Asymmetric Risk of Housing Distress from Property Tax Limitations*

Sebastien Bradley† Da Huang ‡ Nathan Seegert §

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Abstract

Homeowners face risk due to variation in annual property tax liabilities, which may result in financial distress and eventual mortgage foreclosure. By reducing the pro-cyclicality of property tax liabilities, we show that property tax limitations can expose households to greater systematic risk despite reducing intertemporal variation in tax amounts overall. We develop an innovative measure of tax policy risk using Arrow-Debreu securities and obtain simulated measures of risk that capture all of the key characteristics of states' property tax regimes. Using a state border discontinuity design and parcel-level data for the universe of U.S. residential properties, we show that a one standard deviation increase in tax policy risk ($\approx$ \$350) increases the probability of mortgage distress by approximately 0.24 percentage points. The magnitude of this unintended effect is somewhat larger than the increase in probability of mortgage distress associated with owning a home in disrepair and is approximately one seventh as large as the effect of moving between the third and fourth quartiles of the loan-to-value distribution (near the threshold for being underwater).

Keywords: Property Taxation, Assessment Limits, Distress, Mortgage Default, Foreclosure.

JEL Classification: G21, G28, E44, K34, R20

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†*Corresponding author:* School of Economics, LeBow College of Business, Drexel University. 1023 Gerri C. LeBow Hall, 3220 Market Street, Philadelphia, PA 19104. Office phone: (215) 571-4193. E-mail: sbradley@drexel.edu

‡Department of Finance, Northeastern University, Hayden Hall, 412, 370 Huntington Ave, Boston, MA 02115, US. E-mail: da.huang@northeastern.edu

§Department of Finance, University of Utah, 1655 East Campus Center Drive, Salt Lake City, UT 84112, US. Office phone: (801) 585-7131. E-mail: nathan.seegert@eccles.utah.edu

1 Introduction

Concerns over rapidly rising property tax obligations during housing market booms have resulted in the widespread adoption of property tax limitations. Politically, these limitations have proven extremely popular by protecting potentially illiquid homeowners from large increases in their property tax bills while ensuring more stable state and local tax revenues. As such, all but three U.S. states have implemented some type of property tax limitation (Anderson, 2006). These policies reduce intertemporal variation in property tax liabilities by limiting the growth rate of the tax base, tax rates, or their product. However, these policies can also have the perverse effect of increasing homeowners' exposure to systematic risk by allowing property tax liabilities to be higher than they would otherwise be during housing market contractions.

We investigate to what extent this unintended consequence of property tax limitations reallocates risk and leads to costly housing distress. Housing distress can lead to foreclosure and a host of negative externalities related to labor supply (Bernstein, 2021), aggregate demand (Mian et al., 2015), housing investment (Melzer, 2017), and housing prices (Campbell et al., 2011; Hartley, 2014). Indeed, as viewed through the lens of the seminal Domar and Musgrave (1944) risk-sharing result in capital taxation, even without triggering foreclosure, the disproportionate shifting of downside risk onto homeowners under these types of property tax limitations may also dampen housing investment and economic growth.

A priori, the effect of property tax and assessment limitations on mortgage distress is unclear. On the one hand, these limits decrease risk while housing prices are rising because they decrease uncertainty about future tax liabilities. When housing prices are falling, however, assessment limitations may allow liabilities to continue to increase if a parcel's tax assessment remains below its market value. Limits on the growth of aggregate tax revenues may similarly dampen the pro-cyclicality of homeowners' property tax liabilities. As a result, property tax limits have the potential to reduce mortgage distress when housing prices are rising and increase mortgage distress when housing prices are falling—precisely when households are otherwise likely subject to greater illiquidity and possible financial distress. Crucially, this implies that homeowners' property tax burdens from a risk standpoint depend not only on intertemporal variation in tax payments but also on the timing of these payments relative to the state of the economy (i.e., on the *covariance* between tax payments and macroeconomic conditions.)

We construct a measure of tax policy risk that reflects this insight and captures all key features of states' property tax regimes. We estimate the impact of tax policy risk on mortgage distress at the property level to determine whether its magnitude is large enough to warrant consideration in the implementation of state and local property tax systems. This strategy requires parcel-level data, which we obtain from ATTOM Data Solutions and Zillow (ZTRAX) for the universe of residential homes throughout the continental U.S. for the period 2006-2016. These data allow us to observe housing characteristics, property tax assessments and tax liabilities, sales, loan transactions, and foreclosure events. We use imputation and machine learning methods to estimate housing prices for all parcels in years without market transactions to obtain measures of parcel-specific loan-to-value ratios and effective tax rates and thereby isolate their impact on housing distress.

For purposes of identification, we exploit a state border discontinuity design consisting of three different types of border pairs based on county pairs, 10-, and 5 km² U.S. National Grid grid cells and focus on properties located within 20 miles of the nearest state border. We use these resulting border pairs and a within estimator to control for time-varying unobservable local market conditions, including labor or housing market shocks. Our estimation strategy thus compares properties within narrowly defined state border regions as a function of their exposure to tax policy risk resulting from states' varied property tax limitations and related tax system characteristics.

We find that a one standard deviation in tax policy risk ($\approx$ \$350, or slightly more than half the average increase in risk associated with the adoption of assessment limitations) increases the probability of mortgage distress by 0.24 percentage points. This constitutes a significant trigger event for mortgage distress and is somewhat larger in magnitude than the increase in risk of mortgage distress for homes in disrepair, or approximately one seventh as large as the increase in probability of distress associated with moving between the third and fourth quintiles of the loan-to-value distribution (i.e., from an LTV of 0.6-0.91 vs. 0.91-1.6). Furthermore, the effects of tax policy risk are amplified in minority areas and are felt most strongly among severely underwater homeowners (LTV > 1.6), while high average incomes and accumulated housing wealth serve to partially insulate homeowners from risk.

