Property Tax-Induced Mobility and Redistribution: Evidence from Mass Reappraisals*

Rebecca Fraenkel†

November 28, 2022

Click Here For Most Recent Version

Abstract

I investigate the effect of property tax changes on individual homeowner mobility and voted tax rates using a panel of individual assessment and sales records in Ohio. I use regulatory stabilization rules that cause changes in individual taxes with no mechanical change in quantity of public goods to examine how changes in a homeowner's tax bill influence sales, foreclosure events, and home equity loan origination. The changes in taxes I observe are driven by changes in relative assessment growth within school districts and allow me to identify the effects of changes in taxes separately from the effects of changing housing wealth. Using a leave-one-out by county random forest regression on assessed values to instrument for tax changes, I find that a $0.10 increase in the price per dollar of services leads to a 5% increase in the likelihood of sale with no change in the likelihood of foreclosure. I also find suggestive evidence of increased voted tax rates at the school district level when the ratio of median to mean taxable value decreases.

*I would like to thank Prashant Bharadwaj, Jeffrey Clemens, Julie Cullen, Rodger Gordon, Michelle White, Josh Graff Zivin and the UCSD applied seminar participants for advice and feedback on this article. I would also like to thank the University of California, San Diego Social Sciences Computing Facility (SSCF) Team for their technical assistance and the use of the Social Sciences Research and Development Environment (SSRDE) cluster with special thanks to Todd Williams. Isaac Cotter provided excellent research assistance. I acknowledge and thank the National Science Foundation Graduate Research Fellowship under Grant No. DGE-1144086. Any opinion, findings, and conclusions or recommendations expressed in this material are those of the author and do not necessarily reflect the views of the National Science Foundation. Data provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the author and do not reflect the position of the Zillow Group.

†Department of Economics, University of California, San Diego, 9500 Gilman Drive, La Jolla, CA 92093-0508; rfraenkel@ucsd.edu.

1 Introduction

US state and local governments collected $488 billion in property taxes in 2015, and property taxes represent 12% of annual housing costs for mortgage-holding US households (Urban Institute-Brookings Institution Tax Policy Center, 2017, Bradley, 2017). A long literature started by Tiebout (1956) describes how we expect property taxes and the public goods they provide to shape communities.[1] However, it is difficult for existing homeowners to respond to changes in their property taxes. Selling a home is costly and capitalization of property taxes into home values means that homeowners may be unable to escape wealth losses from property tax increases.

Because property taxes fund local public goods, changes in property taxes typically accompany a change in services provided. It is difficult to then determine whether mobility responses are due to the change in taxes or the change in services. Further, homes transact relatively infrequently and property tax changes are often small, so identifying changes in homeowner mobility from changes in taxes requires a large sample.

In this paper, I explore mobility and voting responses to changes in property taxes using unique features of the Ohio property tax collection and assessment system which allow me to overcome these obstacles. Ohio cyclically updates the taxable value of individual homes to redistribute tax burden within jurisdictions. Additionally, the majority of local taxes are approved through time-limited referenda on spending for specific projects and services. These voted levies can only collect a fixed amount of money. These two features combine to provide a change in a homeowner's property tax burden with no mechanical change in public good provision.

I first examine the size of homeowner responses to changes in their property taxes. Under full capitalization, homes sales in response to changes property taxes holding all else equal are either a reallocation of consumption following a wealth shock or a way to gain access to housing wealth that liquidity or borrowing constraints prevent the homeowner from accessing through borrowing.[2] If services do not change and the change in taxes is perceived as permanent, housing wealth would decrease by the present discounted value of the additional stream of future taxes. Recent literature has explored the size of overall consumption responses to changes in housing wealth, particularly in the wake of the financial crisis, but the direct effect on housing consumption is less studied (Chan,

[1] See Ross and Yinger (1999) and Banzhaf (2013) for a review of this literature.

[2] See Oates and Fischel (2016) for a summary of the debate about how to characterize property taxes. See Hamilton (1976) and Caplan (2001) for a full description of how capitalization can prevent Tiebout sorting from exerting pressure on public good provision.

2001, Ferreira et al., 2010, Mian and Sufi, 2011, Mian et al., 2013, Aladangady, 2017, Cloyne et al., 2019). With full capitalization, any large change in property taxes, positive or negative, should increase the likelihood of sale so that homeowners can reoptimize consumption in a new home that better matches the portion of their wealth they would like to spend on housing. If this is the only channel through which property taxes cause sales, we should expect very small effects because property taxes are low compared to the transaction costs associated with selling a house and moving (Hardman and Ioannides, 1995).

If capitalization is incomplete or misunderstood by homeowners, or if liquidity constraints limit the ability of homeowners to access their housing wealth and pay their property taxes, tax increases may be more likely to drive mobility. In a literature survey, Sirmans et al. (2008) reveals that and the most common finding in studies of property tax capitalization is partial capitalization, however several studies have found full capitalization and identification challenges are common.[3] There is also evidence that homeowners misunderstand property tax systems and overpay for property tax savings (Cabral and Hoxby, 2012, Bradley, 2017). In this scenario, homeowners may be responding to an increase in their property taxes as an increase in the price of living in their home that they can escape paying by selling.[4]

To measure homeowner responses to changes in their property taxes, I study changes in their likelihood of moving in the three year period following a change in taxes. To control for endogenous house and neighborhood characteristics that may be correlated both with relative home price appreciation and likelihood of sale, I forecast cyclic changes to the assessed value of individual homes. I use this forecast to estimate the change in each homeowner's tax burden arising from changes in relative assessed value due to statewide shifts in demand. I then examine how these changes in a homeowner's forecast tax burden affects their likelihood of selling their home. I find that homeowners are 5% more likely to sell their home when they experience a one standard deviation increase in the flow price of public goods and no more likely to experience a foreclosure. This corresponds to about \$700 in additional property taxes on an average house over the next three years.

My estimate of the magnitude of mobility responses to changes in property taxes

[3]Related to the setting in this paper, Livy (2018) finds full capitalization of property tax rates in Franklin County, Ohio at a discount rate of 3.5%. Borge and Rattsø (2014) find full capitalization in Norway and Palmon and Smith (1998) find full capitalization in Houston, Texas suburbs.

[4] Literature on mobility responses to property tax levels has looked to populations with low demand for public goods to disentangle the effects of varying provision. Johnson and Walsh (2009) study vacation home purchase decisions while Shan (2010) and Farnham and Sevak (2006) study retirees, and all find that these groups are sensitive to property taxes when making locational choices.

provides an important data point for evaluating the benefits of property tax limitations. Concern about the effect of tax increases on cash-poor households have motivated property tax limitations, which have large effects on local government budgets (Martin, 2008).[5] Assessment limitations hold taxes below the market rate, but only for as long as a homeowner stays in their home. Wasi and White (2005) and Ihlanfeldt (2011) have demonstrated a "lock-in" effect, where assessment growth limitations cause homeowners to stay in their homes longer. Under the types of policies that lead to lock-in, however, sale of a home that has appreciated reduces the wealth of the seller. This discount for infrequent movers generated by property tax limitations may drive people to stay in homes that no longer match their preferences for housing. Politically, the lock-in effect has been described as allowing people to afford to remain in their homes, but O'Sullivan et al. (1995) builds a model where these assessment growth limitations generate additional distortions and excess burden relative to a tax based on current home values. This is consistent with prior evidence that homeowners are unlikely to be priced out of their homes due to property tax increases (Martin and Beck, 2018). Though prior research has found little evidence of homeowners relocating due to financial distress imposed by property tax increases, increases in property taxes can lead to to financial distress and reductions in non-housing consumption (Wong, 2020). I estimate large voluntary increases in mobility in response to property tax increases, suggesting that while property taxes are not forcing people out through foreclosures, property tax limitations do reduce tax-motivated sales.

I next explore the other channel through which homeowners can change their property taxes: voting. Changes in property tax burden may change the demand for public goods of homeowners who remain in their homes. Most property taxes in Ohio are approved through voted levies, providing another channel through which existing homeowners can register their preferences for public good provision. Tiebout (1956) predicts that people will choose communities according to their preferences for public goods and this will result in communities where all residents have similar preferences (and would thus vote similarly). Hamilton (1975) demonstrates that when local revenues are collected through property taxes, preference-based sorting should lead to communities with homogeneous home values. Without this homogeneity, there is within-community variation in the price

[5] One of the most famous, and most restrictive, property tax limitations is California's Proposition 13. The Supreme Court ruled in favor of Proposition 13 saying, "...the existing owner, already saddled with his purchase, does not have the option of deciding not to buy his home if taxes become prohibitively high. To meet his tax obligations, he might be forced to sell his home or to divert his income away from the purchase of food, clothing, and other necessities."(*Nordlinger v. Hahn*, 505 U.S. 1) These limitations are largely the result of property tax revolts that resulted in policies like California's Proposition 13. See Cabral and Hoxby (2012), Martin (2009), Fischel (1998) for a discussion of property tax revolts.

each homeowner is paying for their public goods through their property taxes. We know from Pack and Pack (1977) and Rhode and Strumpf (2003) that in practice communities are not homogeneous, and the communities I study also exhibit substantial variation in home prices.[6]

Given heterogeneous communities, residents must find an agreeable level of public good provision. Economic theory from Meltzer and Richard (1981) suggest that in a right-skewed distribution, greater skew in wealth leading to a larger subsidy to the median voter should lead to higher voted tax rates.[7] However, Benabou (1996), Benabou (2000), and Alesina et al. (1999) build a model where community heterogeneity leads to lower tax rates due to social preferences. Empirical results that directly test this hypothesis have been mixed. Boustan et al. (2013) and Corcoran and Evans (2010) finds that rising income inequality leads to growth in tax revenues and public expenditures in the US, and Borge and Rattsø (2004) find that increasing inequality in municipalities in Norway leads to increased reliance on redistributive forms of taxation, but several studies have not found this association (Alesina et al., 1999, Kenworthy and McCall, 2007, Georgiadis and Manning, 2012). I test how changes in the skewness of the distribution of home values as measured by the ratio of the median to mean forecast home value affects voted tax rates and find suggestive evidence of increases in taxes when this ratio decreases consistent with Meltzer and Richard (1981).

This paper proceeds as follows. Section 2 describes the Ohio property tax collection and assessment system. Section 3 describes how I calculate changes in taxes. Section 4 describes the Zillow ZTRAX data and my procedure to instrument for tax changes through forecast assessed values. Section 5 documents the variation in taxes across Ohio communities and how it diverges from the predictions of Tiebout (1956). Section 6 describes the empirical approach, Section 7 presents the findings, and Section 8 concludes.

2 Background

In this paper, I investigate how changes in property taxes affect the mobility of homeowners and the change in the level of voted taxes in Ohio. Property taxes are strongly disliked by those who pay them but are also seen as an efficient way to raise revenue

[6]For Tiebout sorting to efficiently provide public goods, communities must be homogeneous both in the value of their housing stock and in the public good preferences of their residents (Calabrese et al., 2011, Brueckner, 2000). Barseghyan and Coate (2016) discuss how households with high demand for both housing and public goods may lead to heterogeneous communities.

[7]Epple and Romano (1996) describe how the availability of private education options can break this association for the median income voter. Such a pattern is seen in California by Brunner and Ross (2010).

because they are difficult to avoid (Norregaard, 2013, Chamberlain, 2007). Mobility responses to changes in property taxes provide insight into the extent to which agents attempt to avoid higher property taxes. Property taxes are also an important source of revenue, both in this context and throughout the US. As of 2015, 30% of US school funding came from property taxes (U.S. Census Bureau, 2017). Ohio collected $16.2 billion in property taxes in 2017 from $680.7 billion of property, while the state collected $25.7 billion of tax revenue, mostly through sales and income taxes (Testa, 2018).

Two features of the Ohio property tax system allow me to study the effects of changing property taxes. First, home values for tax purposes change on set three year cycles for each county. Second, the majority of Ohio property taxes are collected through what is known as "outside" millage—voted levies that are authorized to collect only a fixed dollar amount regardless of changes to the value of the existing tax base. Collection through "outside" millage means that the changes to property taxes that occur at reassessment are largely redistributive. With outside millage, any moves caused by these redistributive tax changes are in response to changes in individual taxes, not changes in the current level of public good provision in a community.

2.1 Ohio Reassessment Cycles

Homes in Ohio are reappraised for tax purposes every six years, with an update to value three years following the appraisal. In the years between reappraisals and updates, a homeowner's assessed value for tax purposes does not change. For the purposes of this paper, I will largely treat updates and reassessments as the same event.[8] Ohio's 88 counties are divided into three groups, and each group reassesses on its own fixed schedule. Figure 1 shows the reassessment schedule for each Ohio county and for the subset of counties included in the analysis.

