Distributional Responses to Property Tax Changes

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Abstract

Local property tax capitalization into house prices is an ongoing empirical debate, and county-level responses are under-studied in this vein. This paper contributes to the empirical literature on property tax capitalization by demonstrating varying responses to average nominal property tax rate increases and decreases along the distribution of house prices in counties containing large U.S. cities. The empirical setting uses data on county-level average nominal property tax rates for almost one hundred counties, and within-county standardized tax rate changes are used as to study house price changes in a capitalization framework. Decreases in the average nominal property tax rate tend to increase house prices around 1.26%, and increases tend to decrease house prices around 0.75%. Using recentered-influence functions (RIFs) that analyze unconditional quantile regressions, the responsiveness of households is shown to vary across the distribution of house prices. Specifically, house prices respond to increases in property tax rates by larger percentages on the lower end of the house price distribution, and house prices are unaffected by rate hikes on the high end of the distribution. House prices also respond to decreases in property tax rates, and house prices respond by larger percentages on the lower end of the distribution. The impacts of average nominal property tax rate changes are economically significant in either direction.

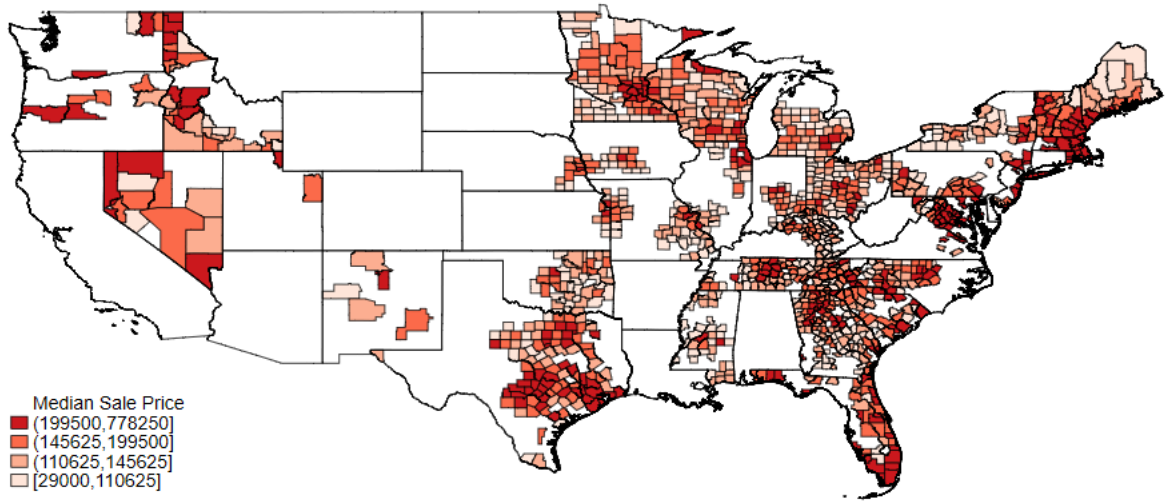
1 Introduction

As of January 2024, the Bureau of Labor Statistics (2024) (BLS) reports that homeowners' equivalent of rental expenditures for primary residences is the largest single expenditure category at 25.44% 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. Further, responses across the distribution of house prices may indicate differential impacts for certain households. Figure 1 contains county-level median sale prices from Redfin (2022) in 2016. Unsurprisingly, there are higher prices in and near major cities[1] across the United States which contributes to heterogeneity within states between urban, suburban, and rural areas. Differences in house prices is even more pronounced at more granular geographies like communities and neighborhoods.

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 taxes affect the price of a house. Property tax rates, in turn, affect the amount of property taxes paid by households. For households with lower income, changes in property taxes represent larger fractions of household income so they may be more affected by changes in the property tax burden. Figure 2 shows the natural log of county average house prices in counties that contain large cities from 2012 to 2018 against average statutory/nominal[2] property tax rates and county average effective property tax rates that descriptively

[1] Some states are not available in the RedFin data at the county level, and much of that attrition is from states with small populations.
[2] This work uses the terms nominal and statutory interchangeably.

Figure 1: County-Level House Price Heterogeneity



Source: Redfin county-level median sales price data for 2016. This demonstrates the substantial heterogeneity in house prices across the United States and within states.

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. In this paper, variation in county-level average nominal property tax rate data are used in several difference-in-differences designs to estimate the extent to which changes in average nominal property tax rates are capitalized into house prices and how responses vary along the distribution of house prices.

Estimation models that include hedonic components are common when studying house price 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[3] characteristics of houses or public amenities in the hedonic models, and there is no theory-driven measure of these amenities.[4] Gibbons and Machin (2008) and Sirmans et al. (2008) survey the empirical literature to show that, while spending on schools is most common[5], almost every study varies on which public amenities to include in estimation and how to measure their chosen proxies.[6] Gárate and Pennington-Cross (2023) focus on property taxes that support school spending finding that the tax costs of local public goods, preferences for public goods, and housing supply elasticities all matter to determine the overall effect of property taxes on house prices.

More recent empirical studies have used boundary discontinuity designs between adjacent fiscal districts to identify useful 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 et al. (2021). Natural experimental approaches to estimate property tax capitalization rates start with Rosen (1982) and California's Proposition 13[7] that exploit variation from specific tax change policies. Boundary discontinuity designs often rely on

[3]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.

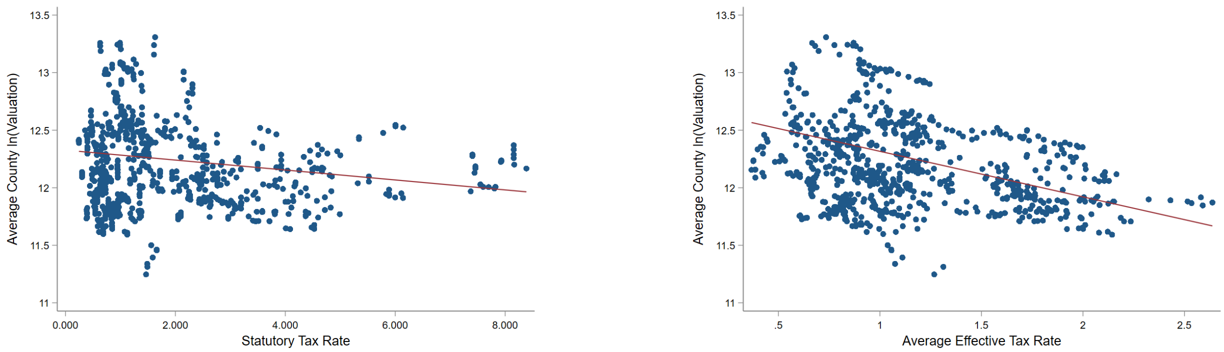
[4]House prices may also be impacted by supply inelasticities of land as in Saiz (2010) that can be, at least partially, mitigated using geography-specific fixed effects.