Our paper combines insights from two important literatures on household finance and property taxation. Previous literature on household finance has shown that differences in government policy can create different incentives and pressures that lead to mortgage distress. Earlier work has considered default rates across areas depending on repossession risk (O'Malley, 2021), deficiency judgements (Clauretie, 1987; Jones, 1993; Ambrose et al., 2001; Ghent and Kudlyak, 2011), and judicial requirements (Mian et al., 2015). Policies that increase the cost of foreclosure for either borrowers or lenders are associated with fewer delinquencies and default. Thus, for example, state laws that require foreclosures to proceed through the court system (i.e., judicial review) reduce the frequency of foreclosures on delinquent homeowners, and likewise for state laws that grant lenders the ability to pursue defaulting borrowers for deficiency judgments, i.e., lender recourse (Ghent and Kudlyak, 2011).

There is also a large body of literature that discusses the possibility of various "trigger events" for financial distress, such as unemployment, illness, or change in marital status. Empirical evidence of significant trigger events is relatively scant due to the difficulty of linking homeowner characteristics to loan and housing characteristics (Tian et al., 2016). Gerardi et al. (2017) is a rare exception that evaluates the impact of both strategic default incentives and unemployment as a trigger event. More recently, Low (2022) exploits newly linked administrative and survey data to document that a substantial majority of 90-day delinquent mortgagees cite liquidity problems as contributing to their payment difficulties, such that only around 4 percent of 90-day delinquencies can be classified as purely strategic. Unfortunately, the American Survey of Mortgage Borrowers dataset used by Low (2022) does not ask explicitly about property tax payments as a source of liquidity problems, consistent with the limited attention devoted to property taxes as a possible precipitating factor for mortgage distress (Anderson and Dokko, 2009, 2016; Bradley, 2013; Hayashi, 2020; Wong, 2020). We add to this literature by showing how the unintended consequences of particular property tax provisions may lead to mortgage distress, all the while controlling for homeowners' strategic default incentives based on their loan-to-value position.

A large literature on property taxation studies to what extent property taxes are capitalized into housing prices (e.g., Oates (1969); Wales and Wiens (1974); Rosen (1982); Yinger et al. (1988); Palmon and Smith (1998); Koster and Pinchbeck (2022)) while more recent studies examine the saliency of particular features of property tax regimes (Bradley, 2017, 2018; Cabral and Hoxby, 2012). Thus, for example, Bradley (2017) shows how household inattention to property tax rules related to the implementation of assessment limitations can lead to homebuyers mistakenly treating temporary tax savings as permanent and thus substantially overpaying for their homes. Further work has focused on capital misallocation due to lock-in effects resulting from assessment limitation rules that benefit incumbent homeowners (Quigley, 1987; Wasi and White, 2005; Ferreira, 2010; Ihlanfeldt, 2011; O'Sullivan et al., 1995b). We add to this literature by studying how property tax limitations *collectively* affect market outcomes and reallocate risk between homeowners and local governments, with implications for mortgage distress and eventually housing investment, pricing, etc.. In the process, we utilize a novel method for simulating tax policy risk and provide a synthesized approach—unique to the literature—to evaluating multiple interacting features of state property tax systems.

The remainder of the paper is structured as follows. Section 2 describes the basic mechanics of property taxation in the U.S. and explains the essential characteristics of different types of property tax limitations. Section 3 explains our theoretical method for pricing tax liabilities and its decomposition into tax policy risk and level components. Section 4 describes our data and the construction of key regression variables. Section 5 lays out our primary empirical strategy; Section 6 presents our main results, including a discussion of heterogenous effects and mechanisms; and Section 7 concludes.

2 Property Tax Limitations

Since California's adoption of Proposition 13 in 1978, all but three U.S. states (Hawaii, New Hampshire, and Vermont) have implemented some form of property tax limitations to constrain the growth of state and local governments' budgets and reduce the volatility of property tax collections due to housing market fluctuations. These limitations differ in whether they are intended to restrict tax rates (i.e., statutory "millage" rates), the tax base (i.e., taxable values), or their product. These are referred to as rate limits, assessment limits, and levy limits, respectively. Overall revenue/expenditure limits may also apply and extend beyond property taxes by encompassing other sources of state and local tax revenue. In practice, as shown in Table 1, all but nine states employ some combination of property tax limitations, including four states (Arizona, Colorado, Michigan, and New Mexico) that use some version of all four types of limits.[1]

[1] See O'Sullivan et al. (1995a) for a discussion of the set of factors that precipitated the widespread adoption of property tax limitations in the U.S. Haveman and Sexton (2008) describe the general char-

In this section, we describe the general characteristics of each of the three types of tax limitations that apply exclusively to property taxes. Importantly, the exact implementation characteristics of particular property tax limitations (along with interactions among these) can vary widely from state to state. As discussed in Section 3, this variation is integral to our simulation framework and thus our calculation of households' exposure to tax policy risk.

2.1 Property Tax Basics

Property tax obligations are calculated at the parcel level as the product of the parcel's *taxable value* and the applicable statutory *millage rate* (i.e., the tax amount per thousand dollars of taxable value). Millage rates are set—subject to statewide limitations—at the local level via the political process and commonly combine rates from multiple overlapping taxing jurisdictions (e.g., counties, municipalities, and school districts) and often differ by property class or owners' residency status. Taxable values, on the other hand, are determined as a function of assessed (market) values. Assessed values are in turn intended to reflect the local assessor's best estimate of fair market value based on a combination of mass appraisal methods and market studies. In the simplest case, under a system of market-value based assessments with annual reassessments and a 100 percent assessment ratio, taxable values and assessed values coincide, and property tax obligations are solely determined by market values and the local millage rate.