Figure 2 shows a joint histogram of the the accuracy of assessments for homes that are sold. Assessments are a very strong predictor of future sale price. Tables 1 and A1 show this in regression form. Without controls it appears that assessments underestimate future sale price, particularly in logs, but with hedonic, time, and place controls, assessments are much more accurate and may even overestimate sales price. An important caveat to this measure of assessment accuracy is that I can only observe the accuracy of assessments for the subset of houses that sell.

Homeowners are notified of their new assessed value in the summer of the reappraisal

[8] In an appraisal, an assessor visits, but does not enter, each property. The procedure for updates varies by county but is often model-based. Figure A1 shows a map of the six year reappraisal schedules.

year.[9] The value assigned is the value as of January 1 of the reappraisal year will be used to assign tax liability for three years. Homeowners do not receive their new tax bill until December of the reappraisal year. As many county auditor websites point out, it is difficult for homeowners to know how their reassessment will change their taxes until they receive their bill.[10]

2.2 Outside Millage

Most property taxes in Ohio are in the form of voted levies earmarked for specific purposes and projects. These levies are time-limited and not indexed to inflation and are known in Ohio as "outside" millage.[11] "Outside" is in reference to those collections that are outside of the restrictions set forth in HB 920, which restricts property tax collections to 1% of assessed value. Ohio uses a 35% assessment ratio statewide, so this restricts collections to .35% of appraised value. All levies outside of this limit must be approved by voters and can only collect what is essentially a fixed amount of revenue (Testa, 2018, Rink, 1981).

Outside millage levies are put to voters and, if approved, allow a taxing authority to collect "the amount that would have been levied if the full rate thereof had been imposed against the total taxable value of such property in the preceding tax year."[12] This means that while a gross tax rate appears on the ballot, homeowners are in fact voting on a pre-set dollar amount to be collected. In the following years, outside millage levies can only change the amount of money they collect through new construction or if property is reclassified into their taxing authority.[13] Since 1980, these adjustment factors have been calculated separately for Class I (Residential and Agricultural) and Class II (commercial) property (Rink, 1981).

Figure 3 shows the share of collections that are from outside millage by year. Aggregate collections have increased over time primarily through newly voted levies and construction of new homes. Inside millage levies change total collections proportionally with home price

[9] Most counties notify in July. Some are as late as September.

[10] For example, the Cuyahoga County reappraisal FAQ says: "Q: How will the value change impact my taxes? A: We will be unable to determine the tax impact until tax rates are certified by the State of Ohio in November." https://treasurer.cuyahogacounty.us/en-US/real-estate-taxes.aspx

[11] In this period, the average age of an existing school district levy is 13.5 years and the median age is 12 years.

[12] Ohio Revised Code 319.302 (D)(1) http://codes.ohio.gov/orc/319.301

[13] For all tax levies, the tax commissioner must, "Determine by what percentage, if any, the sums levied by such tax against the carryover property in each class would have to be reduced for the tax to levy the same number of dollars against such property in that class in the current year as were charged against such property by such tax in the preceding year." Ohio Revised Code 319.302 (D)(1) http://codes.ohio.gov/orc/319.301

changes, however they are a relatively small share of collections ($\approx 15\%$) and, as shown in Figure 4, house price growth exhibited volatility characterized by the housing boom and subsequent collapse, but ended the period roughly where it started.

Figure 5 shows compliance with HB 920. Change in tax collections on carryover property from continuing levies should be zero. While there are some very small ($< 1\%$ in every year but 2007) changes in collections, collections largely do not change with reassessment. I then test that the reassessment cycle does not drive changes in the level of school funding. Table 2 tests this relationship in a regression of an indicator for reassessment on school spending and tax collections. As discussed in the next section, school districts will be the primary taxing entity considered in this analysis because they are the largest collector of property taxes. Here, it appears that collections are less than 1% lower in reassessment years but this effect does not pass through to spending. Legally, the reassessment cycle should not cause a mechanical change in tax collections. Empirically, the relationship between tax collections and the reassessment cycle is economically small.

3 Flow Price of Public Goods

To examine how property tax changes affect mobility separately from changes in the quantity of public goods, I consider changes in the cost to an individual household of each dollar of local collections. I call the cost of a dollar of spending to an individual homeowner that household's "flow price of public goods." It is a "flow" price because if the change is unanticipated and fully capitalized, the wealth shock is absorbed either way and selling only changes how the homeowner pays for the change.

While many types of jurisdictions, including counties, library districts, and municipalities, can levy taxes, school districts are by far the largest collector of property taxes. Figure 6 shows that school districts have consistently received about 60% of property tax collections.[14]

In this analysis, I use school districts as the taxing unit. Because education scales with number of students, I consider its per-household cost. If a school district has many childless households, this measure will suggest a low "price" of education services. Because I am primarily concerned with *changes* in taxes, this will only be a problem if the number of students in a district changes drastically and there is an accompanying change to property tax rates. The per-household cost of education through property taxes is $\bar{T}$,

[14] Another 20% of collections goes to counties, and, as discussed in Section 4 my measure of tax share does respect county boundaries.

which is simply total revenue divided by the number of households.

Due to the HB920 restrictions described above, total collections must stay consistent over time. So for homes with assessed value A and district tax rate r[15]

$$\bar{T}_t = \frac{\sum A_t r_t}{N} \approx \frac{\sum A_{t-3} r_{t-3}}{N} = \bar{T}_{t-3}$$

For each household, its assessment share, $\frac{A_{it}}{\bar{A}_t}$, is its flow price of public goods or its price per dollar of collections. The change in assessment share then gives the change in a household's flow price of public goods.

$$\Delta T_{it} \approx \frac{A_{it}}{\bar{A}_t} - \frac{A_{it-3}}{\bar{A}_{t-3}}$$

Column 1 of Table 3 shows the relationship between change in assessment share and change in tax share. The actual change in assessment share is very similar to the actual change in tax share.

4 Data

The data for this paper come from Zillow ZTRAX and the Ohio Department of Taxation.[16] Zillow ZTRAX contains historical assessment records for 2002-2014 and home sales, foreclosure, and loan records through 2017. I place homes in their school districts using the coordinates provided by Zillow and the Census Bureau's TIGER database for school district boundaries for the year 2000.[17] Figure 7 shows Ohio school districts and Figure 1 shows the counties included in the sample.[18]

The taxing unit I consider is the school district. While jurisdictions other than school districts collect taxes, school districts are the largest recipient of property tax revenue (Figure 6) and school quality is valued by home buyers (Black, 1999, Ries and Somerville, 2010, Bayer et al., 2007). School districts are included in the analysis if at least 90% of the observed homes in the district are in one county. The portion of the district that is outside of the majority county is excluded. This leaves me with a sample of 544 school

[15] The following relationship is approximate because new levies come in and old levies expire.

[16] https://www.tax.ohio.gov/research/property_tax_statistics.aspx,http://www.zillow.com/ztrax

[17] The coordinates provided by Zillow are enhanced Tiger coordinates and are accurate to the block segment level.

[18] Excluded counties are Coshocton, Defiance, Fayette, Harrison, Meigs, Noble, Pike, Vinton, and Wyandot. They are excluded because ZTRAX does not provide a panel of assessment records.

districts.[19] I include only those houses that exist in both their assessment year and $t-3$ because that is the sample for which I can calculate change in tax share. Because voted levies that existed in $t-3$ collect revenue on "continuation property", this is the relevant population for the redistribution of tax liability. Figure 8 shows the number of assessment records available in each year. For many properties and counties, assessment records are only available in assessment or update years.

The assessment records contain data on home characteristics. Summary statistics for continuous hedonic characteristics of the homes are shown in Table 4. Additional categorical controls are building condition and quality grade, heat type, AC type, and land use code. For all variables, indicators for missings are added.

As described in Section 2, taxes for an individual home are relatively stable for the three years between assessment cycles. Figure 11 shows that changes in taxes are much larger in assessment years. Each graph is a histogram of the percent change in taxes on a house-year observation. The upper figure is for non-update or reassessment years while the lower figure is for update years. As shown in the upper figure, there are small changes in collections in off-cycle years. These most commonly occur due to new and expiring levies. The lower figure confirms that the much larger driver of changes in taxes occurs in update years. As expected due to the redistributive nature of reassessments, the median house sees no change in tax liability, however there is large variability around this median. (The median house sees a 5.4% change in assessment share in absolute value.)

Home sales, foreclosure, and home equity loan data also come from Zillow ZTRAX and are merged to the assessment records by parcel ID. Sales are non-distressed sales with a deed type that does not reflect a transfer between family members, an inheritance, or another non-market transfer of property. These definitions are designed to capture arm's length transactions. Foreclosures are transactions coded as tax deeds, foreclosure deeds, commissioner's deeds, redemption deeds, deeds in lieu of foreclosure, receiver's deeds, sheriff's deeds, beneficiary deeds, notices of sale, and notices of lease pendens. This is a liberal definition of foreclosure that includes the first notice of foreclosure. Some homeowners coded as foreclosed under this measure find ways to remain in their homes. Home equity loans are loans coded by Zillow as a HELOC.

For all sale types, I assume that a house will only have one transaction of each type within a 93 day window.[20] I define a transaction event as beginning with the first time a parcel transacts. If another transaction is recorded within the next 93 days, that

[19]As of 2018, Ohio had 608 total school districts.

[20]Many transaction records only provide a month and year of sale. The 93 day window allows for any three month window regardless of month length.

transaction is considered part of the initial transaction, and I check for another transaction within the following 93 days, until a 93 day period with no transaction activity passes.[21] The transaction date is coded as the date of the first event in the transaction window. The price is the maximum price observed over the transaction window.

Data on gross rates, effective rates, and total collections come from the Ohio Department of Taxation. Table 5 shows summary statistics for average effective tax rate, gross tax rate, and total tax collections on residential property. Effective rates are lower than gross rates due to HB 920 adjustments.

4.1 Assessments Forecast

We may be concerned that relative assessments within a school district and probability of sale move together for non-tax-driven reasons. For instance, suppose one neighborhood within a school district experiences an increase in crime while patterns in the rest of the school district are stable. This may cause property values within that neighborhood to fall relative to the rest of the school district while also increasing out-migration from the neighborhood.[22] Because this neighborhood has depreciated relative to the rest of the school district and experienced an increase in out-migration, simple OLS in this context would suggest that tax decreases increase the likelihood of sale.

To address this endogeneity problem, I generate a leave-one-out by county forecast of assessed values. This forecast uses market valuation from the rest of Ohio, excluding the county containing the home, to predict the assessed value of each home. The prediction uses home and neighborhood characteristics from the pre period to forecast assessed value. This means that if homes with four bedrooms are in higher demand, I will forecast a higher assessed value for four bedroom homes. However, if a home is remodeled from two to four bedrooms I will forecast its value as though it were still a two bedroom house. The same is true of neighborhood characteristics. If urban neighborhoods appreciate I will forecast a higher value for houses that were in urban places in 2000. If a neighborhood has become more urban, I will forecast values for homes within it at its prior density. Changes to a home can be remodeling in preparation for sale and changes to a neighborhood can accelerate mobility through sorting. The forecast controls for shocks to homes and neighborhoods that change valuation and mobility through channels other than taxes.

[21] Many events have multiple transactions recorded in the ZTRAX database due to mortgage changes, adjustments, multiple foreclosure notices, etc.

[22] In this example, as with any home sale, a willing buyer must be found. See Kirk and Laub (2010) for a discussion of how crime affects neighborhoods and property values.

I use a random forest regression to generate a non-parametric forecast of assessed values.[23] For each county, I generate a forecast from 20% of the assessment records from the rest of the state, not including the forecasted county. The random forest has 50 trees with a maximum tree depth of 20. From Zillow, I include home characteristics from the prior assessment period and the assessed value from the prior assessment period.[24] I also attach tract characteristics from the 2000 Census, county employment characteristics from the 2000 QCEW, and school district characteristics from the 2000 SAIPE.[25] Figure 9 shows which components of the forecast are most important to predicting change in assessed value. Unsurprisingly, year and prior assessed home value are the most important predictors of change in assessed value. The four home characteristics of year built, total rooms, total bathrooms, and lot size have strong predicted power and contribute much more to the forecast than the other included hedonics. Neighborhood characteristics from the census and QCEW also have strong predictive power in aggregate.