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

[6]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.

[7]Many other papers also study this tax change as well as other event-study designs surrounding specific tax change events

Figure 2: Average Valuations by County



(a) (b)

Note: County average natural log house prices against average nominal property tax rates in Panel (a) and against county average effective property tax rates in Panel (b) pooled from 2012 to 2018. Source: American Community Survey and the Lincoln Institute of Land Policy Significant Features of the Property Tax: Property Tax Rates.

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. Another wrinkle to the empirically mixed evidence in property tax capitalization is that perceptions of property taxes have been shown to influence house prices as in Gindelsky et al. (2023).

This paper complements the existing empirical literature on property tax capitalization in two ways. First, generalizing the setting to households in counties containing large U.S. cities using data on average nominal county-level property tax rates circumvents concerns about external validity. Second, the paper demonstrates that property tax capitalization vary across the distribution of house prices using recentered-influence functions (RIFs) in quantile analysis. Decreases induce slightly larger responses with more variability, but the magnitudes of effects in either direction are comparable overall. Consistent with theory, tax rate increases cause house prices to fall, and tax rate decreases cause house prices to rise. Along the distribution, the highest quantiles of house prices are unaffected by increases in property tax rates. Since house price responses are different, there may be strategic incentives for households to move along the house price distribution by moving to higher- or lower-priced houses, depending on the direction of the property tax rate change.

The rest of the paper is organized as follows: Section 2 discusses the main points of the conceptual model, Section 3 explains the data sources used for estimation, Section 4 explains the main empirical design, Section 5 analyzes the results along the distribution of house prices, Section 6 considers some relevant policy implications from the results, and Section 7 briefly concludes the paper.

2 Conceptual Framework

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). The bidding framework for house prices relies on several assumptions. First, household utility depends on housing services/characteristics, public good provision and quality, and a composite consumption good. Second, house-

that are location-specific.

holds 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 authority's constrained problem does not factor into household utility.

Housing consumption is a vector of physical characteristics, H, that each have a specific price, P. Households discount the future at the real discount rate, r and face property tax rates, τ, set by the local fiscal district. Changes in property taxes may not offset dollar-for-dollar, and δ represents the fraction of each dollar of tax changes are reflected in house prices. Under perfect capitalization, $\delta = 1$ and existing homeowners bear all the burden of changes in property taxes because potential buyers are adjusting their offer prices. Treating property taxes as an annuity, offer prices change by the present discounted stream of future tax payments. When there is no capitalization, $\delta = 0$ and home buyers bear all the burden of the change in taxes since offer prices do not reflect any changes in present or future property tax obligations. Solving the household's problem leads to the well-known capitalization formula:

$$V = \frac{\hat{P}H}{r} - \delta\frac{\tau V}{r} \Rightarrow V = \frac{\hat{P}H}{r + \delta\tau} \tag{1}$$

From here, estimation equations can be derived using natural log transformations among others, but difficulties arise appropriately identifying variation to circumvent the entanglement of several parameters in the regression coefficients when trying to estimate δ. The Appendix enumerates some of these estimation difficulties, but they are not the focus of this paper. This paper measures how magnitudinal changes in the tax rate induce changes in house prices. Any increase in property tax rates should reduce house prices, and decreases should increase house prices based on Equation (1).

3 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 average nominal) 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 the empirical models from 2012 to 2018. This period mitigates some concerns of house price volatility from macro-level factors immediately following the Great Recession as house prices recovered and before the Covid-19 pandemic. Average national house prices are lowest in 2012 and monotonically increasing through 2018.[8] Mortgage rates for single-family homes measured by FreddieMac[9] also dropped dramatically after 2011, on average. This paper focuses almost exclusively on average nominal property taxes so the estimation, results, and discussion are all about average nominal rates unless otherwise specified as the effective rate.

3.1 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, demographic characteristics, and housing unit characteristics.[10] The benefits to using the ACS are the sample sizes, coverages that allow for the

[8] House price indices like the Case-Shiller Home Price Index (CSUSHPINSA) 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.

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

[10] The overall effective tax rate is also imputable using the midpoint of the property tax payment bins supplied by the ACS divided by the self-reported valuation of the house prices, but the effective rate is not used for any substantive purpose in this

generalization of property tax capitalization to many cities, and analysis along the house price distribution due to the rich demographic information. Summary statistics for housing characteristics are in Table 1.

Table 1: Summary Statistics: Housing Characteristics

	Mean	SD	Min	Max	N
Valuation	227,260.66	139,500.46	22,303.97	2,967,157.25	542,615
ln(Valuation)	12.16	0.60	10.01	14.90	542,615
Number of Rooms	6.87	1.81	2.00	10.00	542,615
Number of Bedrooms	4.26	0.82	2.00	6.00	542,615
Built Before 1950	0.11	0.31	0.00	1.00	542,615
Built 1950-1959	0.10	0.31	0.00	1.00	542,615
Built 1960-1969	0.10	0.30	0.00	1.00	542,615
Built 1970-1979	0.14	0.35	0.00	1.00	542,615
Built 1980-1989	0.15	0.36	0.00	1.00	542,615
Built 1990-1999	0.17	0.38	0.00	1.00	542,615
Built 2000-2009	0.18	0.39	0.00	1.00	542,615
Built 2010 or After	0.04	0.19	0.00	1.00	542,615
ln(Density)	7.60	0.90	5.32	10.08	542,615
Unemployment Rate	5.51	1.79	2.00	11.90	542,615

Source: American Community Survey. Summary statistics are pooled from 2012 to 2018. Outliers below the 1st percentile and above the 99th percentile of house prices within county×years are removed as well as logical skips.

The Lincoln Institute of Land Policy provides data sources on property tax rates and local government expenditure and revenue. The Significant Features of the Property Tax: Property Tax Rates[11] repository contains nearly all county property taxation reports sent to their respective state governments to be archived dating back to 1980, and average nominal rates are collected from these annual records between 2012 and 2018. Since not every state and county have records for every year, the sample is limited to county×year observations for which average nominal property tax rate data can be collected in at least two consecutive periods. The number of tax changes, tax increases, tax decreases, and the magnitudes of the tax changes are summarized in Table 2. The average county alters average nominal property tax rates just less than half of the years during the sample period, mixing between increases and decreases, and decreases in tax rates occur slightly more frequently than increases. The average yearly percentage change in the average nominal rates across all counties and all tax changes is about -0.01% but can vary substantially. If the average tax rate difference was largely positive or negative, it might suggest that tax rates are either increasing or decreasing over time, respectively. The mean difference being close to 0 suggests that tax rates are remaining relatively stable across time, on average. This table also lists within-county standardized scores of the level tax changes. The z-scores have a mean of 0 and standard deviation of 1. The t-scores have a mean of 0 with larger standard deviations, unsurprisingly.