In practice, however, states frequently apply assessment ratios of less than 100 percent, do not reassess or appraise property on an annual basis, or apply assessment limitations—all of which can lead taxable values to differ from assessed market values.[2] As reported in the last column of Table 1, the frequency of legally-mandated reassessments varies substantially across states. Reassessment intervals range from as little as one year (e.g., Alabama, Georgia, Idaho, etc.) up to as long as eight years in North Car-

acteristics of assessment limitation regimes and other types of property tax limits. Numerous papers examine whether state and local tax limitations are in fact effective at constraining local governments (e.g., Poterba and Rueben (1995); Cutler et al. (1999); Dye et al. (2005); Brooks et al. (2016); Eliason and Lutz (2018)). We refer the reader to the Lincoln Institute of Land Policy's "Significant Features of the Property Tax" database for a succinct description of individual state provisions and their evolution over time.

[2]Without pre-existing rate limitations, assessment ratio designations are wholly arbitrary as rates could merely be adjusted accordingly in order to raise the desired level of property tax revenue. Anecdotally, assessment ratios of less than 100 percent are said to arise after major statewide reassessments to preserve revenue neutrality without necessitating statewide rate changes.

olina, while several states have no statutes dictating a specific reassessment frequency (e.g., Delaware, New Hampshire, Pennsylvania, etc.).[3] We turn next to a discussion of assessment limitations, but we note first that infrequent reassessments—such as the 20+ year intervals between county assessments that commonly occur in Pennsylvania—can act as a very strict de facto assessment limitation regime. This has important implications for the calculation of tax policy risk and the relevant "no policy" counterfactual against which risk is measured, and we return to this point in Section 3.

2.2 Assessment Limits

Assessment limits generally restrict the growth rate of taxable values that can occur over time, regardless of the evolution of housing prices (and therefore assessed values). However, states differ in their choices of capped growth rates and applicable property classes, as well as in their treatment of properties after a change of ownership. California's Proposition 13, for instance, mandates a maximum annual growth rate equal to the lesser of 2 percent or the rate of statewide inflation for all classes of property, with resetting (i.e., "uncapping") of taxable values to current market value occurring immediately following an arm's length transaction.[4] Other states apply maximum capped growth rates that are unlikely to bind (e.g., Minnesota's since-eliminated Limited Market Value Law, which had a cap equal to the greater of 15 percent or 25 percent of the change in market value), apply to only a small subset of homeowners (e.g., Arkansas) or exclusively to primary residences (e.g., the District of Columbia, Maryland), do not trigger taxable value uncapping as a result of changes of ownership (e.g., Arizona, Oregon), apply only to certain localities as a local option (e.g., Georgia, Illinois, New York), apply only to aggregate taxable values (e.g., Colorado, Iowa), or merely stipulate phasing in of property reassessments (e.g., Connecticut, Montana). For purposes of our analysis, and as shown in Table 1, we hence distinguish the "traditional" acquisition value based assessment limitations that more closely resemble California's Proposition 13 from other forms of assessment limits. Figure 1 depicts the geographic distribution of these different types of assessment limitation regimes.

[3] Not coincidentally, assessment limit states all perform annual "reassessments" either formally or informally.

[4] Ferreira (2010) examines how a carve-out for 55+ year olds moving within county relaxes the lock-in effect that otherwise results from California's restrictive form of acquisition value based assessment limitations.

During housing market downturns, California's Proposition 8 amendment—also adopted in 1978—stipulates that properties' taxable values may temporarily fall below their "factored base year value" in cases where this is justified on the basis of reassessed market values, but subsequent reassessments may dictate increases in taxable values that exceed the 2 percent capped rate (until the factored base year value is once again reached).[5] States with otherwise similar assessment limitation systems likewise allow for reductions in taxable values during market downturns, albeit without necessarily employing the same statutory language as in Proposition 8. For instance, in Michigan, where annual reassessments are automatic, taxable values may continue to rise at the capped growth rate even as property values are falling so long as taxable values remain below the current assessed market value (as might occur after a period of sustained housing price growth in excess of the state's capped growth rate). Once both values converge, further reductions in assessed market values must bring about commensurate reductions in taxable value, and there is no subsequent provision for "catching up" to some alternative base year value once house prices begin rising again. In either case, the treatment of taxable values for homes whose market values are declining implies that reductions in tax liabilities are prone to occur with a lag (if at all) in states with assessment limitations relative to states where taxable values rise and fall in direct proportion to market values, as in states with market value based assessments (assuming frequent reassessment). Figure 2 illustrates a hypothetical version of this scenario. The risk—as we formalize in the next section—is that despite limiting tax liabilities when property values are rising, assessment limitations may result in smaller reductions (or even ongoing increases) in tax liability during market downturns—precisely when times are bad and households may already be at greater risk of financial distress. Asymmetric adjustments to property tax liabilities in assessment limitation states could thereby exacerbate the negative consequences of housing market downturns and act as a trigger event for mortgage foreclosure.

Figure 3 provides preliminary evidence of the aforementioned effects of assessment limits in the data. As shown, homes in assessment limitation states experienced far more pronounced swings in average prices (solid red) than homes in other states (solid blue), both during the initial market downturn and the subsequent run-up. Meanwhile, tax

[5]Factored base year value is defined as a property's market value at the time of purchase (or 1975, whichever is more recent) adjusted by the state's annual growth factor over the set of intervening years of ownership.

liabilities remained relatively elevated in both groups of states (shown in dashed red and blue) through the initial years of the market downturn–suggesting that taxable values are generally sticky downwards everywhere. However, *relative to the magnitude of the corresponding reductions in prices*, taxes adjusted faster and to a greater degree to declining prices in the set of states without assessment limits. These differences in adjustment rates are depicted directly in Figure 4, where each line corresponds to the percent change in tax liability minus the percent change in price. This "tax-price adjustment gap" peaked at nearly 15 percentage points in 2008 and 2009 for assessment limitation states–nearly double the corresponding amounts for states without assessment limits.