Figure 10 shows a joint histogram of the forecast and true values for assessed values below $100,000 (this corresponds to houses with a value below $350,000, which is approximately the 95th percentile of the home value distribution). The R^2 of the forecast is 0.94. Table 6 shows the relationship between the assessment share and the forecast. Column 1 confirms that the school district level assessment share is a very good predictor of the true school district tax share (the coefficient is statistically indistinguishable from 1). I will be using changes in assessments as a proxy for changes in taxes and Table 3 looks at changes. Column 1 shows that actual assessment share changes strongly predict actual tax share changes, where again the coefficient is statistically indistinguishable from 1. Column 2 shows the performance of the forecast change in assessment share. The forecast captures about 25% of the true change in assessment share.

[23]See Hastie et al. (2005) for a discussion of random forest regression. Random forest regression has also been suggested as a technique for performing mass appraisals (Antipov and Pokryshevskaya, 2012).

[24]Included home characteristics are Lot Size, Number of Units, Property Type, Year Built, Total Rooms, Total Bedrooms, Total bathrooms, Building Quality, Building Condition, Architectural Style, Roof Type, Heating Type, AC Type, Water Type, Sewer Type, Lot Site Appeal, and Year.

[25]Included census characteristics are: Fraction HS plus, Fraction College Plus, Fraction Poor, Tract Population, fraction urban, fraction rural, fraction white, fraction black, fraction non-hispanic white, fraction under 18, fraction over 65, fraction of housing that is owner-occupied. School district characteristics are school district size and fraction of children in poverty. County employment characteristics are annual average pay and employment location quotient for the the service industry.

5 Documenting Variation in Tax Share within Communities

A central prediction of Tiebout (1956) and the literature that follows is that homeowners will form communities of homogeneous preferences. When public goods are funded through property taxes, Hamilton (1975) points out that restrictions on home sizes are needed to prevent a game of "musical suburbs, with the poor following the rich in a never-ending quest for tax base." He suggests that these restrictions will take the form of zoning such that there is no cross-subsidisation of public goods.[26] We know that there is heterogeneity in home values within districts, and in this paper I first demonstrate the heterogeneity in within-district taxes and home values that exist in this context. This is consistent with findings by Pack and Pack (1977) and Rhode and Strumpf (2003) that demonstrate the heterogeneity in tax prices of public goods within jurisdictions.

Figure 12 shows the distribution of public goods prices that individual households in the sample face. Those to the right of one are cross-subsidizing education for those to the left. In a frictionless Tiebout-Hamilton setting, we would see a single spike at one. This shows that heterogeneity in preferences for housing and public goods leads to communities that do not match the Tiebout-Hamilton framework. Tiebout-Hamilton predicts that those to the right of one should be induced to move to a community in which they are not cross-subsidizing other residents. Instead, the median assessment share is 0.9, meaning most residents are receiving some subsidy and there is a wide distribution of assessment shares.

Figure 13 shows that there is also substantial variation in the ratio of median to mean home value across communities. Again, communities are concentrated at 0.9, but there is variation in levels of subsidisation of the median voter, especially to the left of the peak, with some communities having a median subsidy of 20-30%.

6 Empirical Strategy

6.1 Flow Price of Public Goods

In the mobility analysis, the variable of interest is the individual change in tax share. The tax share approximates the flow price of public goods each homeowner faces. As described

[26] There has been substantial debate on whether zoning restrictions in practice achieve the necessary stringency. See, for example, Oates and Fischel (2016), Fischel (2013), Mieszkowski and Zodrow (1989).

in Section 3, the change in tax share for each house is approximated by the change in assessment share:

$$\Delta T_{it} \approx \frac{A_{it}}{\bar{A}_{td}} - \frac{A_{it-3}}{\bar{A}_{t-3d}}$$

To control for endogenous changes to local assessments coming from neighborhood improvement or remodeling at the house level, in most specifications I estimate the change in tax share as

$$\Delta \hat{T}_{it} \approx \frac{\hat{A}_{it}}{\bar{\hat{A}}_{td}} - \frac{A_{it-3}}{\bar{A}_{t-3d}}$$

Table 3 shows the relationship between change in assessment share and change in tax share. The actual change in assessment share is very similar to the actual change in tax share, but the forecast only captures about 30% of this relationship.

As discussed in Section 2, taxes for individual homeowners are redistributed based on assessed values every three years. Taxes are based on the share of total residential value that belongs to each homeowner. I examine how this change in taxes based on relative home value appreciation affects mobility, foreclosure, and home equity loan origination. The identifying assumption here is that (forecast) assessment share, conditional on a rich set of controls including the (forecast) wealth change, influences homeowner mobility only through its effect on a homeowner's tax share.[27]

Homeowners estimate their own home values imprecisely and know even less precisely how their home's value has changed relative to other homes in their school district (Benítez-Silva et al., 2015). In this way, the change in taxes that comes through reassessments is a shock. It is a shock to present income because it must be paid today, and, if the change is persistent, the future payments are a shock to housing wealth to the extent that the tax change is capitalized into home values. Further, if mobility is driven by liquidity constraints, homeowners will not face these constraints until their new taxes come due. As discussed in Section 4.1 I use a leave-one-out by county forecast of assessed values to identify how market forces external to the neighborhood of the home itself have changed the value of each home and the share of value in the district held by that home. Columns 1 & 3 of Table 6 show the relationship between (forecast) assessment share and tax share. As expected due to tax collection formulas, the coefficient on assessment share is close to 1 for both the actual and the forecast assessment share.[28]

[27]If residents have a preference for the position of their home value in their community, it could confound findings here (Fligstein et al., 2017).

[28]Some levies are collected and reallocated among entities other than the school district. This causes some of the slippage between assessment share and tax share. Figure 3 shows that about 60% of levies are collected by the school district.

In the voting analysis, I use forecast assessments to examine whether changes in the distribution of assessed values change public good provision. Specifically, I test whether changes in the ratio of median to mean home values predicts changes in the level of spending on school district service provision as predicted by Meltzer and Richard (1981).

6.2 Effect of Change in Tax Share on Mobility

I first estimate the effect of change in tax share on homeowner mobility and home equity loan origination. I estimate mobility changes as cumulative mobility over the three year period following reassessment. This means that for a 2004 reassessment, I look at the likelihood that a homeowner moves in any of 2005, 2006, or 2007. I use this timing because, as described in Section 2, homeowners reassessed in 2004 do not learn their new tax liability until December 2004. I consider sales over the next three years because this is the full period over which I can analyze the effects of the tax change before another reassessment occurs.

I estimate a linear probability model of the following form:

$$Sale_{it+[1,2,3]} = \beta_0 + \beta_1 \Delta T_{it} + f(\frac{A_{it-3}}{\bar{A}_{t-3d}}) + g([A_{it} - A_{it-3}]) + h(A_{it-3}) + \mathbf{X}_i + \mathbf{T}_t \times C + \varepsilon_{it} \quad (1)$$

where i indexes home assessments and t indexes years. $Sale_{it+[1,2,3]}$ is an indicator for whether a house is sold in the 3 years following its reassessment, ΔT_{it} is represented by $\Delta \mathrm{A}_{it}$ and is as described in Section 3, $\frac{A_{it-3}}{\bar{A}_{t-3d}}$ is the initial assessment ratio, $A_{it} - A_{it-3}$ is the change in housing wealth by assessed value, A_{it-3} is initial assessed value, and f, g, h are quartic polynomials to flexibly control for changes and levels of relative and absolute housing wealth. These controls capture the direct effect on mobility of the change in wealth that the homeowner has experienced. Additionally, housing wealth evolves smoothly in the period leading up to the reappraisal while taxes are revealed only at the time of billing. X_i is a vector of home and census tract characteristics and $\mathbf{T}_t \times C$ are county-by-tax year fixed effects to control for county-level trends in the housing market.

The identifying assumption is that the mobility behavior of homeowners who live in observably similar houses, including in terms of absolute assessment growth, but face different appreciation of their home value relative to the mean home in their district is driven only by the induced relative changes in taxes they face. A threat to identification is that a third factor, for instance an increase in crime as described in Section 4.1, will drive both mobility and relative home price appreciation. To address this concern, I use the forecast of relative home price growth described in Section 4.1.

When using forecasts, all instances of A_{it} are replaced with $\hat{A}_{it}$:

$$Sale_{it+[1,2,3]} = \beta_0 + \beta_1 \Delta\hat{T}_{it} + f(\frac{A_{it-3}}{\bar{A}_{t-3d}}) + g([\hat{A}_{it} - A_{it-3}]) + h(A_{it-3}) + \mathbf{X}_i + \mathbf{T}_t \times C + \varepsilon_{it} \quad (2)$$

To test effects on foreclosures and home equity loan origination, I replace $Sale_{it+[1,2,3]}$ with $Foreclosure_{it+[1,2,3]}$ and $HELOC_{it+[1,2,3]}$ in equations 1 and 2. The coefficient of interest in each regression is β_1 which tells us the effect of a change in tax share on the likelihood that a homeowner moves in the three years following the reassessment and accompanying tax shock.

6.3 Voted Tax Rates

Changes to property taxes may also change the way homeowners vote for public spending. If reassessment changes the distribution of tax liability within a community, the preferred level of spending may change. Meltzer and Richard (1981) observe that when the median voter has less than the mean voter, the decisive median voter will desire higher taxes to be spent on redistribution. In Ohio (as is usually true for the distribution of home values), the median home value is almost always less than the mean. Figure 13 shows the distribution of the ratio of the median to mean home value that I observe for the school districts in my sample at the time of reassessment from 2002-2014.

Extending this hypothesis, it should be the case that as the ratio of median to mean increases, the median voter should prefer less redistribution, and tax rates should fall. Alternatively, if the model of redistribution proposed by Benabou (1996) operates, an increase in this ratio may increase voted tax rates, as in this model voters are more likely to support redistribution in homogeneous communities and an increase in this ratio implies movement toward homogeneity. Figure 14 shows the distribution of ratio changes. It shows that changes in the ratio of median to mean assessments are centered around zero, making this an interesting context in which to test how changes in inequality affect redistribution.

To test these theories, I look at the effect of changes in the ratio of median to mean forecast assessments within a school district on changes in tax rates and collections. To address the association between wealth and tax growth, I control for the ratio of forecast median assessment to median assessment in the pre period. I also control for initial wealth and include county by year fixed effects in the following regression:

$$\Delta Rate_{ds(t)} = \beta_0 + \beta_1 \Delta \frac{Med\hat{A}_{dt}}{\bar{\hat{A}}_{dt}} + \frac{Med\hat{A}_{dt}}{MedA_{dt-3}} + log(MedA_{dt-3}) + \mathbf{C} \times \mathbf{T} + \varepsilon_{dt} \quad (3)$$

where d indexes districts, t indexes years and s indexes years since reappraisal. Change in the ratio, $\Delta \frac{Med\hat{A}_{dt}}{\bar{\hat{A}}_{dt}}$, is observed from three years before reappraisal to the year of reappraisal and constructed using the forecast described in Section 4.1. The outcome variable, $\Delta Rate_{ds(t)}$ is change in voted or effective rate from $t-1$ to t, t to $t+1$, or $t+1$ to $t+2$. Elections after homeowners observe their new tax bill first occur in $t+1$. I test the effect of changes in the ratio of the forecast median to mean assessment on gross tax rates, effective tax rates, and percent change in total collections. Effective tax rates move mechanically with total assessed value in a district due to HB 920, as discussed in Section 2. Gross tax rates adjust through newly voted levies. Collections change with new construction and new levies.

The sign of β_1 tells us whether the framework proposed by Meltzer and Richard (1981) or by Benabou (1996) dominates in this environment. If β_1 is negative, rates decrease when the ratio of the median to mean home price increases, suggesting residents are voting based on their preferred level of own subsidy. If β_1 is positive, it suggests that residents are voting based on their preferences for redistribution as described by Benabou (1996).

7 Results

Table 7 shows the effect of tax changes on sales decisions by homeowners as described in Section 6.2. Columns 1 and 2 show results for using actual assessments (Equation 1), while 3 and 4 show results for forecast assessed values (Equation 2). The results for forecast assessments are larger but statistically indistinguishable from those using actual assessments. These results suggest that tax increases increase the likelihood of home sales. A one standard deviation increase in forecast tax share leads to an approximately 5% (0.34 percentage point) increase in the likelihood a home is sold.[29] In absolute terms this is a very small change, but given that for an average home a one standard deviation increase in tax share increases taxes $230, or about 0.175% of the total value of an average home, and selling a home costs at least 5% of the home's value the size of this response is large.