While the data listed allow for estimation of property tax capitalization, there are drawbacks to relying only on the ACS in this context. First, the implied effective property tax rate in the ACS cannot be used to isolate the effective property tax rates from overlapping 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.[12] Second, each yearly wave of the ACS surveys

paper since the variation is in the county-level average nominal property tax rate. Given the magnitudes of the county average nominal property tax rates and the fact that the overall effective tax rate is the sum of all average nominal 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.

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

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

Table 2: Summary Statistics: Tax Changes

	Mean	SD	Min	Max	N
Nominal Tax Rate	2.21	1.92	0.24	8.39	542,615
Effective Tax Rate	1.29	0.71	0.16	4.05	542,615
Change in Nominal Tax Rate	-0.01	0.13	-2.64	0.49	542,615
Percentage Change in Nominal Tax Rate	-0.20	4.75	-43.01	35.41	542,615
t-Score of Change	0.00	2.26	-6.63	6.74	451,954
Z-Score of Change	0.00	1.00	-2.50	2.55	451,954
Number of Tax Changes	2.96	2.05	0.00	7.00	542,615
Number of Tax Increases	1.31	1.31	0.00	6.00	542,615
Number of Tax Decreases	1.65	1.57	0.00	6.00	542,615

Source: Significant Features of the Property Tax: Property Tax Rates. Standardized Z and t scores are calculated using households within the same county from 2012 to 2018, and each standardized score has a mean of zero. All households are in counties that experienced at least one tax change. The typical household experienced more tax rate decreases than increases, and the typical tax rate change was a decrease of 0.01%. The sample excludes percentage changes more than 50% in either direction to prevent outliers, and the attrition from this condition is around 1% of the overall number of counties.

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 that maintain heterogeneity within counties 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, and methodological differences drive empirical debates in the literature as to the nature of differences between the two. Since there is little consensus as to the direction of these differences, self-assessments and market values are treated as synonymous for the purposes of this work. Models of portfolio choice typically assume that capital stock owners know with certainty the value of their property[13] which may be an overly strong assumption for self-reported house prices in the ACS. Self-assessments are useful in the context of a bidding model, and household-level observations are used in the empirical approach.

Any 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 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. While county-level average nominal changes are used for variation, the empirical strategy uses household-level responses to county-level changes. That way, useful heterogeneity within counties across households is preserved.

3.2 Sample Selection

Households are in the sample if reside in the county containing the city center for large U.S. cities or in a geographically adjacent county as seen in Figure 3. The counties with missing data in 2016 have observations in other years so they are included in the coverage map. The counties in the sample appear as small clusters

a specific county:

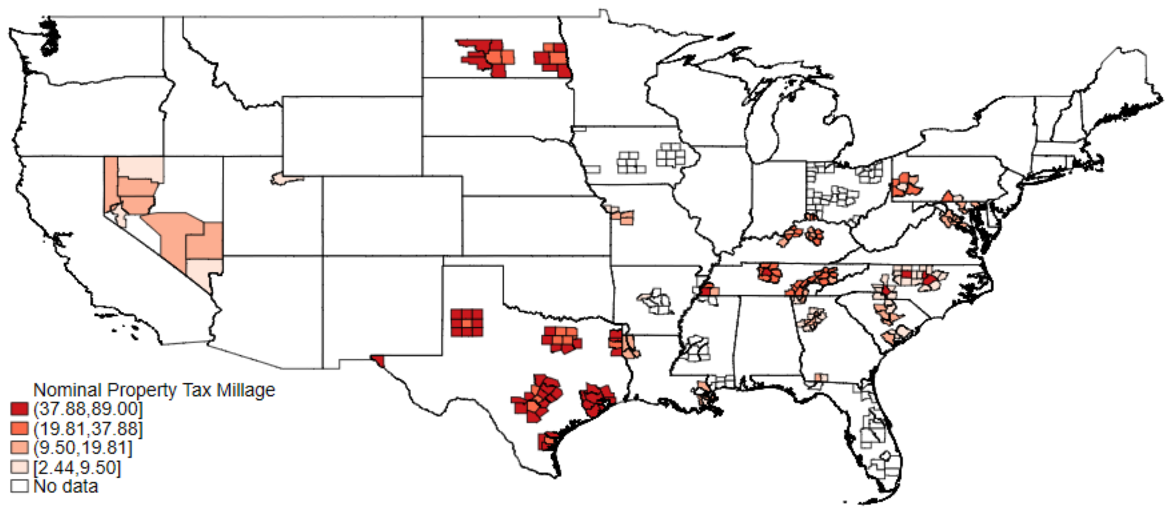
$$\tau^e_{ct} = \frac{V^a_{ict}}{V^m_{ict}} \times \sum_d \tau^s_{dt}$$

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 average nominal 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 average nominal tax rates are additively separable.

[13] 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.

since the city center and bordering counties are included. Some metropolitan areas expand into multiple states, and some states do not have sufficient county populations to be identifiable in the ACS down to the county level. Some states also have attrition from non-response from some counties in the Lincoln Institute data. In all specifications, results are population weighted using ACS household-level weights. House price data in the ACS is continuous after 2008, but the sample period contains years from 2012 to 2018. The sample is further narrowed to include homeowners[14] in counties where percentage changes in property tax rates that are less than 50% in either direction.

Figure 3: 2016 Coverage Map



Note: Average nominal property tax millages from 2016. States included have sufficient coverage at the county level in the American Community Survey to be merged to non-missing millage rates in the Lincoln Institute of Land Policy's Significant Features of the Property Tax: Property Tax Rates database. Counties with missing data in 2016 have data for other years so they are included in the sample.

4 Generalized DiD

Household-level observations experience county-level changes in average nominal property tax rates. Households are considered treated if their county experienced a average nominal property tax rate change in a given year and untreated if their average nominal property tax rate remained constant from the previous year.

$$ln(V_{ict}) = \alpha + \beta_1(D_{ct} \times T_{ct}) + \beta_2 D_{ct} + \beta_3 T_{ct} + \phi R_{ct} + H'_{ict}\lambda + \psi_c + \eta_t + \varepsilon_{ict} \tag{2}$$

Here, $ln(V_{ict})$ is the natural log of the house price reported in the ACS. In this formulation, D_{ct} is an indicator for whether a household is treated. This specification is run separately for average nominal property tax rate increases and decreases. For increases, D_{ct} is active if a household is in a county whose rate increased from the previous year compared to households in counties whose rate remained the same. Likewise, for decreases, D_{ct} is active for rate decreases relative to no change from the previous year. To capture the intensity of the average nominal property tax rate change, T_{ct} is the within-county t-score[15]

[14] 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 have no logical skips in number of bedrooms, number of rooms, self-assessed house price, or tax payments. Further, households reporting a house price outside the 5th and 95th percentile for their county and removed after removing logical skips to reduce the potential influence of outliers.