2.3 Rate Limits

Rate limits restrict the rate at which property may be taxed by the tax authorities. These are most often expressed in terms of millage rates and commonly involve different caps for different levels of government. For purposes of our analysis, we aggregate these limits across taxing jurisdictions to obtain a single state-level maximum millage rate.[6] Elsewhere, rate limits are instead set on statewide basis as a percentage of fair market value, without specifying each taxing jurisdictions' allowed rate, or they restrict millage rate *growth*.[7] Figure 5 depicts the geographic distribution of statutory millage rate limitations (expressed as percentages of fair market value for comparability across states). Outside of the Northeast, rate limits are commonplace.

In many cases, only a subset of taxing jurisdictions' millage rates are capped (e.g., by excluding school districts, such as in Alabama, Arkansas, Delaware, etc.), rate limits do not apply to rates for debt servicing, or they are subject to voter override (with differing vote thresholds). It is reasonable to expect that different states' rate limits may therefore be more or less effective at constraining overall property tax rates.[8] Insofar

[6]For example, the Lincoln Institute's Significant Features database says the following about Kentucky's property tax rate cap: "[t]he tax rate shall not exceed for counties 5 mills, for municipalities 7.5-15 mills on a sliding scale based on population, and for school districts 15 mills." In this case, we treat Kentucky as if it has a state-wide rate limit of 35 ($= 5 + 15 + 15$) mills.

[7]Colorado, for example, caps municipal rates at the prior year's level, thereby effectively imposing a growth rate limit of zero. South Carolina instead limits the growth in millage rates in relation to inflation plus population growth.

[8]In order to gauge whether rate limits are binding for purposes of our tax risk simulations, we compare states' median effective tax rates for newly-purchased homes (to avoid the confounding influence of assessment limits) with their statutorily capped rates (standardized to be defined relative to 100 percent of fair market value). If the effective rates observed in the data are significantly higher, we either treat the

as rate limits are ever binding, this is more likely to occur when property values are falling as a result of local jurisdictions trying to raise the same amount of property tax revenue off of a smaller tax base. If a jurisdiction previously imposed a tax rate of 1.4% and property values fell by 10 percent, for example, the tax rate would need to rise to 1.56% ($1.4\%/(1-0.1)$) in order to maintain the same level of property tax revenue. A rate limit of 15 mills in this case would interfere with this adjustment, and the tax rate would be restricted to 1.5% despite the jurisdiction wanting to collect a higher amount of revenue from its property tax. From the perspective of individual taxpayers, this implies that rate limits should dampen counter-cyclical fluctuations in millage rates and—absent other property tax limitations—should yield more pro-cyclical tax liabilities, contrary to assessment limitations.

2.4 Levy Limits

Levy limits restrict the amount of aggregate property tax revenue (i.e., tax levies) that a local government can collect from property owners within its jurisdiction. Typically, these are expressed in terms of limiting the percentage growth in aggregate property tax revenues relative to the prior year and can be defined as a fixed percentage amount, a number anchored to inflation, or some function of the two. Other states instead restrict property tax levies as a share of aggregate fair market value, while some states restrict both the growth rate and total tax levy in relation to aggregate market values.[9] Figure 6 depicts the geographic distribution of levy limits (based on percentage growth limits—limits on levy amounts or other revenue/expenditure limits are included in "Other"). Outside of the Southeast, these are widely used.

Levy limits are more likely to bind when property values are rising as a result of

state as if it does not have a rate limit at all (e.g., Alabama, Arkansas, Georgia, etc.) or look to additional legislative language that might suggest an alternative higher limit. (For example, Michigan's basic rate limitation is set at 15 mills, excluding debt service; however, this rate can be increased by voter override up to a rate of 50 mills. Given a 50 percent assessment ratio, this translates to a 2.5% rate as a percent of market value. In the data, we observe a median effective rate ranging from 1.6 to 3.1% over our sample period, with most years falling within $\pm$ 0.3 percentage points of 2.5%, and we thus treat Michigan as having a binding rate limit of 2.5%.)

[9] For instance, Massachusetts' Proposition $2\frac{1}{2}$ restricts local property tax levies to grow no faster than 2.5 percent per year and to collect an amount of tax revenue not to exceed 2.5 percent of assessed market value. The latter is comparable to a rate limit of 2.5%, albeit one which only applies to the local tax base in the aggregate, such that individual properties in MA may still face a tax rate over this amount (e.g., commercial property).

property tax revenues exceeding the allowed amount, in which case local jurisdictions must reduce their millage rates to comply with the levy limit. For example, if a jurisdiction in a state with a 5% growth levy limit expected to raise 110 percent of the prior year's revenue at unchanged tax rates due to housing price appreciation, it would need to reduce its millage rates by 4.8 percent ($0.0476 = 1.1/1.05 - 1$) in order to yield no more than 105 percent of the prior year's levy amount. When combined with restrictive rate limits that are also defined in terms of percentage growth (e.g., Colorado), this can result in a "ratcheting down" phenomenon, whereby rate reductions that occur during boom times can never be relaxed thereafter and thereby limit states' flexibility in raising rates during housing market downturns. More generally, levy limits should dampen pro-cyclical fluctuations in property tax obligations, especially in states that do not otherwise limit taxable value growth.[10] Much like assessment limits, however, this dampening effect ought to predominantly affect tax obligations during periods of rising housing prices. During periods of declining values, levy limits of the percentage growth variety do not preclude rising tax obligations.