[29] Standard deviation of forecast assessment share change is 0.061, baseline sale probability is 0.071. 0.061*0.0562/0.071

Table 8 looks at the effect of tax changes on foreclosures. Recall that the foreclosure variable I use here is an indicator for the first foreclosure filing with the county, and not all of these proceed to evictions. The baseline rate is fairly high, with about 4% of homes receiving a notice of foreclosure every three years during this period.[30] While the tax changes faced by homeowners are small in dollar terms relative to home values, policymakers have long been concerned about property taxes leading to homeowner displacement, and foreclosures are one way to measure displacement due to financial distress.[31] Columns 1 & 2 show that for true assessment changes there is no significant effect of tax increases on the likelihood of foreclosure. Columns 3 & 4 using forecast assessment changes suggest that tax increases lead to a decrease in the likelihood of foreclosure. This result emphasizes the importance of forecast assessments for causal identification. As described in Mallach (2009), disinvestiment often precedes foreclosure, thus lowering true assessments. The assessment forecast addresses this reverse causality.

Taken together, the results in Tables 7 and 8 suggest that property tax increases do induce a small number of homeowners to move, but homeowners are at least able to sell their homes on the market and are not facing foreclosure as a result of their tax increases. While it does not appear that tax increases from assessment growth are causing these homeowners to "lose their homes" in the most stringent sense of facing foreclosure, the welfare implications of these sales due to tax increases are unclear.

I check that the results I see for sales are driven by tax changes and not wealth changes or other trends not absorbed by the controls and instrument by testing the effect of the change in assessment ratio in the year of the reassessment on the likelihood of sale in the two years *before* the new tax bill is released to the homeowners. Results of this regression are shown in Table 10. As expected, changes in taxes have no effect on the likelihood of sale before they are released to homeowners.

I then test whether the effects I see are consistent with what we would expect if the change in taxes operates as a wealth shock through tax capitalization. Under full capitalization, an increase in tax share is a decrease in wealth, and this result suggests that some homeowners are induced to shift some of their consumption away from housing following a decrease in housing wealth coming from an increase in tax shares. Unfortunately, I am unable to observe where those who sell end up at this stage, so I cannot confirm that their new residence is less expensive and so reduces housing consumption. However, if these sales operate only through preferences for the consumption of housing as a share

[30]This is consistent with other reports on foreclosure rates in Ohio. In 2008 almost 4% of mortgages were in foreclosure (Mallach, 2009).

[31]See Martin and Beck (2017) for a discussion of the rhetoric surrounding homeowner displacement.

of total wealth, we would expect that wealth increases from tax reductions might also drive some sales decisions. In this case, decreases in taxes might also increase sales. Tax decreases may both increase home values and increase the amount of money homeowners have to spend on things other than housing. If they wish to spend some of this money on housing services they may be induced to move. To test this, I interact the variable of interest $\Delta\widehat{Assess_i}/\overline{\widehat{Assess}}$ with an indicator equal to one when the variable of interest is positive, and an indicator equal to one for positive home price increases.[32] Table 11 shows this analysis. For sales, there is no statistically significant difference in the coefficient on $\Delta\widehat{Assess_i}/\overline{\widehat{Assess}}$ regardless of the sign of the change or the sign of the change in housing values. Instead, homeowners are more likely to move if they experience a smaller tax decrease or a larger tax increase. The effect of the tax change on the likelihood of foreclosure is only statistically significant when the direct change in housing wealth and the indirect change in housing wealth through tax capitalization have opposite signs. Again, the effect of tax increases on foreclosures is either zero or negative. These interaction effects help to confirm that homeowner mobility increases with tax increases throughout the distribution of tax change. The results suggests that homeowners are moving away from an increase in the price of public goods.

7.1 Heterogeneity in Sales Responses

While Table 11 suggests that tax changes, and not their associated wealth changes, are the driver of the effects shown here, further exploring who moves in response to tax changes helps to answer questions about who is motivated to sell due to changes in taxes and why.

First, we might expect homeowners with lower value homes to be more likely to experience a change in taxes as a financial shock. Figure 15 interacts $\Delta\widehat{Assess_i}/\overline{\widehat{Assess}}$ with indicators for deciles of the home value distribution, both overall and within-district. The effect size for sales increases with home values. This could reflect either a sensitivity to change in taxes in absolute terms, as a \$0.10 change in the flow price of public goods results in a larger absolute change to the overall tax bill, or a greater sensitivity to the price of public goods among those who are subsidizing service provision. In Figure 16, I interact $\Delta\widehat{Assess_i}/\overline{\widehat{Assess}}$ with indicators for deciles of the predicted change in the flow price of public goods. Particularly within-district, the effects are larger for larger changes in taxes, which is consistent with requiring a large enough change to overcome the fixed

[32]While the quartic polynomials for wealth should absorb any effect of assessed value change on likelihood of moving, in theory we may expect effects to be larger if the wealth effect from taxes and home value appreciation move in the same direction.

costs of moving.

Larger predicted changes in the flow price of public goods are not associated with an increase in the likelihood of forelosure, but in Figure 15 we do see that the effect on foreclosures is largely concentrated in the bottom decile of the initial home value distribution. Homeowners who experience and increase in taxes due to an increase in assessment share may be able to sell to avoid foreclosure.

In Tables 12 and 13 I test for differences in effect sizes by housing tenure. The tenure results should be interpreted with caution as tenure is constructed from most recent prior sale, and, particularly for long-tenured owners, is not available. Tenure is available for only about 40% of homes in the sample. Coefficients are generally not statistically significantly different from one another, but with forecast assessments, likelihood of sale may increase slightly with tenure. Because homeowner preferences, household composition, and community public good provision all change over time, longer tenured homeowners may be less well matched with their current homes and communities, and thus more sensitive to changes in their property taxes. For instance, they are potentially more likely to be empty nesters like those studied in Farnham and Sevak (2006). However, in Appendix Table A4, I use homes with three or more bedrooms as a proxy for households more likely to have children, who we might expect to be more willing to pay for the education services funded through property taxes and find no difference in effects.

For the foreclosure results by tenure in Table 13, there is not a substantial pattern in effect sizes using forecast assessments. With actual assessments, increases in the price of a dollar of services may slightly increase the likelihood of foreclosure for the shortest tenure households. This could reflect liquidity constraints for new homeonwers who spent down their savings to purchase a home and cannot absorb the financial shock of a property tax increase. Given the negative or zero effect for long-tenured households, it is unlikely that older, long tenured homeowners are facing foreclosures through the tax increases associated with reassessment.

7.2 Home Equity Loans

If homeowners are selling due to liquidity constraints caused by tax increases, we may expect that they would first attempt to access their home equity. Selling and buying homes are both costly transactions, with at least 7% of the value of the house paid in these costs (Chatterjee and Eyigungor, 2015). The average effective tax rate is less than 2%. This suggests that homeowners are unlikely to sell their homes in response to tax changes unless their housing consumption is already out of equilibrium. Instead homeowners may choose to take out a home equity loan as a less costly way to pay higher-than-expected taxes.

Cloyne et al. (2019), Aladangady (2017), and Mian and Sufi (2011) have all found that households borrow against their homes to consume following housing wealth shocks. Further, households consume less when their borrowing is constrained due to decreases in home value (Mian et al., 2013). Wong (2020) finds that property tax increases resulting from increases in home value lead to decreases in consumption and increases in mortgage delinquency without increases in home equity loans. Here, I examine whether a shock to housing wealth through tax capitalization or the liquidity constraint generated by an increased property tax bill affects the propensity of households to take out home equity loans. In this context, households face two opposing forces: If taxes are fully capitalized, an increase in taxes (controlling for home price appreciation) should decrease home equity loans because homeowners are now poorer and less able to consume out of their housing wealth. If homeowners are income constrained such that they are not able to pay for the increase in taxes they face out of current income, an increase in taxes may increase the likelihood of taking out a home equity loan and using the loan to pay for the property tax increase.

Table 9 shows how tax changes affect home equity loan origination. New home equity loan origination is an imperfect measure of the object we would like to study: the additional home equity extracted as a result of the tax change. Homeowners must have a line of credit to extract additional housing wealth, so new loans at least capture one step of the process. However, if these homeowners already had an active credit line, I will miss any additional borrowing they do. Households are less likely to take out a new home equity loan when their assessment share increases, increasing their taxes. This suggests that households are not using home equity loans to pay their property taxes. Unfortunately, I cannot tell if this is because they do not face binding liquidity constraints or because they lose access to this margin for borrowing when their taxes increase. This is true across the distribution of tax and wealth changes, with the exception of those households who see both their assessment decrease and their tax share increase (Table 11 Column 3).

7.3 Voted Tax Rates

I now turn to the question of how homeowners respond to changes in their property taxes through voting. Tables 14, 15, and 16 present results from estimating equation 3. I find some evidence that an increase in the price of a dollar of public goods to the median voter lowers tax rates in the first year after homeowners experience their new tax bill, with no effect in other years.

In the first and third year, increasing median assessments are associated with a decrease in effective rates (confirming the mechanical relationship from HB 920 for the first year) and a small decrease in gross rates.

The coefficient on Δ Median $\hat{A}_t/\bar{\hat{A}}_t$ tests whether changes in rates and collections are consistent with the predictions of the Meltzer-Richard model. I find some suggestive evidence of the Meltzer Richard type redistribution only in year 1, the second year in which homeowners are paying taxes on their new assessed value. For effective rates, a decrease of .01 in the ratio of the median to the mean, which is about the 25th percentile, is associated with a .6 mil increase in the effective tax rate. This is a very small movement relative to the average tax rate of 156 mils, but about 10% of the average movement in effective tax rates. Results for gross rates and effective rates are very similar, which is consistent with a change in rates through newly-voted levies. The sign of the result for percent change in collections (Table 16) in year 1 is consistent with the results on voted rates but is not statistically significant.

Overall, I find suggestive evidence of small changes in voted tax rates consistent with the median voter seeking higher tax rates when their level of redistribution increases.

8 Conclusion

Homeowners do respond to changes in their property taxes, both by moving and by voting. It appears that, consistent with the predictions of Tiebout (1956), homeowners attempt to move away from increases in taxes, with a one standard deviation increase in taxes leading to a 5% increase in the likelihood of selling. Tax increases do not increase the likelihood that a home is foreclosed upon, including among long-tenured homeowners. One of the policy goals of property tax limitations is to keep residents from being forced from their homes. The results here suggest that homeowners are not being forced from their homes through property taxes in a strict sense, as they are no more (or possibly less) likely to face a foreclosure following an increase in property taxes. However, if policymakers wish to prevent a larger set of tax-motivated moves, for instance because homeowners invest in their neighborhoods, property tax limitations may be an effective tool as homeowners who face a tax increase are more likely to sell their homes (DiPasquale and Glaeser, 1999). I cannot determine whether these additional sales are due to financial constraints, though results for home equity loan origination suggests that those who stay are not taking out new loans in order to pay their property taxes. Homeowners may be responding to the flow price they see and attempting to escape their increase in taxes. These types of sales reflect either homeowners failing to understand how their taxes are capitalized or incomplete capitalization. I also find that homeowners who stay may be attentive to their tax shares in their voting choices. I find suggestive evidence that increases in the subsidy to the median voter lead to increases in voted taxes.

References

Aladangady, A. (2017). Housing wealth and consumption: Evidence from geographically-linked microdata. *American Economic Review*, 107(11):3415–46.

Alesina, A., Baqir, R., and Easterly, W. (1999). Public goods and ethnic divisions. *The Quarterly Journal of Economics*, 114(4):1243–1284.

Antipov, E. A. and Pokryshevskaya, E. B. (2012). Mass appraisal of residential apartments: An application of random forest for valuation and a cart-based approach for model diagnostics. *Expert Systems with Applications*, 39(2):1772 – 1778.

Banzhaf, H. S. (2013). The market for local public good. *Case W. Res. L. Rev.*, 64:1441.

Barseghyan, L. and Coate, S. (2016). Property taxation, zoning, and efficiency in a dynamic tiebout model. *American Economic Journal: Economic Policy*, 8(3):1–38.

Bayer, P., Ferreira, F., and McMillan, R. (2007). A unified framework for measuring preferences for schools and neighborhoods. *Journal of political economy*, 115(4):588–638.

Benabou, R. (1996). Heterogeneity, stratification, and growth: macroeconomic implications of community structure and school finance. *The American Economic Review*, pages 584–609.

Benabou, R. (2000). Unequal societies: Income distribution and the social contract. *American Economic Review*, 90(1):96–129.