[15] In an unreported exercise, z-scores are substituted. Mechanically, z-scores are smaller and lead to larger coefficients while conveying the same qualitative implications. Using t-scores is more appropriate since the sample period has relatively few years, and there is no loss of statistical variation.

of the level change in the average nominal property tax rate from the previous year. The standardized t-scores measure the magnitudes of the changes relative to each county's recent history and lends to ease of interpretation. This accounts for county-specific norms[16] that might be masked with percentage changes alone. If, for instance, residents in a county were used to average nominal property tax rate increases of a certain magnitude, there could a tolerance for certain percentage changes not present in other counties. Using t-scores measures responses for each respondent using shocks that are comparable across districts while allowing for tolerance to their own district's recent tax history. There are fixed effects for county and year in ψ_c and η_t, respectively. H'_{ict} is a vector of physical characteristics of the respondent's household found in the ACS, population density, and the natural log of the unemployment rate to control for macro-level differences across counties that may not be accounted for in the fixed effects.

R_{ct} controls for the level of the average nominal property tax rate to account for rate differences across counties. This further accounts for tolerance of households to the prevailing property tax rate environments across locations. In some specifications, the level is replaced with the natural log of the average nominal rate in order to naively estimate a property tax elasticity with respect to the average nominal property tax rate[17] which should be interpreted as descriptive only. The theoretical bidding framework indicates that the regression coefficient of such a specification is the entanglement of several other parameters including the discount rate, the capitalization rate, and the tax rate.

4.1 Threats to Identification

In this context, identifying an ATT requires a few assumptions. First, no anticipation of average nominal property tax rate changes that would create the opportunity for strategic behavior surrounding house prices with the knowledge of impending changes. Second, parallel trends requires that the evolution of house prices in counties whose average nominal 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 average nominal tax rates causes house prices to adjust on average by the same amount for any county that received the same change in average nominal tax rates which is a version of parallel trends for each magnitudinal change in average nominal rates.

Regarding the main identifying assumptions for estimating an ATT, there are several main categories of how those assumptions might 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 average nominal county property tax rate is likely not exogenous 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. Any strategic behavior may bias results toward no effects in the year of the tax rate change since the responses would be anticipatory leading up to the tax change year to smooth overall portfolio wealth.

[16]For example, in unreported ancillary specifications, school test scores are added as a control on the quality of public goods provision that would be funded partially through property tax revenue. School spending varies dramatically across overlapping fiscal districts and across space. The test scores are averages of all school districts that fall within a county, and are measured as the percentage of students that failed to meet minimum standards and the percentage of students who exceeded high standards for math and reading. These four variables (math and reading, low and high) do not substantially alter the signs or significance of the main results. Further, the coefficients on the test scores are mostly economically small and statistically insignificant across specifications.

[17]In an unreported exercise, this elasticity coefficient is shown to increase in negative magnitude as house prices increase to the median then stabilize thereafter around -0.35 in the upper half of the house price distribution. Another alternative could be that households with higher prices are subject to high property tax rates.

Even if homeowners do not *strategically* vote for favorable average nominal 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. Related, property owners may speculate on real estate as a portfolio enhancement so speculators, vacationers, and other situations where the housing unit is not occupied as a main residential domicile may bias the results since potential voting right may induce strategic behavior. That said, households who own more than one housing unit like vacationers and speculators would need to be apprised of property tax rates in more than one district, including where they do not primarily live in some cases. In some states, non-owner occupied units are charged higher property tax rates and may not granted the same voting rights as residents, so these types of real estate market agents have more incentive to closely follow property tax rate policies.

Another threat to identification in terms of anticipatory effects is announcements and overall salience of future average nominal 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 (1) in Section 7. 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.[18] Related to announcements is whether local governments publish their spending/revenue strategies before each new fiscal year.[19]

If homeowners perceive average nominal tax rate changes as both unanticipated and permanent, the measured effects may be the largest. 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 average nominal rate changes are seen as temporary, the results may tend toward no effects and may have anticipatory impacts. 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 two-way fixed effects may reduce some of the possible systemic bias from changing expectations across counties and time.

Since this work aims to generalize property tax capitalization to many geographically diverse fiscal districts, this may introduce other identification issues since the statistical variation is not localized. If there are counties in the sample that have any of the characteristics listed in this section, the variation may not be fully exogenous. Further, the natural experiment assumes that homeowners are not strategically choosing county average nominal property tax rates in a way that affects house prices and that other local district-level average nominal property tax rates are fixed. To the extent possible, the sample excludes homeowners in counties with property tax revenue caps that would necessarily require local governments to offset rates to accommodate changes in market prices. The worry of revenue caps may be less of a concern in the ACS where house prices are self-assessments and not sale prices, but there could still be information about expectations in the self-assessments. If residents in revenue cap districts where included, the estimates in the empirical design may be larger due to the mechanical offset between property tax rates and the property tax base of house values. 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.

Table 3 provides balance tests of unconditional outcomes of house prices for both states of treatment: increases and decreases. Both treatments use the same comparison group of households in counties who did not have a average nominal property tax rate change at the same time. Across all groups, the average

[18] 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.

[19] 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.

nominal rate and effective rates are not statistically different. In the full sample, the average household self-assesses their house around $191,186, or a natural log of 12.161. In the both treatment states, there is no difference in the unconditional outcome variable means. Counties with decreases start at statistically larger property tax rates than the full sample. Unsurprisingly, the standardized scores are statistically higher and lower for counties who have increased and decreased property tax rates, respectively.

Table 3: Treatment Balance Table

Variable	Full	Control	Up=1	Down=1	Diff Up	Diff Down
ln(Valuation)	12.161	12.176	12.093	12.199	-0.083	0.023
	(0.596)	(0.584)	(0.624)	(0.582)	(0.213)	(0.659)
Nominal Tax Rate	2.210	1.974	2.194	2.583	0.220	0.609**
	(1.916)	(1.887)	(1.874)	(1.936)	(0.584)	(0.043)
Effective Tax Rate	1.292	1.221	1.374	1.327	0.153	0.106
	(0.713)	(0.672)	(0.757)	(0.725)	(0.150)	(0.214)
ln(Density)	7.598	7.599	7.648	7.554	0.049	-0.044
	(0.903)	(0.946)	(0.903)	(0.832)	(0.760)	(0.733)
Unemployment Rate	5.512	5.835	5.886	4.696	0.051	-1.139***
	(1.792)	(1.898)	(1.596)	(1.500)	(0.864)	(0.000)
t-Score of Change	-0.000	0.007	1.806	-1.565	1.799***	-1.572***
	(2.260)	(1.282)	(2.135)	(1.905)	(0.000)	(0.000)
Z-Score of Change	-0.000	0.014	0.787	-0.693	0.773***	-0.707***
	(1.000)	(0.615)	(0.939)	(0.827)	(0.000)	(0.000)
Observations	542,615	243,759	138,642	160,214	382,401	403,973

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Balance test of pooled unconditional variable means for the entire sample, the group of untreated observations, the average nominal property tax rate increase treatment status, and the average nominal property tax decrease treatment status. The right-most columns are the differences between the control group and treated group for each treatment status with standard errors of the t-tests in parenthesis clustered at the county level.