3 Pricing Property Tax Risk

3.1 Framework for pricing tax risk

People generally dislike paying taxes, dislike paying higher taxes, and especially dislike paying higher taxes in bad times when the economy is slowing. We define tax risk to capture people's dislike of paying higher taxes in bad times. In the context of property taxation, property tax limitations can shift tax liability relative to the state of the economy. [11]

Consider assessment limits. If a property with an initial value of $100,000 has a 10% annual growth rate, its market value will increase to $110,000 in the second year, $121,000 in the third year, and $235,794 in the tenth year. If there is a 3% assessment limit, its taxable value will increase to $103,000 in the second year, $106,090 in the third

[10] As noted above, some states also limit growth in tax revenues from all sources, not just property taxes. We treat such revenue limitations as having a proportional effect on property taxes (i.e., equivalent to levy limitations).

[11] Note, that in the context of income taxation, progressivity acts as an automatic stabilizer where people pay less in taxes and at a lower rate in bad times and higher taxes and at a higher rate in good times (Dauchy et al., 2021).

year, and \$130,477 in the tenth year. Now, suppose there is a market downturn after 11 and 12 years and the market value drops to \$170,000 and \$140,000, respectively. The taxable value in these years continues to increase (because it is below the market value) to \$134,391 and \$138,423. As a result, property tax payments can increase even as market values are decreasing. We demonstrate this scenario in Panel (a) of Figure 2. The blue line depicts the tax payments under market value assessments, where the payments increase in good times and decrease in bad times. The red dashed line depicts the tax payments under ,assessment limitations, where tax payments increase at a slower rate than market value assessment in the good times and continue to increase in the bad times. The red solid line adjusts tax payments for revenue neutrality, noting that governments with assessment limits often have higher mill rates to keep average payments the same. This figure demonstrates the shift in tax payments with assessment limits; lower payments in good times and higher payments in bad times relative to market value assessments.

In panel (b) of Figure 2, we show that in the data tax payments often increase when market values decrease. This panel plots the distribution of the probability that a property sees its tax liability increase while the property value decreases within each state-year in our sample. The most common scenario is that tax payments increase as the market values increase, roughly 45% of the time. The second most common scenario, however, is that tax payments increase when market values decrease, roughly 35% of the time. This panel highlights that the scenario depicted in Panel (a) is a common occurrence in the data.

In panels (c) and (d) of Figure 2, we show tax payments for a representative property in California, which has assessment limitations, and Nevada, which does not. In Panel (c), we see that tax payments for this property in California (depicted as a red line) increased from 2006 to 2012 despite the property value (depicted as a blue line) decreasing. In Panel (d), we see that tax payments for this property in Nevada (depicted as a red line) decreased from 2007 to 2011 as property values (depicted as a blue line) decreased.

The key insight is that an individual's tax burden depends on both their tax liability (how much they have to pay) and their economic conditions (when they have to pay it). We capture this insight by calculating the tax burden as a weighted sum of tax liability where tax liability in bad economic times is weighted more than tax liability in good times. Two tax schedules that generate the same tax liability will have different tax burdens if the timing of those payments differ. For example, if one tax schedule has higher payments in good times and lower payments in bad times, that tax schedule will have a lower tax burden than the tax schedule that has relatively lower payments in good times and higher payments in bad times. Tax risk, therefore, is about when tax payments arise. This type of risk is likely systemic, such that it cannot be diversified away, because it depends on economic conditions such as recessions and wars.

One way to weight tax liability is with Arrow-Debreu security prices. Arrow-Debreu state-contingent securities capture the value of an asset paying an additional dollar in a given state of the world. Consider the following example with two states of the world, good times and bad times, that occur with equal probability. The price of the AD security that pays 1 in the good state is 0.2 (less than the expected return of 0.5) and the price of the AD security that pays 1 in the bad state is 0.8 (more than the expected return again of 0.5). These prices combine the value of a marginal dollar in each state of the world and the probability that the state of the world occurs (e.g., $0.8 = 1.6 \times 0.5$). The price is greater for the AD security that pays out in the bad state of the world because the value of additional consumption is higher (i.e., marginal utility in the bad state is higher). The following table describes this hypothetical economy:

	Good Times	Bad Times	Price
Arrow Debreu 1	1	0	0.2 ($= 0.4 \times 0.5$)
Arrow Debreu 2	0	1	0.8 ($= 1.6 \times 0.5$)
Risk-free Bond	1	1	1 ($= 0.2 \times 1 + 0.8 \times 1$)

In this economy, a risk-free bond that pays 1 in both states (by implicitly combining both AD securities) would be priced at $1 ($1 = 0.2 \times 1 + 0.8 \times 1$). The payment of 1 is weighted by 0.2 in the good times and 0.8 in the bad times. A security that would pay $2 in good times and $0 in bad times has a price of $0.4 ($= 0.2 \times 2$) and a security that pays $2 in bad times and 0 in good times has a price of $1.6 ($= 0.8 \times 2$). Each of these securities has an expected payoff of $1 but has very different prices. The security that pays in the bad times is worth more than the security that pays in good times. Arrow-Debreu securities, therefore, capture the key insight that the pattern of payments matters.