Benítez-Silva, H., Eren, S., Heiland, F., and Jiménez-Martín, S. (2015). How well do individuals predict the selling prices of their homes? *Journal of Housing Economics*, 29:12–25.

Black, S. E. (1999). Do better schools matter? parental valuation of elementary education. *The Quarterly Journal of Economics*, 114(2):577–599.

Bogin, A., Doerner, W., and Larson, W. (2019). Local house price dynamics: New indices and stylized facts. *Real Estate Economics*, 47(2):365–398.

Borge, L.-E. and Rattsø, J. (2004). Income distribution and tax structure: Empirical test of the meltzer–richard hypothesis. *European Economic Review*, 48(4):805 – 826.

Borge, L.-E. and Rattsø, J. (2014). Capitalization of property taxes in norway. *Public Finance Review*, 42(5):635–661.

Boustan, L., Ferreira, F., Winkler, H., and Zolt, E. M. (2013). The effect of rising income inequality on taxation and public expenditures: Evidence from us municipalities and school districts, 1970–2000. *Review of Economics and Statistics*, 95(4):1291–1302.

Bradley, S. (2017). Inattention to deferred increases in tax bases: How michigan homebuyers are paying for assessment limits. *Review of Economics and Statistics (forthcoming)*, 99.

Brueckner, J. K. (2000). A tiebout/tax-competition model. *Journal of Public Economics*, 77(2):285–306.

Brunner, E. J. and Ross, S. L. (2010). Is the median voter decisive? evidence from referenda voting patterns. *Journal of Public Economics*, 94(11-12):898–910.

Cabral, M. and Hoxby, C. (2012). The hated property tax: salience, tax rates, and tax revolts.

Technical report, National Bureau of Economic Research.

Calabrese, S. M., Epple, D. N., and Romano, R. E. (2011). Inefficiencies from metropolitan political and fiscal decentralization: Failures of tiebout competition. *The Review of Economic Studies*, 79(3):1081–1111.

Caplan, B. (2001). Standing tiebout on his head: Tax capitalization and the monopoly power of local governments. *Public Choice*, 108(1-2):101–122.

Chamberlain, A. (2007). What does america think about taxes. *The 2007 annual survey of US attitudes on taxes and wealth. Tax Foundation Special Report*, (157).

Chan, S. (2001). Spatial lock-in: Do falling house prices constrain residential mobility? *Journal of urban Economics*, 49(3):567–586.

Chatterjee, S. and Eyigungor, B. (2015). A quantitative analysis of the us housing and mortgage markets and the foreclosure crisis. *Review of Economic Dynamics*, 18(2):165–184.

Cloyne, J., Huber, K., Ilzetzki, E., and Kleven, H. (2019). The effect of house prices on household borrowing: A new approach. *American Economic Review*, 109(6):2104–36.

Corcoran, S. and Evans, W. N. (2010). Income inequality, the median voter, and the support for public education. Technical report, National Bureau of Economic Research.

DiPasquale, D. and Glaeser, E. (1999). Incentives and social capital: Are homeowners better citizens? *Journal of Urban Economics*, 45(2):354–384.

Epple, D. and Romano, R. E. (1996). Ends against the middle: Determining public service provision when there are private alternatives. *Journal of Public Economics*, 62(3):297–325.

Farnham, M. and Sevak, P. (2006). State fiscal institutions and empty-nest migration: Are tiebout voters hobbled? *Journal of Public Economics*, 90(3):407–427.

Ferreira, F., Gyourko, J., and Tracy, J. (2010). Housing busts and household mobility. *Journal of urban Economics*, 68(1):34–45.

Fischel, W. A. (1998). School finance litigation and property tax revolts: How undermining local control turns voters away from public education. *Lincoln Institute of Land Policy, Cambridge, MA*.

Fischel, W. A. (2013). Fiscal zoning and economists' views of the property tax. *Lincoln Institute of Land Policy, Cambridge, MA*.

Fligstein, N., Hastings, O. P., and Goldstein, A. (2017). Keeping up with the joneses: How households fared in the era of high income inequality and the housing price bubble, 1999–2007. *Socius*, 3:2378023117722330.

Georgiadis, A. and Manning, A. (2012). Spend it like beckham? inequality and redistribution in the uk, 1983–2004. *Public Choice*, 151(3):537–563.

Hamilton, B. W. (1975). Zoning and property taxation in a system of local governments. *Urban Studies*, 12(2):205–211.

Hamilton, B. W. (1976). Capitalization of intrajurisdictional differences in local tax prices. *The*

American Economic Review, 66(5):743–753.

Hardman, A. M. and Ioannides, Y. M. (1995). Moving behavior and the housing market. *Regional Science and Urban Economics*, 25(1):21–39.

Hastie, T., Tibshirani, R., Friedman, J., and Franklin, J. (2005). The elements of statistical learning: data mining, inference and prediction. *The Mathematical Intelligencer*, 27(2):83–85.

Ihlanfeldt, K. R. (2011). Do caps on increases in assessed values create a lock-in effect? evidence from florida's amendment one. *National Tax Journal*, 64(1):7.

Johnson, E. B. and Walsh, R. (2009). The effect of property taxes on location decisions: Evidence from the market for vacation homes. Technical report, National Bureau of Economic Research.

Kenworthy, L. and McCall, L. (2007). Inequality, public opinion and redistribution. *Socio-Economic Review*, 6(1):35–68.

Kirk, D. S. and Laub, J. H. (2010). Neighborhood change and crime in the modern metropolis. *Crime and justice*, 39(1):441–502.

Livy, M. R. (2018). Intra-school district capitalization of property tax rates. *Journal of Housing Economics*, 41:227 – 236.

Mallach, A. (2009). *Addressing Ohio's foreclosure crisis: Taking the next steps*. Metropolitan Policy Program at Brookings.

Martin, I. W. (2008). *The permanent tax revolt: How the property tax transformed American politics*. Stanford University Press.

Martin, I. W. (2009). Proposition 13 fever: How california's tax limitation spread. *California Journal of Politics and Policy*, 1(1).

Martin, I. W. and Beck, K. (2017). Property tax limitation and racial inequality in effective tax rates. *Critical Sociology*, 43(2):221–236.

Martin, I. W. and Beck, K. (2018). Gentrification, property tax limitation, and displacement. *Urban Affairs Review*, 54(1):33–73.

Meltzer, A. H. and Richard, S. F. (1981). A rational theory of the size of government. *Journal of Political Economy*, 89(5):914–927.

Mian, A., Rao, K., and Sufi, A. (2013). Household balance sheets, consumption, and the economic slump. *The Quarterly Journal of Economics*, 128(4):1687–1726.

Mian, A. and Sufi, A. (2011). House prices, home equity-based borrowing, and the us household leverage crisis. *American Economic Review*, 101(5):2132–56.

Mieszkowski, P. and Zodrow, G. R. (1989). Taxation and the tiebout model: the differential effects of head taxes, taxes on land rents, and property taxes. *Journal of Economic Literature*, 27(3):1098–1146.

Norregaard, M. J. (2013). *Taxing immovable property revenue potential and implementation challenges*. Number 13-129. International Monetary Fund.

Oates, W. E. and Fischel, W. A. (2016). Are local property taxes regressive, progressive, or what? *National Tax Journal*, 69(2):415.

O'Sullivan, A., Sexton, T. A., and Sheffrin, S. M. (1995). Property taxes, mobility, and home ownership. *Journal of Urban Economics*, 37(1):107–129.

Pack, H. and Pack, J. R. (1977). Metropolitan fragmentation and suburban homogeneity. *Urban Studies*, 14(2):191–201.

Palmon, O. and Smith, B. A. (1998). New evidence on property tax capitalization. *Journal of Political Economy*, 106(5):1099–1111.

Rhode, P. W. and Strumpf, K. S. (2003). Assessing the importance of tiebout sorting: Local heterogeneity from 1850 to 1990. *American Economic Review*, 93(5):1648–1677.

Ries, J. and Somerville, T. (2010). School quality and residential property values: evidence from vancouver rezoning. *The Review of Economics and Statistics*, 92(4):928–944.

Rink, R. P. (1981). After house bill 920: An analysis of needed real property tax reform. *Clev. St. L. Rev.*, 30:137.

Ross, S. and Yinger, J. (1999). Sorting and voting: A review of the literature on urban public finance. *Handbook of regional and urban economics*, 3:2001–2060.

Shan, H. (2010). Property taxes and elderly mobility. *Journal of Urban Economics*, 67(2):194–205.

Sirmans, S., Gatzlaff, D., and Macpherson, D. (2008). The history of property tax capitalization in real estate. *Journal of Real Estate Literature*, 16(3):327–344.

Testa, J. W. (2018). Annual report: Fiscal year 2018. Technical report, Ohio Department of Taxation.

Tiebout, C. M. (1956). A pure theory of local expenditures. *Journal of Political Economy*, 64(5):416–424.

Urban Institute-Brookings Institution Tax Policy Center (2017). State & local government finance data query system. Technical report.

U.S. Census Bureau (2017). Public education finances: 2015. Technical report.

Wasi, N. and White, M. J. (2005). Property tax limitations and mobility: The lock-in effect of california's proposition 13. Working Paper 11108, National Bureau of Economic Research.

Wong, F. (2020). Mad as hell: Property taxes and financial distress. *Available at SSRN 3645481*.

subcaption,graphicx

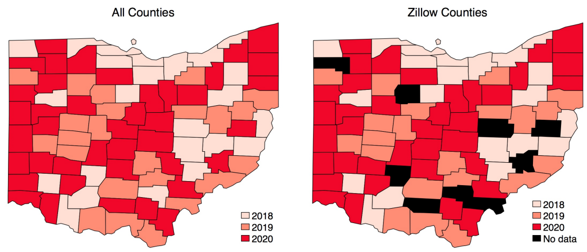


Figure 1: Reassessment Cycle

This figure shows Ohio counties by their reassessment cycle. Coshocton, Defiance, Fayette, Harrison, Meigs, Noble, Pike, Vinton, and Wyandot counties are excluded from the analysis due to missing assessment records. There is geographic variation in which county reassesses when.

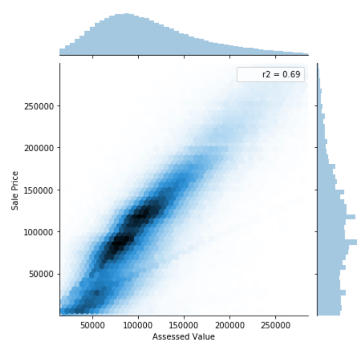


Figure 2: Assessment Accuracy

This figure is a joint histogram of assessed value and sale price for market sales as recorded in the Zillow ZTRAX historical assessment and sales data.

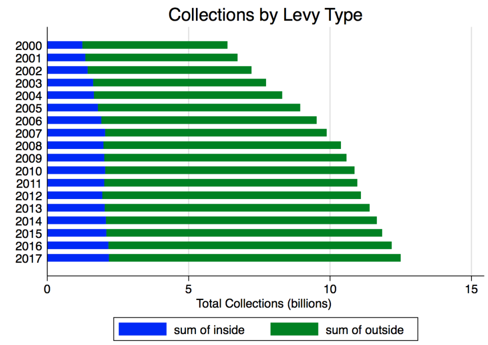


Figure 3: Collections by Millage Type

This figure shows nominal total property taxes in Ohio from 2000-2017. Collections through inside millage appreciate through new construction and appreciation of existing properties. Collections through outside millage increase due to newly voted levies and new construction. Data is from the Ohio Department of Taxation.

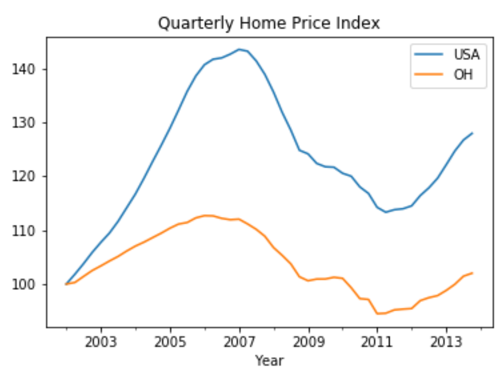


Figure 4: Ohio Home Price Index

Seasonally adjusted quarterly home price indicies from the FHFA for Ohio and the US from 2002-2014 (Bogin et al., 2019).

