-0.0114**	-0.0289***	-0.0303***
	(0.005)	(0.005)	(0.007)	(0.008)
(t = 4)*Statutory Tax Rate	-0.0114**	-0.0130**	-0.0197**	-0.0187*
	(0.005)	(0.006)	(0.010)	(0.010)
Observations	386649	386649	237096	237096
R-squared	0.388	0.543	0.374	0.527
Physical Characteristics	No	Yes	No	Yes
Budget Controls	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Estimated Effect in t=0 (%)	-0.461	-0.445	-1.190	-1.168

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Dependent variable is the natural log of the ACS self-reported valuations of their house in 2016 dollars. The estimates are the π_t coefficients from Equation (2). The final row is the percentage response in the outcome variable in the first year after the tax increase event. Clustered standard errors are computed at the county×year level.

Figure 11: Flexible π_t Estimates including Event Time Indicators



Note: Estimates of π_t from an alternative specification of Equation (2) including event time indicator variables where the y-axis is the magnitude of the coefficient relative to the omitted period, $t = -1$. The average natural log ACS self-assessed valuation in the reference year is 12.127 which corresponds to about \$184,795. Clustered standard errors are computed at the county$\times$year level.

Table 12: Baseline Event-Study Quantile Regressions Relative to the Median

	IQR(50-10)	IQR(50-20)	IQR(50-30)	IQR(50-40)	Median	IQR(60-50)	IQR(70-50)	IQR(80-50)	IQR(90-50)
t = -4	-0.0619*	-0.0588	0.0025	0.0072	0.0240	-0.0166	-0.0235	0.0075	-0.0440
	(0.035)	(0.041)	(0.021)	(0.012)	(0.045)	(0.014)	(0.023)	(0.035)	(0.054)
t = -3	-0.0352	0.0198	0.0114	0.0237**	0.0093	-0.0217**	-0.0172	-0.0048	-0.0190
	(0.029)	(0.032)	(0.016)	(0.009)	(0.036)	(0.011)	(0.021)	(0.031)	(0.048)
t = -2	0.0062	0.0003	-0.0053	0.0023	0.0151	-0.0069	-0.0144	-0.0179	-0.0537
	(0.017)	(0.019)	(0.011)	(0.006)	(0.022)	(0.007)	(0.012)	(0.021)	(0.045)
t = 0	-0.0088	0.0161	0.0111	0.0046	-0.0555***	0.0081	0.0144	0.0219	0.0619*
	(0.017)	(0.016)	(0.011)	(0.006)	(0.019)	(0.007)	(0.009)	(0.016)	(0.034)
t = 1	-0.0278	0.0193	0.0020	-0.0017	-0.1072***	0.0046	0.0257**	0.0514***	0.1054***
	(0.020)	(0.019)	(0.012)	(0.007)	(0.028)	(0.008)	(0.012)	(0.019)	(0.033)
t = 2	-0.0358	0.0253	0.0039	0.0014	-0.1370***	0.0025	0.0391**	0.0616**	0.1105**
	(0.028)	(0.022)	(0.017)	(0.009)	(0.039)	(0.010)	(0.016)	(0.024)	(0.043)
t = 3	-0.0575	-0.0152	-0.0305	-0.0245*	-0.1860***	-0.0252*	0.0228	0.0530	0.1007**
	(0.038)	(0.030)	(0.023)	(0.013)	(0.054)	(0.015)	(0.024)	(0.034)	(0.049)
t = 4	0.1295**	0.2134***	0.1063***	0.0756***	-0.0797	0.0504***	0.1338***	0.2058***	0.1695***
	(0.050)	(0.041)	(0.038)	(0.023)	(0.067)	(0.017)	(0.027)	(0.041)	(0.059)
Observations	237096	237096	237096	237096	237096	237096	237096	237096	237096
R-squared	0.057	0.035	0.028	0.028	0.330	0.040	0.049	0.106	0.211
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: *** p<0.01, ** p<0.05, * p<0.10. Dependent variable is the difference in the RIF of natural log of the ACS self-reported valuations of their house in 2016 dollars from Equation (1) at the two deciles listed. The center column is the Median column from Table 7, and each column is the interquantile range of the given decile and the median where the signs are always the larger decile minus the smaller decile. Clustered standard errors are computed at the county×year level.