Weighting tax payments with Arrow-Debreu securities comes with the additional benefit that we can quantify the risk of tax payments in terms of a risk price. To see this, consider three property tax regimes with either no tax limits, loose limits, or strict limits. Under the no-limit regime, the property owner pays \$4 in property taxes in the good state in which property values are high and pays \$1 in property taxes in the bad state when property values are low. Property tax limits restrict how much tax liabilities may rise in good states, but they also restrict how much they may fall in bad states, and indeed more restrictive tax limitations can even give rise to increased tax liabilities in bad states of the world. In the good state, suppose therefore that the property owner subject to the loose-limit regime pays \$3 instead of the \$4 in the no-limit regime. In the bad state, the property owner pays \$2 instead of \$1 in the no-limit regime. Under the strict-limit regime, the property owner pays even less property tax in the good state, specifically, \$2, and pays more in the bad state, specifically, \$3. One interpretation of the payments in the strict-limit regime is that the government charges more in the bad state to hit its expected revenue targets. The following table describes this stylized example:

	Good Times	Bad Times	Expected	Std. Dev.	Arrow-Debreu Price	CE Price	Risk Price
No Limit	4	1	2.5	1.5	1.6 ($= 0.2 \times 4 + 0.8 \times 1$)	2.5	-0.9
Loose Limit	3	2	2.5	0.5	2.2 ($= 0.2 \times 3 + 0.8 \times 2$)	2.5	-0.3
Strict Limit	2	3	2.5	0.5	2.8 ($= 0.2 \times 2 + 0.8 \times 3$)	2.5	0.3

In all three limit regimes, the expected payment is the same, \$2.5. The difference in the regimes is in its standard deviation *and* the timing of the payments. The standard deviation of tax payments is highest in the no limit example, at 1.5. The standard deviation of tax payments in the loose limit and strict limit are both the same, 0.5. Note, however, despite the standard deviation being the same with loose and strict limits, the timing of the payments differs and this will lead to different risk prices.

We calculate the Arrow-Debreu prices for these three property tax limit regimes and decompose them into a certainty equivalent price and a risk price. The Arrow-Debreu prices weight the payment in the good times by 0.2 and payments in the bad times by 0.8. This leads to Arrow-Debreu prices of 1.6, 2.2, and 2.8 in the no limit, loose limit, and strict limit property tax limit regimes, respectively. We calculate the certainty equivalent price by considering the price if tax payers paid the expected value in both good times and bad times; $2.5 = 0.2 \times 2.5 + 0.8 \times 2.5$. In this case, the certainty equivalent price is the expected value, which is the same for all three property tax limit regimes.[12]

The risk price is the difference between the total Arrow-Debreu price and the certainty equivalent price. This risk price, therefore, abstracts from level differences in tax payments.[13]In the no limit regime, the risk price is -$0.9, which means that from a risk perspective, the no limit regime provides insurance to individuals. In the loose limits regime, the risk price is -$0.3. Again, the property tax provides insurance but less than in the no-limit regime. Finally, in the strict limit regime, the risk price is $0.3, meaning that the limit increases risk, such that individuals would be willing to pay $0.3 to pay the certainty equivalent price rather than the amount owed under the strict limit regime.

The strict limit has the highest risk price despite it having a lower standard deviation than the no-limit regime and the same standard deviation as the loose limit regime. This example highlights the difference between risk and volatility. The no-limit regime has higher volatility (measured by, for example, standard deviation) but is less risky than the strict-limit regime.

3.2 Tax Policy Simulation

We use a purpose-built property tax simulation to isolate the policy effect of property limitations. As discussed in Section 2, property tax liabilities reflect the effects of both tax policies and economic conditions. Our simulation allows us to hold fixed economic conditions.[14] The simulation provides us with tax payments as a result of different property tax limitations that exist in each state-year. We then apply our tax risk framework to price the risk associated with the policy choices of each state.

Concretely, we construct a panel of 500 simulated properties (indexed by i) over 50

[12]Note, that the certainty equivalent price does not always equal the expected value. For example, if the Arrow-Debreu prices in the good times were 0.6 instead of 0.8, then the certainty equivalent prices would be less than the expected values; $2 = 0.2 \times 2.5 + 0.6 \times 2.5$.

[13]For example, consider the scenario where in the good times in the no limit regime tax liability is $5 instead of $4. In this case, the expected payment is $3, the Arrow-Debreu price is $1.8, and the certainty equivalent price is $2.4. The risk price, then is -$1.2.

[14]We do not model local option tax limitations, as the details of these regimes are poorly tracked, especially on a historical basis. Thus, for example, we treat Georgia as having no assessment limitations outside of the years 2009-2010, despite the state allowing local assessment freezes in other years, or we assume a 10 percent capped taxable value growth rate for Maryland's assessment limitation regime, despite the state allowing for lower caps at the county level.

years (indexed by z). We capture the economic conditions with a property's market value, whether it transacts that year or not, and the property owner's consumption (consisting of both aggregate and idiosyncratic shock components). We calibrate the economy using the Case-Shiller U.S. National Home Price Index, Consumer Price Index, and personal consumption expenditures from the Consumer Expenditure Survey. We apply the tax policy of state s in year t and calculate the tax liability, $q_{i,z,s,t}$, using the same underlying economic conditions. We repeat the simulation 1,000 times with different underlying economic processes.

In Figure 7, we graph the property tax liability, $q_{i,z,s,t}$, over the simulation horizon for the same property (i.e., for a particular i) with the same economic shocks under different states' tax policy in 2016 (i.e., $t = 2016$). Vertical lines indicate recession years. Differences between tax amounts across series are due only to differences in states' combined property tax policies, including property tax limits, property tax rates, and assessment frequency. The two highlighted series are Nevada and California. Compared to the rest of the states (displayed in gray), Nevada and California's property tax systems yield relatively low property tax liabilities due to their stringent tax limits (3% levy limit for NV and the lower of 2% or CPI inflation assessment limit for CA). A key distinction between the two tax systems is that California's assessment limitation regime triggers taxable value uncapping upon sale. The uncapping results in the spike in property tax liability for California property at year 45, while Nevada's levy limit regime leads to a much more stable series of property tax liability.

For additional details about this simulation procedure, see Appendix A.

3.3 Tax Policy Risk

We calculate the risk price for the series $q_{i,z,s,t}$ and take the mean across properties to obtain a risk price, $\mathbb{R}_{s,t}$, for state s and year t. We also calculate a counterfactual risk price, $\mathbb{R}'_{s,t}$, from a tax liability series for state s in year t without any tax limitation policy. The increase of tax risk attributable to tax limitation policy, which we define as *Tax Policy Risk*, is therefore:

$$\textit{Tax Policy Risk}_{s,t} = \mathbb{R}_{s,t} - \mathbb{R}'_{s,t}$$

We similarly calculate *Tax Policy Level Diff* as the certainty equivalent part of the overall tax price.