4.2 Generalized Model Results

Table 4 contains descriptive results for the coefficients on the average nominal property tax rate and its natural log for different sets of the sample. In general, these are the ϕ coefficients from Equation (2). The first pair of columns is the full sample, and the second pair of columns is on the set of households that are in neither treatment status. Each pair of columns is otherwise similar. These are meant to be descriptive baseline estimates for comparison and should be interpreted with caution. The level change in Column (1) indicates that a 1% increase in the average nominal rate would decrease house prices by 5.91%.[20] The descriptive elasticity with respect to the property tax rate is -0.2407 in Column (2) which should be interpreted as changes in percentage point terms of the average nominal rate (e.g. a percentage change in the average nominal property tax percentage rate). For households in neither treatment status in Column (3), increasing the level of average nominal rates by 1% indicates a decrease in house prices by 5.27%. Columns (3) and (4) correspond to the sample in Column (2) of Table 3.

Table 5 contains the estimates of the main variables of interest that estimate β_1 from Equation (2) and is organized by treatment status. In the first two pairs of columns, the odd columns use the level of the average nominal rate, and the even columns use the natural log of the average nominal rate. In the last pair of columns, the control for the level or natural log of the average nominal property tax rate is left out due to potential endogeneity concerns between house prices and the effective property tax rate due to the mechanical connection between average nominal and effective rates. Each pair of columns is otherwise similar. The last row of coefficients is the constant term for the natural log of house prices, and the very

[20] Calculate this from the coefficient by reversing the natural log transformation: $\% = (e^{\beta} - 1) \times 100$.

bottom row of the table displays the implied treatment impacts in percentage terms on house prices. Each specification clusters the standard errors at the county level.

Table 4: Descriptive Results

	Full	Full - ϵ	No Treatment	No Treatment - ϵ
Nominal Tax Rate	-0.0609***		-0.0541**	
	(0.018)		(0.026)	
ln(Nominal Tax Rate)		-0.2407***		-0.3049***
		(0.046)		(0.084)
Constant	11.6214***	11.6006***	12.1346***	12.1115***
	(0.240)	(0.241)	(0.501)	(0.510)
Observations	542615	542615	243759	243759
R-squared	0.505	0.505	0.493	0.493
Year FE	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes

Note: *** p<0.01, ** p<0.05, * p<0.10. Estimates of the ϕ coefficients from Equation (2) are organized by treatment status. The odd columns estimate the models that estimate the level of the average nominal property tax rate, and the even columns estimate the natural log of the average nominal property tax rate. The first pair of columns use the entire sample, and the second pair of columns is for households in neither treated state. These estimates are meant to be descriptive only. Standard errors are clustered at the county level.

Columns (1) and (2) contain results for the tax rate increase treatment status. The coefficient of interest is the interaction of treatment status and measure of the magnitude of the tax increase which is β_1 from Equation (2). Column (1) controls for the level of the average nominal rate, and the main coefficient of interest indicates that increasing the magnitude of the tax rate increase by one standard deviation in the t-score lowers house prices by 0.728% relative to households in counties whose average nominal rates did not change. This effect is statistically significant at conventional levels and is economically large.

Columns (3) and (4) contain results for the tax rate decrease treatment status. Again, the coefficient of interest is the interaction between treatment status and magnitude of the tax decrease. Column (3) controls for the level of the average nominal rate, and the main coefficient of interest indicates that decreasing the magnitude of the tax rate by one standard deviation raises house prices by 1.523% relative to households in counties whose average nominal rates did not change. This effect is significant at conventional levels and even larger in economic significance.

Columns (5) and (6) do not control for the average nominal property tax rate to address potential endogeneity concerns. The impacts of tax rate changes are slightly larger in absolute value for both increases and decreases where the impact of a one standard deviation increase in average nominal rate changes leads to a 0.859% decrease in house prices, and a one standard deviation decrease in rate changes leads to a 1.754% increase in house prices.

Taken together, these results represent intuitive relationships between the magnitudes of average nominal property tax rate changes and house prices in a bidding-type framework. The opposite signs in treatment status and relative comparability in magnitudes provides some evidence of internal validity. Decreases in rates have a larger impact in absolute value of around twice as much as increases across specifications, and both treatment statuses have reduced magnitudes when controlling for the natural log of the average nominal rate rather than the level.

5 Quantile Analysis

This section allows responses to changes in property tax rates may vary along the distribution of house prices in the main designs. Using unconditional quantile methods proposed in Firpo et al. (2009) that rely on the

Table 5: House Price Responses by Treatment Status

	Up=1	Up=1 - ϵ	Down=1	Down=1 - ϵ	Up=1 - No Rate	Down=1 - No Rate
Nominal Tax Rate	-0.0563*		-0.0651***			
	(0.033)		(0.024)			
Increase=1	-0.0012	-0.0031			-0.0014	
	(0.008)	(0.008)			(0.008)	
t-Score of Change	0.0072**	0.0062*	-0.0136**	-0.0106**	0.0074**	-0.0174***
	(0.003)	(0.003)	(0.006)	(0.005)	(0.003)	(0.007)
Increase=1 × t-Score of Change	-0.0075**	-0.0054			-0.0086**	
	(0.004)	(0.004)			(0.004)	
ln(Nominal Tax Rate)		-0.2224***		-0.3007***		
		(0.054)		(0.066)		
Decrease=1			0.0021	0.0023		0.0001
			(0.009)	(0.008)		(0.009)
Decrease=1 × t-Score of Change			0.0151**	0.0125**		0.0174**
			(0.007)	(0.006)		(0.007)
Constant	11.3010***	11.2938***	11.4266***	11.4561***	11.1995***	11.2734***
	(0.227)	(0.211)	(0.145)	(0.127)	(0.205)	(0.127)
Observations	291740	291740	313680	313680	291740	313680
R-squared	0.514	0.514	0.513	0.513	0.514	0.512
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Estimated Effect (%)	-0.748	-0.535	1.523	1.262	-0.859	1.754

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.10$. Estimates of the β coefficients and ϕ from Equation (2) are organized by treatment status. The odd columns estimate the models that control for the level of the average nominal property tax rate, and the even columns control for the natural log of the average nominal property tax rate. The first pair of columns adds a level effect for the within-county t-score of the tax rate change, an indicator for being a tax rate increase, and the interaction between the two. The second pair of columns is similar to the third for the tax rate decrease treatment status. The last two columns do not control for average nominal property tax rates to circumvent some concern of endogeneity between property tax rates and the house prices. Standard errors are clustered at the county level.