Table 13: Flexible Event-Study Quantile Regressions Relative to the Median

	IQR(50-10)	IQR(50-20)	IQR(50-30)	IQR(50-40)	Median	IQR(60-50)	IQR(70-50)	IQR(80-50)	IQR(90-50)
Statutory Tax Rate	-0.0787	0.0282	0.0492	0.0085	0.0398	0.0586*	0.0629*	0.0185	-0.0816
	(0.053)	(0.051)	(0.035)	(0.023)	(0.064)	(0.030)	(0.035)	(0.046)	(0.079)
(t = -4)*Statutory Tax Rate	-0.0458**	-0.0537**	-0.0004	-0.0040	0.0083	-0.0099	-0.0069	0.0056	-0.0194
	(0.020)	(0.026)	(0.013)	(0.007)	(0.024)	(0.007)	(0.015)	(0.021)	(0.025)
(t = -3)*Statutory Tax Rate	-0.0191**	0.0034	0.0028	0.0044	-0.0112	-0.0099***	0.0008	-0.0015	0.0129
	(0.007)	(0.008)	(0.004)	(0.003)	(0.008)	(0.003)	(0.005)	(0.006)	(0.008)
(t = -2)*Statutory Tax Rate	0.0021	-0.0023	0.0006	-0.0001	0.0034	-0.0027	-0.0030	-0.0024	-0.0075
	(0.004)	(0.003)	(0.002)	(0.001)	(0.005)	(0.002)	(0.003)	(0.005)	(0.008)
(t = 0)*Statutory Tax Rate	0.0040	0.0030	-0.0010	-0.0008	-0.0195***	-0.0034	-0.0007	0.0047	0.0237**
	(0.005)	(0.005)	(0.003)	(0.002)	(0.007)	(0.002)	(0.003)	(0.005)	(0.010)
(t = 1)*Statutory Tax Rate	0.0047	0.0069	0.0003	-0.0003	-0.0276***	-0.0028	0.0006	0.0103	0.0296***
	(0.006)	(0.006)	(0.004)	(0.003)	(0.009)	(0.003)	(0.004)	(0.006)	(0.011)
(t = 2)*Statutory Tax Rate	0.0069	0.0114*	0.0025	0.0023	-0.0313***	-0.0034	0.0051	0.0122*	0.0221**
	(0.007)	(0.006)	(0.004)	(0.003)	(0.010)	(0.003)	(0.004)	(0.006)	(0.010)
(t = 3)*Statutory Tax Rate	-0.0020	-0.0047	-0.0099*	-0.0066**	-0.0401***	-0.0125***	-0.0016	0.0062	0.0181
	(0.009)	(0.008)	(0.006)	(0.003)	(0.013)	(0.004)	(0.006)	(0.009)	(0.013)
(t = 4)*Statutory Tax Rate	0.0288**	0.0662***	0.0401***	0.0212***	-0.0097	0.0235***	0.0447***	0.0536***	0.0221
	(0.014)	(0.013)	(0.010)	(0.006)	(0.017)	(0.007)	(0.008)	(0.011)	(0.018)
Observations	237096	237096	237096	237096	237096	237096	237096	237096	237096
R-squared	0.057	0.035	0.028	0.028	0.329	0.040	0.049	0.106	0.210
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: *** p<0.01, ** p<0.05, * p<0.10. Dependent variable is the RIF of the natural log of the ACS self-reported valuations of their house in 2016 dollars from Equation (2). The rows are estimates of the π_t coefficients on the event time indicator dummy variables interacted with the statutory property tax rate relative to the omitted period, $t = -1$. The RIF(Q) row is the unconditional mean in that decile. Clustered standard errors are computed at the county×year level.