Figure 9 shows how *Tax Policy Risk* differs across states. The dollar amounts shown on the map represent the amount of money (averaged across policy years 2006-2016) that the owner of a $300,000 home would be willing to pay in different states to eliminate all risk associated with property tax limits.[15] As shown, there is considerable variation across states, from a high of $1,279 in New York state to a low of -$270 in South Carolina. These estimates indicate that New York's tax system adds considerable risk while South Carolina's property tax regime provides some insurance. Broadly, these differences reflect the effects of all of the interactions among states' multiple property tax system characteristics. We replicate Figure 9 in Figure 10 with risk prices rescaled to match states' median house prices. This implies a substantially lower level of risk for the median property owner in lower property value states like Michigan, whereas this has less impact on tax policy risk in states with higher property values.[16]

In Table 3, we provide evidence of how much different types of property tax limits affect our estimates of property tax risk. The fullest specification (column 4) includes indicator variables denoting the application of particular tax limits in a given state-year—$\mathbb{1}(\text{Levy Limit})_{s,t}$, $\mathbb{1}(\text{Rate Limit})_{s,t}$, and $\mathbb{1}(\text{Assessment Limit})_{s,t}$. This specification is given by

$$\begin{aligned} \textit{Tax Policy Risk}_{s,t} = &\beta_0 + \beta_1 \mathbb{1}(\text{Levy Limit})_{s,t} + \beta_2 \mathbb{1}(\text{Rate Limit})_{s,t} \\ &+ \beta_3 \mathbb{1}(\text{Assess. Limit})_{s,t} + \varepsilon_{s,t}. \end{aligned} \tag{1}$$

We report the effects of levy, rate, and assessment limits on *Tax Policy Risk* estimated separately in columns 1-3 of Table 3, respectively. Relative to an unconditional average

[15]Note that this is distinct from the amount that homeowners would be willing to pay to avoid the overall difference in property tax obligations that is attributable to property tax limits, which reflects both the certainty equivalent (*Tax Policy Level Diff*) and risk components (*Tax Policy Risk*) of the tax price. Abstracting from level differences can be justified on the grounds that such differences should be fully capitalized into prices; that property taxes are a pure benefits tax; or that states raise similar amounts of revenue across all tax instruments at their disposal, such that lower property taxes are offset by higher taxes on household consumption elsewhere.

[16]Insofar as a $300,000 home represents a different segment of the housing market in different states, however, it may be inappropriate to base states' revenue requirements on non-representative housing values. For example, Michigan might not levy as high of effective property tax rates if median house prices were $300,000 instead of between $75,000 and $125,000, as in the data. This issue is a moot point for our empirical analysis as we control explicitly for parcel-level housing prices and effective tax rates.

value of \$319, *Tax Policy Risk* is on average \$198 higher in states with levy limits, \$143 higher in states with rate limits, and \$336 higher in states with assessment limits. These numbers are similar when we include all types of property tax limitations in the same specification (column 4), albeit somewhat smaller for levy limits (\$105) and assessment limits (\$325) and larger for rate limits (\$254).

In Figure 8, we show how policy risk (vertical axis) changes as different property tax limits increase (horizontal axis). In Panel a, we consider property tax limits in isolation, with the others turned off. With strict limits, on the left of the graph, policy risk is between \$500 and \$400. As the limit increases, and becomes less strict, policy risk decreases. The policy risk is near zero for mill rate limits near 5%, levy limits near 5.5%, and assessment limits near 8%. In Panel b, we set the other property tax limits to their average amount. For strict limits, on the left of the graph, the policy risk is between \$500 and \$750. The policy risk decreases as the property tax limits become less strict, moving right on the graph, but do not go to zero because the other property tax limits remain at their average level.

Overall, these results imply that households would be willing to pay between approximately \$150 and \$350 annually—*on average*—to avoid the risk consequences associated with these different types of property tax limitations. For the set of households that are more susceptible to liquidity shocks, such that this risk leads to mortgage distress, the costs are certainly much higher.

We end this section with a quick review of our approach to defining tax policy risk and relevant terminology. First, we defined the *tax price* as the Arrow-Debreu security price of the stream of tax payments. Second, we decomposed the *tax price* into the *risk price* and *certainty equivalent price* to separate differences in risk and level of tax payments. Finally, we defined *tax policy risk* and *tax policy level diff* as the risk price and certainty equivalent price of simulated tax payments that isolate the effect of property tax limitations by holding fixed economic conditions across states in the simulation. We use *tax policy risk* to test whether property tax limits are increasing tax risk in a way that leads to more housing distress.

4 Data

We combine data from ATTOM Data Solutions and Zillow (ZTRAX) into a comprehensive panel of parcel-level data spanning the continental U.S. for the period 2006-2016 to ensure the broadest possible coverage of property tax assessment, realty transaction, loan, and foreclosure records for our analysis. To the best of our knowledge, we are the first to combine both data sources in this manner, which consists of matching parcels based on county-level administrative parcel identification numbers or street address and zip code. This has the virtue of allowing us to fill gaps in the ATTOM data wherever it is lacking in terms of historical coverage, geographic coverage, or available variables, while overlapping observations serve to validate our matching procedure and general data reliability.[17]

These data include variables on sale prices and dates, assessed values, tax payments, loan amounts, indicators for distress or foreclosure transactions, and housing characteristics such as square footage, lot size, number of bedrooms, number of bathrooms, garage type and size, etc.. In order to account for potential strategic default incentives, we augment these data by calculating annual property values and loan balances that allow us to construct loan-to-value ratios (LTV). Property values are also used in the construction of effective property tax rates (ETRs) to control for households' relative tax burdens, as well as in the measurement of housing price growth relative to tax liability.