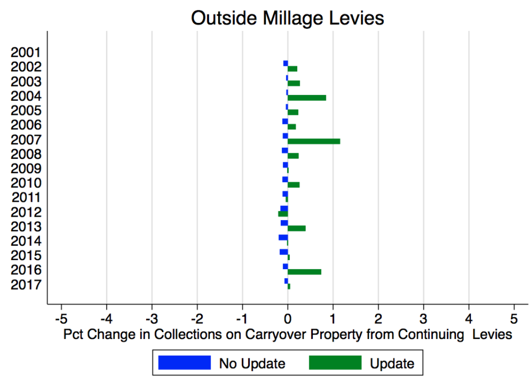


Figure 5: Change in Collections from Continuing Outside Millage Levies on Carryover Property

This figure shows the percent change in collections at the county level on carryover property from outside levies that exist in both t and $t-1$. The total change in collections is summed across all reassessing (updating) and non-reassessing counties. Under HB 920, this change should be zero. Data is from the Ohio department of taxation.

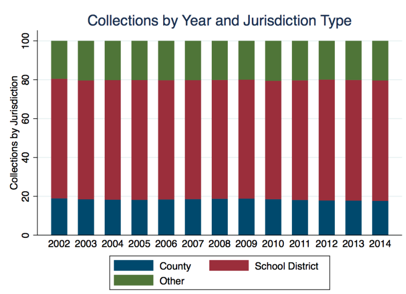
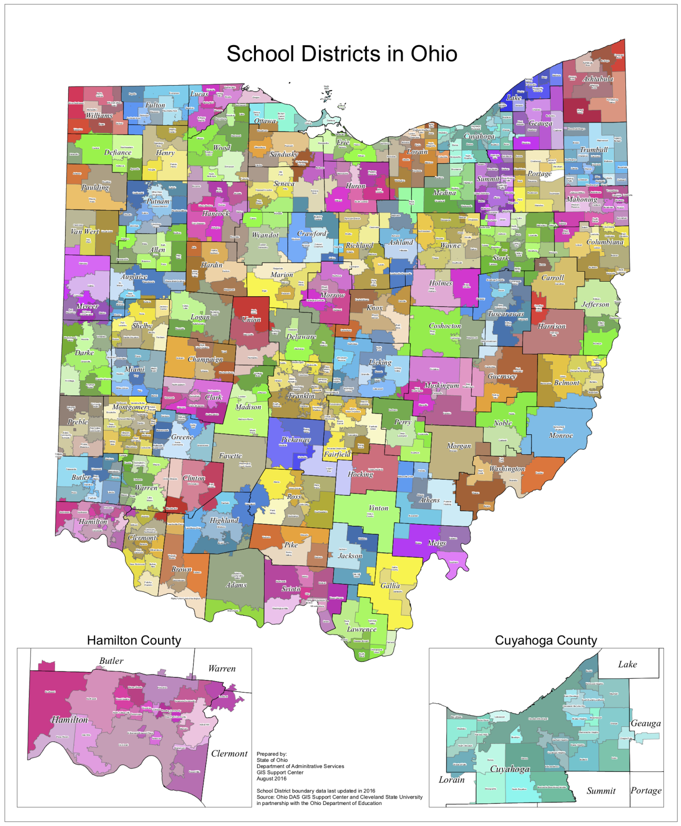


Figure 6: Share of Taxes Collected by Taxing Entity

This table shows the share of total collections that goes to each type of jurisdiction that levies taxes. School districts are the largest collector of revenues. Other includes municipalities, library districts, etc.

Figure 7: Ohio School Districts



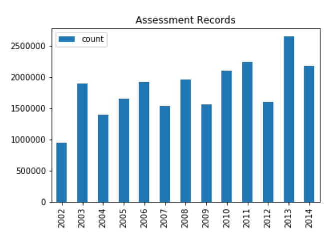


Figure 8: Assessment Records

This figure shows the number of assessment records available in each year of the sample. Some counties only provide assessment records in assessment years, which gives the three year cyclic pattern in number of records.

Data provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the author and do not reflect the position of the Zillow Group.

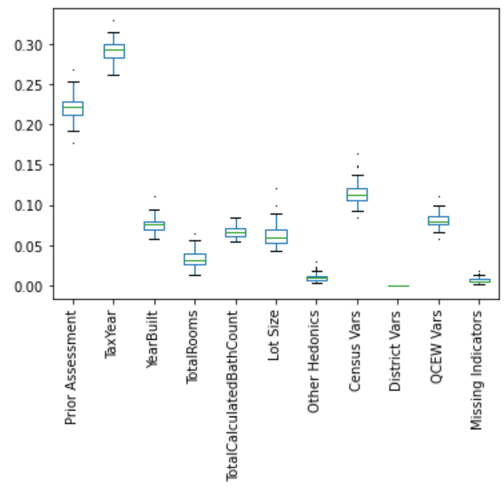


Figure 9: Feature Importance

This figure shows box-and-whisker plots for the importance of groups of features of the prediction model across the 79 counties for which a model is generated. Other hedonics include Lot Size, Number of Units, Property Type, Year Built, Total Rooms, Total Bedrooms, Total bathrooms, Building Quality, Building Condition, Architectural Style, Roof Type, Heating Type, AC Type, Water Type, Sewer Type, and Lot Site Appeal. Included census characteristics are: Fraction HS plus, Fraction College Plus, Fraction Poor, Tract Population, fraction urban, fraction rural, fraction white, fraction black, fraction non-hispanic white, fraction under 18, fraction over 65, fraction of housing that is owner-occupied. School district characteristics are school district size and fraction of children in poverty. County employment characteristics are annual average pay and employment location quotient for the the service industry.

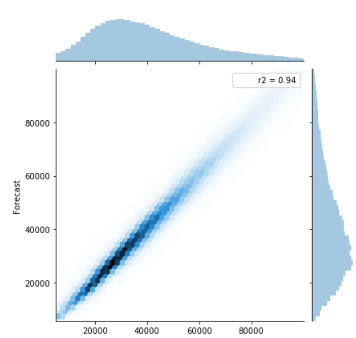


Figure 10: Forecast Quality

This figure is a joint histogram of true and forecast assessed values.

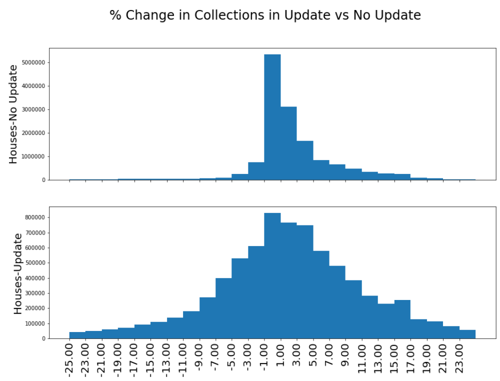


Figure 11: Change in Taxes

The top panel of this figure is a histogram of the percent change in year-to-year tax collections for houses with recorded collections two years in a row when the second year is not an assessment year. Collections in non-assessment years change very little because the value of the property against which taxes are levied does not change. There are some small upward and downward increases in taxes primarily due to new and expiring levies. This is in contrast with the bottom panel, which shows the distribution of changes in collections when the second year is an update year. Changes to the assessed value of the underlying property in generates variance in change in collections.

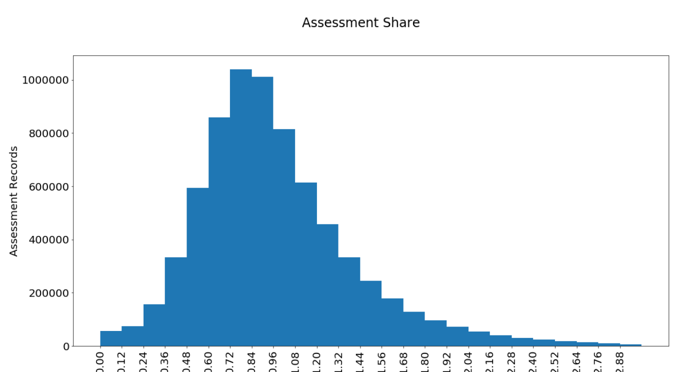


Figure 12: Household Tax Shares

This is a histogram of the ratio of home price to mean home price within a home's district for each time an assessment of a home is observed in an update year. The median ratio is .9, so the majority of residents are receiving a "subsidized" public goods relative to the per-household expenditure in their district.

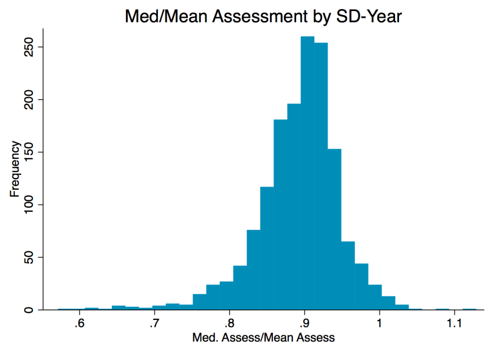


Figure 13: Distribution of Assessed Value Ratios

This is the distribution of median to mean household assessment ratios by school district-year. Districts appear in this sample only in update years between 2002 and 2014.

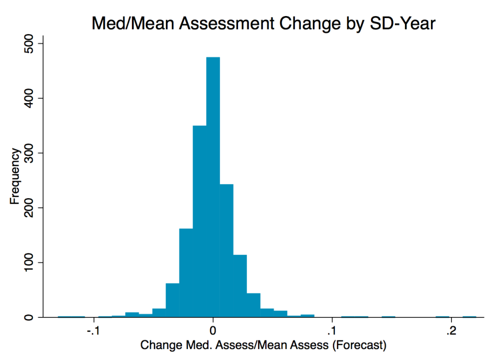
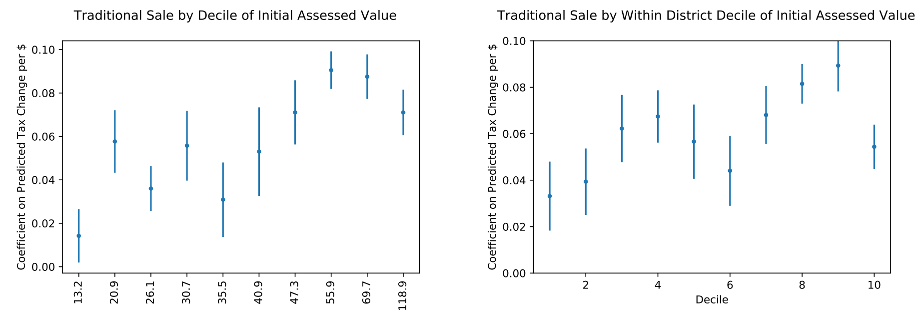
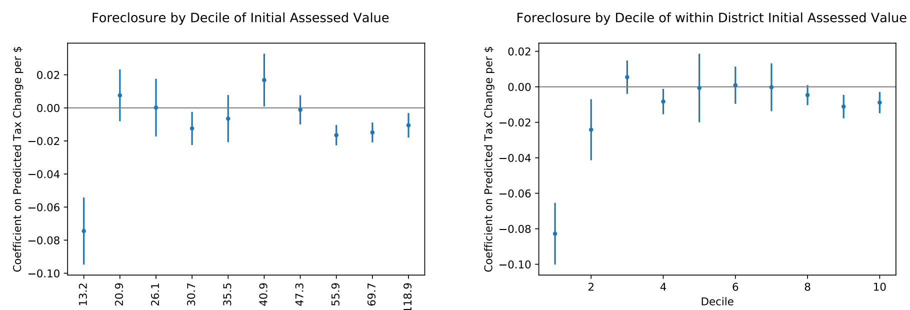


Figure 14: Distribution of Change in Assessed Value Ratios

This shows the assessment to assessment change at the school district level of of the ratios plotted in Figure 13. Most communities see a relatively small change in this ratio. Districts appear in this sample only in update years between 2002 and 2014.