marginal distribution of house prices, this section investigates whether capitalization effects from shocks 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:

$$RIF(Y; q_\theta, F_Y) = q_\theta + \frac{\theta - \mathbb{I}[Y \leq q_\theta]}{f_Y(q_\theta)} \tag{3}$$

The unconditional quantile regression is then accomplished by replacing house prices with their RIF[21] quantile values, assuming linearity in the parameters. 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 $\beta_{i,\theta}$ be estimates of the coefficients of interest at quantile θ. This section will use similar specifications as Equation (2) with the resulting RIF on the left-hand side to examine responses along the distribution of

[21] 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 (3) of the distributional statistic, q_θ, and the influence function (IF) is called the recentered-influence function (RIF).

house prices:

$$RIF(ln(V_{ict}); q_\theta, F_{ln(V_{ict})}) = \alpha + \beta_{1,\theta}(D_{ct} \times T_{ct}) + \beta_{2,\theta} D_{ct} + \beta_{3,\theta} T_{ct} + \phi_\theta R_{ct} + H'_{ict}\lambda_\theta + \psi_{c,\theta} + \eta_{t,\theta} + \varepsilon_{ict,\theta} \quad (4)$$

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 average nominal 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 the county average nominal property tax rate as in (2). Household variation is preserved in this procedure so the observational unit is still the household, and the coefficients are still relative to households who are in counties that did not change their average nominal property tax rates in that year.

Tests of the coefficients of interquantile ranges are used to evaluate whether quantile regression coefficients are statistically different from each other along the distribution. The interquantile ranges will test whether decile coefficients are different from the seventh decile, Q70. For both increases and decreases in property tax rates, the seventh decile indicates a change in the pattern of responses as seen in Figure 4. Specifically, households are not statistically responding positively or negatively with any regularity to property tax rate changes of either kind in terms of house prices. Insignificant results relative to Q70 do not necessarily indicate that there is not heterogeneity along the distribution, and this point is chosen only because of the apparent change in behavior on either side. Interquantile ranges are differences in the RIF values at those quantiles which amount to testing the differences in the estimated coefficients.

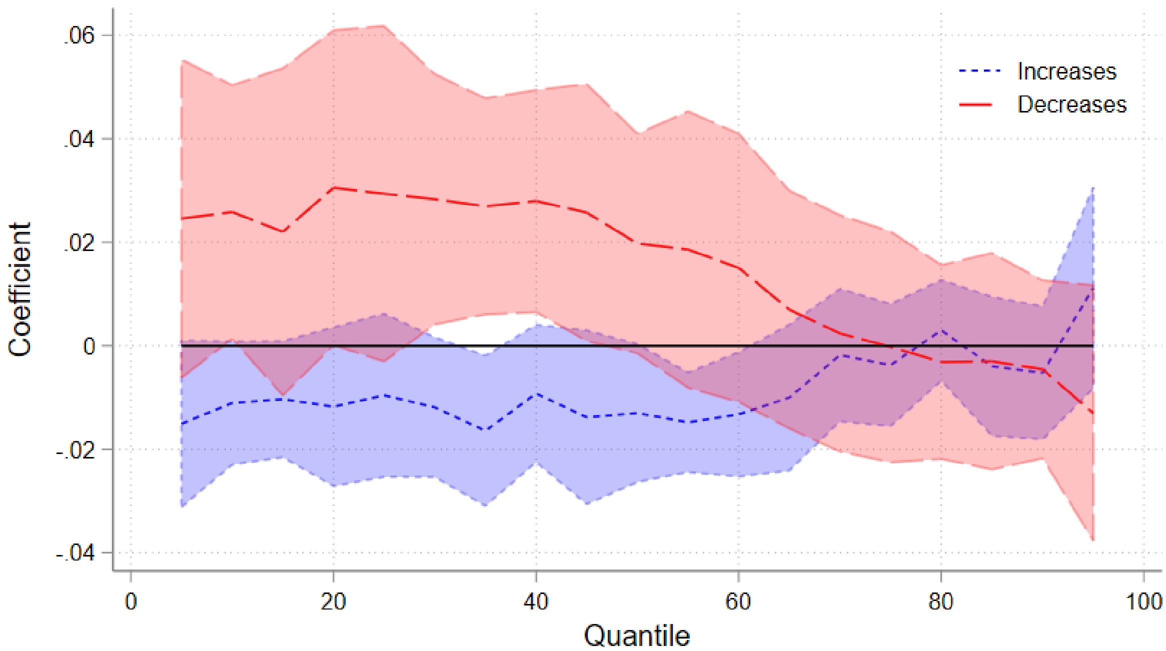
5.1 Quantile Results

To measure differences in treatment effects from average nominal tax rate changes, quantile analysis is performed on the $\beta_{i,\theta}$ coefficients from Equation (4) using the RIF as the dependent variable. Figure 4 contains the distribution of the $\beta_{1,\theta}$ coefficients at every fifth percentile of house prices from Q5 to Q95. The confidence bands are cluster-bootstrapped at the county level. For comparison, Tables 6 and 7 contain coefficients of $\beta_{1,\theta}$ from Equation (4) at each decile along the distribution of self-assessed house valuations. The coefficients are interpreted as the percentage change in house prices induced by increasing the size of the tax change by one standard deviation in the t-distribution. Larger increases are theoretically expected be negatively capitalized into house prices in the bidding framework, and larger decreases are expected to be positively capitalized into house prices.

In Figure 4, tax increases are negatively capitalized below the seventh decile, and tax decreases are positively capitalized below the sixth decile. This range of house prices is consistent with the implications from Section 4.2 where increases in tax rates reduce house prices and decreases in tax rates increase house prices. In either case, coefficients on the high end of the house price distribution are close to 0. This indicates that households in the highest three deciles of house prices do not respond to changes in average nominal property tax rates. Conversely, there is evidence that households on the low end of the distribution are most impacted both in magnitude and significance of the coefficients. In absolute value, tax rate decreases have a larger effect than tax rate increases by nearly 1% in the lower half of the distribution.

In both treatment statuses, the most striking result is that effects tend toward 0% the higher house prices become. House prices and self-assessments are highly correlated with household income, and the pattern is consistent with the idea that households become increasingly unaffected by changes in average nominal property tax rates as house prices and income increase. One interpretation of this pattern is that changes in property taxes constitute larger user cost adjustments to credit or income constrained households. As a result, they may be more impacted by changes in property tax rates and self-assess their own houses correspondingly. Consistent with that idea, households on the high end of the distribution may not care about changes in annual user costs because they are not as income constrained. Mortgage lenders consider property taxes when determining the credit worthiness of borrowers so homeowners who have financed their houses may have more recent information on current property tax rates. At the extreme low end of the

Figure 4: Distributional Responses to Tax Rate Changes



Note: Regressions of every fifth percentile using the RIF approach are used to estimate the $\beta_{1,\theta}$ coefficients from Equation (4) along the distribution of house prices focused on the within-county t-scores of the average nominal property tax rate increases (blue dotted series) and decreases (red dashed series). Each shaded region represents the confidence intervals for each set of quantile estimates. Standard errors are cluster-bootstrapped at the county level for 95% confidence.

distribution, participation in income-based housing subsidies or other social insurance may be offsetting some of the implied changes in the property tax rates.