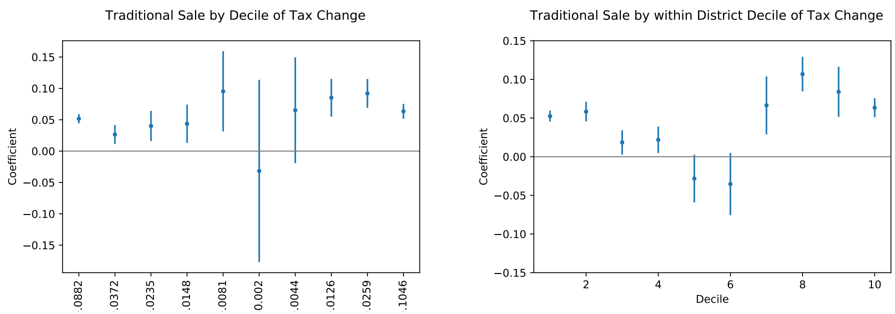
(a) Sales



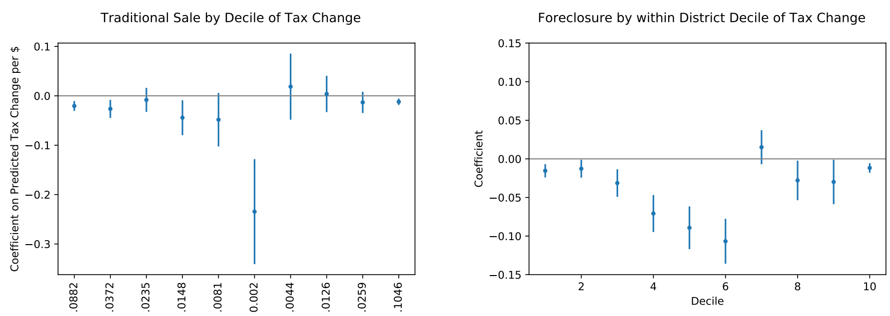
(b) Foreclosures

Figure 15: Effect by Decile of Initial Assessed Value

Graphs show the effects of the forecast change in the flow price of public goods on sales and foreclosures where the forecast change is interacted with an indicator for position in the assessed value distribution. Graphs on the left show deciles of the statewide distribution and graphs on the right show results using a home's position within the assessed value distribution of its district. Regressions include controls for hedonics and census tract characteristics, quartic polynomials of initial assessment, assessment change, and initial assessment ratio and FE for tax year X county. Standard errors clustered at county level.



(a) Sales



(b) Foreclosures

Figure 16: Effect by Decile of Forecast Tax Change

Graphs show the effects of the forecast change in the flow price of public goods on sales and foreclosures where the forecast change is interacted with an indicator for position in the forecast tax change distribution. Graphs on the left show deciles of the statewide distribution and graphs on the right show results using a home's position within the distribution of its district. Regressions include controls for hedonics and census tract characteristics, quartic polynomials of initial assessment, assessment change, and initial assessment ratio and FE for tax year X county. Standard errors clustered at county level.

Table 1: Price vs. Assessment

	(1) Price	(2) Price	(3) Price	(4) Price	(5) Price	(6) Price
Assessed Value/.35	1.033***	1.027***	0.956***			
	(0.00103)	(0.00146)	(0.00270)			
Forecast Assessed Value/.35				1.036***	1.030***	0.958***
				(0.00105)	(0.00150)	(0.00278)
Year One Only		X	X		X	X
Controls			X			X
N	563153	218682	218175	563153	218682	218175
Adjusted R2	0.642	0.693	0.725	0.632	0.683	0.719

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Controls are month-of-year by school district and year by school district fixed effects and hedonic controls. This table shows the relationship between assessed values and realized prices for houses that sell. The sample is restricted to single family homes. Assessed values and forecast assessed values are divided by .35 because Ohio uses a 35% assessment ratio.

Data provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the author and do not reflect the position of the Zillow Group.

Table 2: Cyclic Change in Expenditures and Revenue

	(1) Exp./Stud	(2) Expenditure	(3) Prop. Tax/Student	(4) Prop. Tax Revenue
Update	0.457	–0.665	–0.917***	–0.884***
	(0.507)	(1.088)	(0.311)	(0.258)
r2	0.049	0.079	0.111	0.148
N	7339	8635	7340	7944

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

FE for School District and Year. Standard Errors clustered at the county level. All outcomes measured in percent change. Data from *Rutgers Graduate School of Education/Education Law Center: School Funding Fairness Data System.* Table shows the extent to which the property reassessment cycle in Ohio predicts spending and revenue collected at the school district level.

Table 3: Δ Assessment Share and Δ Tax Share

	(1) Tax Share Change	(2) $\Delta \text{Assess}_i / \overline{\text{Assess}}$	(3) Tax Share Change
$\Delta \text{Assess}_i / \overline{\text{Assess}}$	1.038***		
	(0.0312)		
$\Delta \widehat{\text{Assess}}_i / \overline{\widehat{\text{Assess}}}$		0.263***	0.317***
		(0.0303)	(0.0619)
N	8952580	8952580	8952580
Number of Clusters	79	79	79
Adj R2	0.191	0.0494	0.0121

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Controls for hedonics and census tract characteristics. Includes quartic polynomial of initial assessment, assessment change, and initial assessment ratio. FE for tax year X county. Standard errors clustered at county level. This table shows the relationship of changes in assessment share and forecast assessment share with tax share and forecast assessment share. Controls are those that will be used in later mobility regressions.

	count	mean	sd	p50
Rooms	8413780	6.225	1.695	6.00
Bedrooms	8633639	3.019	0.811	3.00
Baths	4375835	1.968	0.764	1.50
age	8533890	49.892	29.544	48.00
Lot Size (Sq. Ft.)	7879039	53317.288	1238194.936	10542.00
Year Built	8533890	1958.375	29.447	1960.00
Move	8952580	0.114	0.318	0.00
Trad. Sale	8952580	0.072	0.258	0.00
Foreclosure	8952580	0.043	0.202	0.00
Home Equity Loan	8952580	0.052	0.222	0.00
Sale Yr 1	8952580	0.028	0.165	0.00
Sale Yr 2	8952580	0.025	0.157	0.00
Sale Yr 3	8952580	0.024	0.153	0.00
Price	805273	118791.340	121296.768	92667.00
Assessed Value	8952580	46427.892	34200.589	38606.00
Assessment T-3 (000)	8952580	45.911	33.709	38.10
Tax T-3	8952580	2441.507	2077.986	1915.28
$\Delta\text{Assess}_i/\overline{\text{Assess}}$	8952580	-0.004	0.095	-0.00
$\Delta\widehat{\text{Assess}}_i/\overline{\widehat{\text{Assess}}}$	8952580	-0.003	0.061	-0.01
$\lvert\Delta\text{Assess}_i/\overline{\text{Assess}}\rvert$	8952580	0.054	0.078	0.03
$\lvert\Delta\widehat{\text{Assess}}_i/\overline{\widehat{\text{Assess}}}\rvert$	8952580	0.032	0.052	0.02
$A_{t-3}/\ \bar{A}_{t-3}$	8952580	0.997	0.517	0.90
Observations	8952580			

Table 4: Assessment Summary Statistics

Table shows summary statistics for assessment records in the ZTRAX sample. A house will appear each time it appears in the sample between 2002 and 2014 in an update year.

	count	mean	sd	p50
Δ Median A_t / $\bar{A}_t$	1160	-0.003	0.016	-0.00
Δ Median $\hat{A}_t$ / $\bar{\hat{A}}_t$	1160	-0.002	0.022	-0.00
$\bar{\hat{A}}_t$	1160	46169.880	19643.929	42613.52
$\bar{A}_t$	1160	45629.825	19437.424	42038.56
Median A_t	1160	40581.233	16219.851	37466.50
Median $\hat{A}_t$	1160	41154.162	16764.771	38122.69
Median A_{t-3}	1160	40544.743	16444.608	37677.50
$\bar{A}_{t-3}$	1160	45440.213	19727.029	41789.83
Effective Tax Rate	4941	157.167	81.360	143.33
Δ Effective Tax Rate	4941	2.656	12.800	0.01
Gross Tax Rate	4941	250.963	128.877	232.80
Δ Gross Tax Rate	4941	2.731	14.830	0.00
Collections	4941	9955004.421	12605863.679	5085717.97
%Δ Collections	4941	0.021	0.052	0.01
Observations	4941			

Table 5: School District Summary Statistics

This table shows school district by year summary statistics for tax collections and assessed home values. Rate variables come from the Ohio department of taxation. Home value variables are from Zillow ZTRAX. Home value variables are available only in update years.

Table 6: Assessment Share and Tax Share

	(1) Tax Share	(2) $\text{Assess}_i / \overline{\text{Assess}}$	(3) Tax Share
$\text{Assess}_i / \overline{\text{Assess}}$	0.990***		
	(0.00607)		
$\widehat{\text{Assess}} \,/\, \overline{\widehat{\text{Assess}}}$		0.981***	0.972***
		(0.00524)	(0.00751)
N	8952580	8952580	8952580
Number of Clusters	79	79	79
Adj R2	0.877	0.960	0.843

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Controls for hedonics and census tract characteristics. FE for tax year X county. Standard errors clustered at county level. This table shows the relationship between assessment share and tax share, forecast assessment share and assessment share, and forecast assessment share and tax share. Controls are those that will be used in later mobility regressions.

Table 7: Traditional Sales

	(1) Trad. Sale	(2) Trad. Sale	(3) Trad. Sale	(4) Trad. Sale
$\Delta\text{Assess}_i / \overline{\text{Assess}}$	0.0394***	0.0369***		
	(0.0139)	(0.0126)		
$\Delta\widehat{\text{Assess}}_i / \overline{\widehat{\text{Assess}}}$			0.0562***	0.0585***
			(0.00855)	(0.00920)
Sample	Full	Single Family	Full	Single Family
N	8952580	8342381	8952580	8342381
Number of Clusters	79	79	79	79
Adjusted R2	0.0131	0.0118	0.0132	0.0119

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Controls for hedonics and census tract characteristics. Includes quartic polynomial of initial assessment, assessment change, and initial assessment ratio. FE for tax year X county. Standard errors clustered at county level. Table shows how true and forecast change in assessment share affect the likelihood of sale.

Table 8: Foreclosures

	(1) Foreclosure	(2) Foreclosure	(3) Foreclosure	(4) Foreclosure
$\Delta \text{Assess}_i / \overline{\text{Assess}}$	0.00557	0.00746		
	(0.00982)	(0.0104)		
$\Delta \widehat{\text{Assess}}_i / \overline{\widehat{\text{Assess}}}$			–0.0178***	–0.0156***
			(0.00464)	(0.00495)
Sample	Full	Single Family	Full	Single Family
N	8952580	8342381	8952580	8342381
Number of Clusters	79	79	79	79
Adjusted R2	0.0243	0.0245	0.0243	0.0245

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Controls for hedonics and census tract characteristics. Includes quartic polynomial of initial assessment, assessment change, and initial assessment ratio. FE for tax year X county. Standard errors clustered at county level. Table shows how true and forecast change in assessment share affect the likelihood of foreclosure.

Table 9: Home Equity Loans

	(1) Home Equity Loan	(2) Home Equity Loan	(3) Home Equity Loan	(4) Home Equity Loan
$\Delta \text{Assess}_i / \overline{\text{Assess}}$	–0.0520***	–0.0498***		
	(0.0117)	(0.0122)		
$\Delta \widehat{\text{Assess}}_i / \overline{\widehat{\text{Assess}}}$			–0.0964***	–0.0951***
			(0.0110)	(0.0116)
Sample	Full	Single Family	Full	Single Family
N	8952580	8342381	8952580	8342381
Number of Clusters	79	79	79	79
Adjusted R2	0.0444	0.0450	0.0444	0.0450

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Controls for hedonics and census tract characteristics. Includes quartic polynomial of initial assessment, assessment change, and initial assessment ratio. FE for tax year X county. Standard errors clustered at county level. Table shows how true and forecast change in assessment share affect the likelihood of new home equity loan origination.

Table 10: Sale Before Reassessment

	(1) Sale t–1, t	(2) Sale t–1, t
$\Delta\widehat{\text{Assess}}_i/\overline{\widehat{\text{Assess}}}$	0.00349	–0.00209
	(0.00755)	(0.00877)
Sample	Full	Single Family
N	8952580	8342381
Number of Clusters	79	79
Adjusted R2	0.0182	0.0189

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Controls for hedonics and census tract characteristics. Includes quartic polynomial of initial assessment, assessment change, and initial assessment ratio. FE for tax year X county. Standard errors clustered at county level. Table shows how forecast change in assessment share affect the likelihood of sale before tax change takes place.