Tables 6 and 7 report the coefficients at each decile along the distribution in Figure 4 as well as the implied impacts on house prices in the last row. The signs of the implied impacts dictate how prices are changing, so negative signs indicate house prices are decreasing and positive signs indicate increasing house prices. For tax rate increases in Table 6, effects are statistically and economically different than 0 in the middle of the distribution below the seventh decile. The negative impacts as large as -1.316% at the sixth decile on house prices from a standard deviation increase in the property tax rate and vary from -1.101% in the first decile down to -0.523% in the ninth decile. The impacts are relatively stable, as large as 3.102% in the second decile, in magnitude in the lower two-thirds then shrink toward no effects thereafter. For tax rate decreases in Table 7, impacts are economically larger in absolute value, but there is only marginal significance below the median. In the highest two deciles, the coefficients change sign. There is more variability in decreases since the effects range from 2.619% in the first decile down to -0.454% in the ninth decile. The overall change from the bottom to the top of the house price distribution is about three times as large for decreases which suggests more consistency in the responses to tax rate increases.

To investigate whether of the estimates are statistically different across deciles, Tables 8 and 9 contain the results of statistical tests of the interquantile range of the $\beta_{t,\theta}$ coefficients relative to Q70 where the "Q70" column has the same coefficients from Tables 6 and 7, respectively. The main takeaway from these tables is that coefficients in the center of the distribution are statistically different than the seventh decile. Each column is the coefficient of the larger decile minus the coefficient of the smaller decile. For example, the difference between the fifth and seventh decile is calculated as Q70-Q50, and the difference between the ninth and seventh decile is calculated as Q90-Q70. Above Q70, the magnitudes are relatively stable and

Table 6: Quantiles for Increases

	Q10	Q20	Q30	Q40	Median	Q60	Q70	Q80	Q90
Increase=1 × t-Score of Change	-0.0111*	-0.0118	-0.0119	-0.0092	-0.0130*	-0.0133***	-0.0018	0.0030	-0.0052
	(0.006)	(0.009)	(0.008)	(0.007)	(0.007)	(0.005)	(0.005)	(0.006)	(0.007)
Observations	291740	291740	291740	291740	291740	291740	291740	291740	291740
RIF(Q)	11.327	11.573	11.793	11.962	12.116	12.268	12.449	12.646	12.900
R-squared	0.153	0.232	0.286	0.320	0.352	0.365	0.356	0.338	0.305
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimated Effect (%)	-1.101	-1.171	-1.182	-0.919	-1.292	-1.316	-0.180	0.299	-0.523

Note: *** p<0.01, ** p<0.05, * p<0.10. Regressions using the RIF approach are used to estimate the $\beta_{1,\theta}$ coefficients from Equation (4) along the distribution of house prices at each decile focused on the within-county t-scores of the average nominal property tax rate *increases* as continuous treatment. Standard errors are cluster-bootstrapped at the county level.

Table 7: Quantiles for Decreases

	Q10	Q20	Q30	Q40	Median	Q60	Q70	Q80	Q90
Decrease=1 × t-Score of Change	0.0259*	0.0305*	0.0283**	0.0280**	0.0198	0.0151	0.0024	-0.0031	-0.0045
	(0.014)	(0.016)	(0.014)	(0.011)	(0.013)	(0.011)	(0.014)	(0.012)	(0.007)
Observations	313680	313680	313680	313680	313680	313680	313680	313680	313680
RIF(Q)	11.383	11.682	11.878	12.028	12.188	12.348	12.501	12.663	12.903
R-squared	0.178	0.259	0.309	0.344	0.360	0.356	0.342	0.317	0.271
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Estimated Effect (%)	2.619	3.102	2.872	2.836	1.996	1.517	0.239	-0.312	-0.454

Note: *** p<0.01, ** p<0.05, * p<0.10. Regressions using the RIF approach are used to estimate the $\beta_{1,\theta}$ coefficients from Equation (4) along the distribution of house prices at each decile focused on the within-county t-scores of the average nominal property tax rate *decreases* as continuous treatment. Standard errors are cluster-bootstrapped at the county level.

close to 0 so the order is less important for the sign than below Q70 where there are noticeable patterns. The signs of the differences are positive for tax rate increases because Q70 is higher than the negative coefficinets at lower deciles, and the opposite is true for differences between Q70 and lower deciles since those coeffecents are positive. Tests of statistical differences from any decile do not necessarily preclude heterogeneous effects along the distribution, and there are clear visual patterns in Figure 4 that demonstrate these differences. The $\beta_{t,\theta}$ tend toward 0 as house prices get higher and are not statistically different for the highest third of house prices.

6 Policy Considerations

On the whole, property taxes are typically more economically efficient than other taxes. They are easily determined and enforced while also being difficult to avoid. Property tax revenue is determined by two main factors: the tax rate and the tax base. The tax rate is the policy instrument that matters most for this work. The tax base is determined by many different factors like the number of taxable housing units, available exemptions, possible deductions, the assessment ratio, and the methodology in the valuation process by the county assessor. Salience is an essential consideration for determining responses to any tax, and property taxes have further considerations since many real estate purchases are financed over a long time horizon. Salience may be difficult to determine since it may be that salience is higher among higher-income

Table 8: Quantiles for Increases Relative to Q70

	IQR(70-10)	IQR(70-20)	IQR(70-30)	IQR(70-40)	IQR(70-50)	IQR(70-60)	Q70	IQR(80-70)	IQR(90-50)
Increase=1 × t-Score of Change	0.0093	0.0100	0.0101	0.0074	0.0112**	0.0115***	-0.0018	0.0048	-0.0034
	(0.007)	(0.009)	(0.008)	(0.007)	(0.005)	(0.004)	(0.005)	(0.004)	(0.007)
Observations	291740	291740	291740	291740	291740	291740	291740	291740	291740
R-squared	0.079	0.062	0.053	0.045	0.026	0.019	0.356	0.019	0.053
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. Regressions using the RIF approach are used to estimate the $\beta_{1,\theta}$ coefficients from Equation (4) along the distribution of house prices at each decile focused on the within-county t-scores of the average nominal property tax rate *increases* as continuous treatment. Standard errors of the differences are cluster-bootstrapped at the county level.