Table 11: Change in Assessment and Change in Tax

	(1) Trad. Sale	(2) Foreclosure	(3) Home Equity Loan
Home Value DecreaseXTax DecreaseX$\Delta\widehat{\text{Assess}}_i/\overline{\widehat{\text{Assess}}}$	0.0513***	–0.0347**	–0.108***
	(0.0149)	(0.0147)	(0.0158)
Home Value DecreaseXTax IncreaseX$\Delta\widehat{\text{Assess}}_i/\overline{\widehat{\text{Assess}}}$	0.0743**	–0.0254	–0.0365
	(0.0309)	(0.0299)	(0.0223)
Home Value IncreaseXTax DecreaseX$\Delta\widehat{\text{Assess}}_i/\overline{\widehat{\text{Assess}}}$	0.0488***	0.00686	–0.0983***
	(0.0127)	(0.0166)	(0.0250)
Home Value IncreaseXTax IncreaseX$\Delta\widehat{\text{Assess}}_i/\overline{\widehat{\text{Assess}}}$	0.0625***	–0.0156**	–0.0992***
	(0.0134)	(0.00605)	(0.0186)
Sample	Single Family	Single Family	Single Family
N	8342381	8342381	8342381
Number of Clusters	79	79	79
Adjusted R2	0.0119	0.0245	0.0450

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Controls for hedonics and census tract characteristics. Includes quartic polynomial of initial assessment, assessment change, and initial assessment ratio. FE for tax year X county. Standard errors clustered at county level. Regression estimates the effect of change in assessment share separately for homes that decreased in value and saw a tax decrease, homes that decreased in value and saw a tax increase, and the opposite.

Table 12: Sales by Tenure

	(1) Trad. Sale	(2) Trad. Sale
Tenure 0-5 $\times$ $\Delta \text{Assess}_i / \overline{\text{Assess}}$	0.0396***	
	(0.0109)	
Tenure 6-10 $\times$ $\Delta \text{Assess}_i / \overline{\text{Assess}}$	0.0411***	
	(0.0154)	
Tenure 11-15 $\times$ $\Delta \text{Assess}_i / \overline{\text{Assess}}$	0.0441**	
	(0.0167)	
Tenure 16-20 $\times$ $\Delta \text{Assess}_i / \overline{\text{Assess}}$	0.0277	
	(0.0189)	
Tenure 20 + or unknown $\times$ $\Delta \text{Assess}_i / \overline{\text{Assess}}$	0.0328**	
	(0.0125)	
Tenure 0-5 $\times$ $\Delta \widehat{\text{Assess}}_i / \overline{\widehat{\text{Assess}}}$		0.0333*
		(0.0179)
Tenure 6-10 $\times$ $\Delta \widehat{\text{Assess}}_i / \overline{\widehat{\text{Assess}}}$		0.0489***
		(0.0121)
Tenure 11-15 $\times$ $\Delta \widehat{\text{Assess}}_i / \overline{\widehat{\text{Assess}}}$		0.0646***
		(0.0166)
Tenure 16-20 $\times$ $\Delta \widehat{\text{Assess}}_i / \overline{\widehat{\text{Assess}}}$		0.0700***
		(0.0254)
Tenure 20 + or unknown $\times$ $\Delta \widehat{\text{Assess}}_i / \overline{\widehat{\text{Assess}}}$		0.0652***
		(0.00952)
Sample	Single Family	Single Family
N	8428658	8428658
Number of Clusters	79	79
Adjusted R2	0.0119	0.0120

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Controls for hedonics and census tract characteristics. Includes quartic polynomial of initial assessment, assessment change, and initial assessment ratio. FE for tax year X county. Standard errors clustered at county level. Table shows how true and forecast change in assessment share affect the likelihood of mobility.

Table 13: Foreclosure by Tenure

	(1) Foreclosure	(2) Foreclosure
Tenure 0-5 × $\Delta \text{Assess}_i/\overline{\text{Assess}}$	0.0471***	
	(0.0172)	
Tenure 6-10 × $\Delta \text{Assess}_i/\overline{\text{Assess}}$	–0.0272***	
	(0.00622)	
Tenure 11-15 × $\Delta \text{Assess}_i/\overline{\text{Assess}}$	–0.0235***	
	(0.00867)	
Tenure 16-20 × $\Delta \text{Assess}_i/\overline{\text{Assess}}$	–0.0244***	
	(0.00581)	
Tenure 20 + or unknown × $\Delta \text{Assess}_i/\overline{\text{Assess}}$	0.00718	
	(0.00903)	
Tenure 0-5 × $\Delta \widehat{\text{Assess}}_i/\overline{\widehat{\text{Assess}}}$		–0.0378***
		(0.00586)
Tenure 6-10 × $\Delta \widehat{\text{Assess}}_i/\overline{\widehat{\text{Assess}}}$		–0.0581***
		(0.00604)
Tenure 11-15 × $\Delta \widehat{\text{Assess}}_i/\overline{\widehat{\text{Assess}}}$		–0.0485***
		(0.0119)
Tenure 16-20 × $\Delta \widehat{\text{Assess}}_i/\overline{\widehat{\text{Assess}}}$		–0.0330*
		(0.0186)
Tenure 20 + or unknown × $\Delta \widehat{\text{Assess}}_i/\overline{\widehat{\text{Assess}}}$		0.00857
		(0.00874)
Sample	Single Family	Single Family
N	8428658	8428658
Number of Clusters	79	79
Adjusted R2	0.0249	0.0248

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Controls for hedonics and census tract characteristics. Includes quartic polynomial of initial assessment, assessment change, and initial assessment ratio. FE for tax year X county. Standard errors clustered at county level. Table shows how true and forecast change in assessment share affect the likelihood of mobility.

Table 14: Δ Gross Tax Rate

	(1) [t]-[t-1]	(2) [t+1]-[t]	(3) [t+2]-[t+1]
Δ Median $\hat{A}_t$ / $\bar{\hat{A}}_t$	3.016	–52.177*	–18.547
	(18.259)	(28.670)	(24.957)
Med $\hat{A}_t$ / Med A_{t-3}	–22.357**	–2.040	–49.833***
	(11.265)	(12.810)	(16.041)
Log(Med. A_{t-3})	0.940	2.036	4.058*
	(1.291)	(1.659)	(2.104)
Constant	14.471	–17.321	10.419
	(14.675)	(18.759)	(24.358)
r2	0.202	0.123	0.180
N	1153	983	903

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.
FE for County by Year. Standard Errors clustered at the school district level. Rates are in mils This table shows how changes in the ratio of median to mean home value within a school district affect voted gross tax rates for school districts.

Table 15: Δ Effective Tax Rate

	(1) [t]-[t-1]	(2) [t+1]-[t]	(3) [t+2]-[t+1]
Δ Median $\hat{A}_t$ / $\bar{\hat{A}}_t$	10.043	–59.730**	–25.127
	(17.210)	(27.679)	(21.847)
Med $\hat{A}_t$ / Med A_{t-3}	–69.983***	–8.232	–47.007***
	(10.898)	(9.833)	(15.797)
Log(Med. A_{t-3})	0.236	2.060	3.860**
	(1.243)	(1.395)	(1.829)
Constant	69.716***	–11.094	9.715
	(15.324)	(13.805)	(18.644)
r2	0.327	0.133	0.196
N	1153	983	903

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

FE for County by Year. Standard Errors clustered at the school district level. Rates are in mils. This table shows how changes in the ratio of median to mean home value within a school district affect effective tax rates for school districts.

Table 16: % Δ Collections

	(1) [t]-[t-1]	(2) [t+1]-[t]	(3) [t+2]-[t+1]
Δ Median $\hat{A}_t$ / $\bar{\hat{A}}_t$	0.012	–0.005	0.016
	(0.063)	(0.017)	(0.022)
Med $\hat{A}_t$ / Med A_{t-3}	0.739***	0.013**	0.013
	(0.049)	(0.006)	(0.008)
Log(Med. A_{t-3})	0.011**	0.012***	0.010***
	(0.004)	(0.001)	(0.001)
Constant	–0.819***	–0.135***	–0.111***
	(0.059)	(0.014)	(0.014)
r2	0.869	0.696	0.483
N	1153	983	903

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.
FE for County by Year. Standard Errors clustered at the school district level. Outcome in percent change. This table shows how changes in the ratio of median to mean home value within a school district following reassessment lead to changes in collections from school district levies in subsequent years.

A Appendix Figures

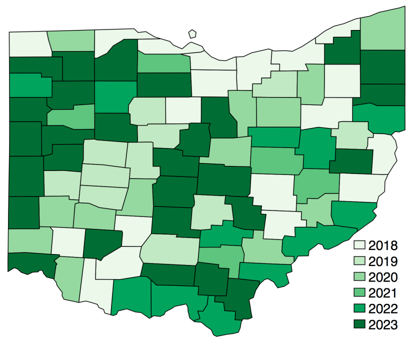


Figure A1: Reappraisal Schedule

B Appendix Tables

Table A1: Price vs. Assessment

	(1) Log Price	(2) Log Price	(3) Log Price	(4) Log Price	(5) Log Price	(6) Log Price
Log(Assessed Value/.35)	1.172***	1.193***	0.983***			
	(0.00122)	(0.00198)	(0.00399)			
Log(Forecast Assessed Value/.35)				1.201***	1.227***	1.050***
				(0.00128)	(0.00208)	(0.00429)
Year One Only		X	X		X	X
Controls			X			X
N	563153	218682	218175	563153	218682	218175
Adjusted R2	0.621	0.623	0.706	0.611	0.614	0.705

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Controls are month-of-year by school district and year by school district fixed effects and hedonic controls. This table shows the relationship between assessed values and realized prices for houses that sell in logs. The sample is restricted to single family homes. Assessed values and forecast assessed values are divided by .35 because Ohio uses a 35% assessment ratio.

Table A2: Linear Controls

	(1) Trad. Sale	(2) Trad. Sale	(3) Foreclosure	(4) Foreclosure	(5) Home Equity Loan	(6) Home Equity Loan
$\Delta \text{Assess}_i/\overline{\text{Assess}}$	0.0361***		0.0129		–0.0512***	
	(0.0121)		(0.00959)		(0.0131)	
$\Delta \widehat{\text{Assess}}_i/\overline{\widehat{\text{Assess}}}$		0.0596***		–0.00172		–0.118***
		(0.00830)		(0.00513)		(0.0119)
Assess-A[t-3] (000)	–0.000871***		–0.000221*		0.00149***	
	(0.000301)		(0.000123)		(0.000397)	
Hat Assess -A[t-3] (000)		–0.00152***		–0.000100		0.00227***
		(0.000272)		(0.0000660)		(0.000333)
Ratio t-3	–0.00198	–0.000571	–0.000595	–0.000635	0.00654***	0.00409**
	(0.00202)	(0.00171)	(0.00172)	(0.00165)	(0.00222)	(0.00156)
Assessment T-3 (000)	–0.0000546	–0.0000669***	–0.000189***	–0.000196***	0.000218***	0.000223***
	(0.0000360)	(0.0000219)	(0.0000416)	(0.0000424)	(0.0000649)	(0.0000516)
N	8952580	8952580	8952580	8952580	8952580	8952580
Number of Clusters	79	79	79	79	79	79
Adjusted R2	0.0130	0.0131	0.0235	0.0235	0.0427	0.0430

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Controls for hedonics and census tract characteristics. FE for tax year X county. Standard errors clustered at county level.

Data provided by Zillow through the Zillow Transaction and Assessment Dataset (ZTRAX). More information on accessing the data can be found at http://www.zillow.com/ztrax. The results and opinions are those of the author and do not reflect the position of the Zillow Group.

Table A3: Forecast Error

	(1) Trad. Sale	(2) Foreclosure	(3) Home Equity Loan
Forecast Error	0.0236**	0.00962	–0.0187**
	(0.0100)	(0.00675)	(0.00744)
N	8952580	8952580	8952580
Number of Clusters	79	79	79
Adjusted R2	0.0131	0.0243	0.0442

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Controls for hedonics, census tract characteristics, and quartic polynomial of initial assessment. FE for tax year X county. Standard errors clustered at county level.

Table A4: Traditional Sales by Home Size

	(1) Trad. Sale	(2) Trad. Sale	(3) Trad. Sale	(4) Trad. Sale
$\Delta\text{Assess}_i/\overline{\text{Assess}}$	0.0341**	0.0342***		
	(0.0135)	(0.0115)		
$\Delta\widehat{\text{Assess}}_i/\overline{\widehat{\text{Assess}}}$			0.0617***	0.0531***
			(0.0153)	(0.0102)
Sample	< 3 beds	3+ beds	< 3 beds	3+ beds
N	1708383	6720274	1708383	6720274
Number of Clusters	79	78	79	78
Adjusted R2	0.0144	0.0116	0.0145	0.0117

Standard errors in parentheses. * $p < .10$, ** $p < .05$, *** $p < .01$.

Controls for hedonics and census tract characteristics. Includes quartic polynomial of initial assessment, assessment change, and initial assessment ratio. FE for tax year X county. Standard errors clustered at county level. Table shows how true and forecast change in assessment share affect the likelihood of sale by number of bedrooms.