Table 9: Quantiles for Decreases Relative to Q70

	IQR(70-10)	IQR(70-20)	IQR(70-30)	IQR(70-40)	IQR(70-50)	IQR(70-60)	Q70	IQR(80-70)	IQR(90-50)
Decrease=1 × t-Score of Change	-0.0235	-0.0282	-0.0259	-0.0256*	-0.0174***	-0.0127**	0.0024	-0.0055	-0.0069
	(0.022)	(0.026)	(0.019)	(0.013)	(0.006)	(0.005)	(0.011)	(0.005)	(0.012)
Observations	313680	313680	313680	313680	313680	313680	313680	313680	313680
R-squared	0.070	0.061	0.048	0.037	0.027	0.022	0.342	0.020	0.050
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. Regressions using the RIF approach are used to estimate the $\beta_{1,\theta}$ coefficients from Equation (4) along the distribution of house prices at each decile focused on the within-county t-scores of the average nominal property tax rate *decreases* as continuous treatment. Standard errors of the differences are cluster-bootstrapped at the county level.

households who are more likely to own their houses without a mortgage because their property tax payment is semi-annually and is often paid directly to the county assessor. Or, it may be that salience is higher for homeowners with mortgages since the mortgage company is updating the homeowners frequently if changes in property tax rates cause necessary changes in the mortgage payments.

Homeowners usually face non-negligible moving costs that prevent frequent relocation that would allow property tax avoidance. For most, the cost of moving drastically outweighs the potential property tax payment differentials, even if the potential tax savings are present-discounted as an annuity payment. Differences in property tax rates are correlated with differences in local public amenities across different fiscal districts, but the degree of correspondence between tax revenue and public goods provision need not be one-for-one. For this reason, the quality of the signal between local amenities and property tax rates may not be reliable. Furthermore, potential residents may prioritize their job market prospects and expenses that constitute larger fractions of their potential budget over property tax rate differentials, which may be smaller fractions of their income.

While property taxes are progressive, the responses suggest that homeowners who are more income constrained are responding the most to changes in property tax rates. If salience of property tax rates in high among potential buyers and existing homeowners, lower offer and list prices may prevail in local housing markets. If salience is low and market prices remain unchanged, the county government may be able to raise property tax revenues without impacting the tax base since homeowners will be less likely to recognize the change or move as a result. The results may also be consistent with property tax *regressivity* since higher tax burdens results in lower house prices at the low end of the house price distribution, disadvantaging lower income households. Conversely, the same households enjoy benefits from higher prices from lower tax rates. An alternative interpretation is that overall wealth for homeowners in expensive houses is relatively unaffected. Perhaps a smaller fraction of their savings portfolio is housing so the property tax is less influential to their wealth. However, the identification strategy in this paper is not able to disentangle the true mechanism behind the results.

Policy makers might induce shuffling within a city through downsizing by increasing property tax rates to lower house prices for lower-priced houses. This would make smaller houses relatively more attrative to potential movers. Similarly, policy makers might induce homeowners to upsize by decreasing property tax rates to raise house prices for lower-priced houses. This would make sale prices higher for the vacated unit to be used as a down payment on a more expensive house whose price is relatively constant. Consider first that reducing property tax rates may be a way to increase house prices for less expensive units which disincentivizes potential buyers and may give rise to a lock-in effect for property tax payments for existing homeowners. To stay in the same district, homeowners would have to sell their current house and buy another one subject to the same tax rates. Homeowners who are upsizing may be able to avoid paying more for houses if the difference in house price is sufficiently large. Conversely, downsizers may be faced with higher prices for less expensive units. The opposite considerations apply for property tax rate increases: upsizers are would be impacted more from taxes due to lower prices for the house they just sold while downsizers would enjoy lower prices for smaller houses. Specifically, homeowners who are considering moving to a house in the opposite side of Q70 from their current position on the house price distribution would face different responses than for houses in the same quintile.

7 Conclusion

This paper estimates treatment effects of changes in property tax rates across the distribution of house prices, and these results generalize the capitalization framework to counties across the United States that contain large cities. These estimates do not rely on specific locations or settings. Using data on average nominal county-level property tax rates, several strategies are used to provide estimates of capitalization elasticities and treatment effects in response to tax rate changes.

The generalized difference-in-differences approach is made possible through exploiting variation in average nominal property tax rate data. Treatment intensity is measure by within-county t-scores in county average nominal property tax rate changes. Property tax rate increases by one standard deviation cause households to reduce their self-assessed valuations by 0.748% on average, but these responses can range from 0.180% to 1.316% decreases depending on the position in the house price distribution. Similarly, property tax rate decreases by one standard deviation in the t-scores cause households to increase their self-assessments by an average of 1.523% with wider fluctuations between 3.102% increases to 0.454% decreases. These treatment effects are statistically significant, economically large, and reasonably comparable in magnitude. Using quantile analysis, these treatment effects affect households in the lower two-thirds of the distribution but show no impacts on the higher end of the distribution. Increases in property tax rates are more consistent in magnitude along the distribution while decreases almost fall toward 0% monotonically. Owners of the most expensive houses do not seem to respond to average nominal property tax rate changes by adjusting their self-assessed valuations despite receiving the same magnitudinal changes to property tax rates. There is strong evidence that there is heterogeneity across the distribution in responses to property tax rate changes.

While the descriptive estimates of the property tax capitalization elasticity should be interpreted with caution, the implied capitalization elasticity is less than 1 suggesting that average nominal property tax rate changes at the county level induce inelastic responses into house prices. 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 counties in the sample so the effects may be generalized to counties that contain large cities in the United States.

Policy makers ought to consider unintended consequences of altering property tax rates. There may be induced resorting within the fiscal district from upsizing and downsizing to take advantage of house price differentials that changes the income composition of neighborhoods. It is not clear which homeowners have more salient property tax rates which may give rise to other unintended responses. Last, policy makers need to consider the perceived correspondence between local public amenities and property tax rates as well as the relative importance of property taxes when households determine where to live and how long to stay there.

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Appendix

A: Household Bidding Model Theory

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.[22]

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

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

[22] Epple et al. (1984) is one such example that uses an indirect utility derivation as a form of user cost.
[23] Ross and Yinger (1999) use alternative notation for τ^* in place of τ^e/r where $T = \tau^e V = PH\frac{\tau^e}{r} = \tau^* PH$.

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[24] to a multiplicative 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[25] 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:

[24] 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 $T \to \infty$:

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

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

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

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

[25] 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 $V = \frac{PH}{r} = \frac{\hat{P}H}{r+\tau^e} = \frac{\hat{P}H/r}{1+\tau^*}$.

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

Under full capitalization[26] 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 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 average nominal property tax rate limitations that prevent taxes from being high enough to fully finance public goods demanded by constituents.[27] 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[28] of Equation (1) 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 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:

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

Algebraically rearranging Equation (13) by solving for δ[29] 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

[26]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.

[27]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.

[28]Another common way to derive an estimation equation using panel data is to take first-differences of Equation (1) before the substitution of τV for T, say during a reassessment, and assume constant tax rates after reassessment. The resulting estimation equation is: $\Delta V = \frac{-\delta}{r}\Delta T$.

[29]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 $\tau < -1/\beta$.

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.