We use two different methods to calculate annual property values—an imputation method and a hedonic estimation method—and we use whichever method produces the longer parcel-specific history for each property in our analysis. For the imputation method, we link arm's-length real estate transaction records to Zillow's monthly zip-level housing price indices and the Federal Housing Finance Agency's (FHFA) annual zip-level indices, and we extrapolate housing values forward and backward based on local pricing trends using both indices individually. Each provide different coverage.[18] Where feasible, we average the resulting imputed annual values. This procedure has the advantage of being straightforward to implement. However, it only works for properties

[17]In cases where values for the same parcel-year observation disagree between data providers, we first strive to use observations that are adjacent in time to identify possible mistakes in the data; otherwise, we default to the use of data from ATTOM Data Solutions based on their reputation (for superior coverage of foreclosure events) and practical considerations related to data licensing.

[18]Zillow's housing price indices are available back to January 1996 for approximately half of all zip codes, with gradually increasing coverage over time, whereas the FHFA's indices are available back to 1975.

for which we observe at least one arm's-length transaction during the period for which the Zillow or FHFA housing price indices are available. Our hedonic estimation method circumvents the lack of own-price transaction information by using transaction prices for nearby properties and applying machine learning methods to estimate annual house prices as a function of available property characteristics. Concretely, we use machine learning techniques in two steps. First, we use machine learning methods to select the set of property characteristics to include in the hedonic model, which we allow to differ by Census tract as a function of data availability and predictive fit. The model selected for properties in each tract is the one that performs the best in predicting house prices out of sample. Second, we use machine learning methods to select the size of the training set—specifically, the number of neighboring Census tracts to include for each focal tract. How many neighboring Census tracts we use is allowed to differ for each Census tract and is determined by the set that performs the best out of sample.

To calculate annual loan amounts, we combine data from the Federal Housing Administration on average national monthly interest rates and average state-level annual rates to construct state-specific monthly interest rate series for the two most popular mortgage types identified in our data—15 and 30-year fixed-rate mortgages. We use the resulting series to impute annual loan balances for all loan transaction records assuming full monthly payments.[19] Taking the ratio of imputed loan balances to property values yields our desired time-varying parcel-specific estimates of LTV, which we subsequently classify into discrete intervals.

We geocode all parcels with valid street address and zip code information using ArcGIS, and we use the resulting latitude and longitude coordinates to calculate the shortest distance as the crow flies from each parcel to all neighboring counties located in other states, up to 20 miles. We also link parcels based on latitude and longitude to the U.S. National Grid coordinate system, which bears no relationship to administrative boundaries, and we assign parcels to both 5- and 10 km^2 grid cells accordingly.

The resulting dataset consists of approximately 390 million parcel-year observations with non-missing property values distributed throughout the continental U.S., of which roughly 100 million are located in state border counties within 20 miles of the nearest

[19] Initial interest rate information is infrequently populated in either ATTOM or ZTRAX and typically only for adjustable rate mortgages. Term information is more consistently recorded, but it is also nevertheless imperfect. Absent other information, we assume 30-year fixed rate mortgage rates for all new mortgage loans and refinancing transactions to calculate monthly payments.

state border. Besides restricting ourselves to parcels within (at most) 20 miles of a state border for purposes of our state-border discontinuity design, we also exclude from our initial sample (i) all homes that are ever valued in excess of $5 million or less than $1000 in an arm's-length transaction, (ii) newly built or substantially remodeled properties, (iii) properties with effective property tax rates that fall below the 1st percentile or above the 99th percentile of the relevant state distribution, and (iv) properties that exhibit excessively large changes in annual tax obligations or assessed values that cannot be attributed to (re)construction, changes in owner occupancy, or, as in states with acquisition value assessment limitations, changes of ownership. Broadly speaking, the intent of these sample restrictions is to capture the experiences of the vast majority of property owners with respect to property taxation while mitigating the influence of misrecorded data and (rare) true outliers. The argument for (ii) is somewhat distinct and reflects both practical and theoretical considerations in that it is very difficult to establish what constitutes an "excessive" change in annual tax liability for construction that occurs over multiple years, and the owners of such properties commonly face distinct mortgage financing environments, either as developers, flippers, or buyers of builder-financed homes.

We also exclude data from ten price non-disclosure states due to a lack of sufficient transaction information to estimate our hedonic pricing model or to credibly implement our border pair fixed effects analysis. These states are Idaho, Kansas, Louisiana, Mississippi, Montana, New Mexico, North Dakota, Texas, Utah, and Wyoming. The existence of non-disclosure laws restricting the availability of transaction prices information also dictates the exclusion of all but four political subdivisions of Missouri.[20]

For purposes of our empirical analyses, missing data for certain key variables naturally result in further sample truncation. Nevertheless, our initial border sample represents approximately $2.75 trillion in total property value and $49.6 billion in property tax liabilities as of 2016 and encompasses nearly 1.9 million foreclosure events over the period 2006-2016.[21] After implementing all of the aforementioned sample restrictions,

[20] St. Louis City, St. Louis County, Jackson County, and St. Charles County each require sale price disclosure via local ordinance, unlike the rest of the state of Missouri.

[21] Altogether, we capture 8.1 million foreclosure events in our full sample for the continental U.S., slightly less than half the number reported by ATTOM Data Solutions in their annual tallies. (See e.g., `https://www.attomdata.com/news/market-trends/foreclosures/attom-webinar-summary-what-to-expect-in-the-distressed-real-estate-market/`.) This discrepancy owes in part to our inability to match foreclosure events to parcels for which we otherwise do not observe any arm's length real estate transactions, along with other sample restrictions. It is also unclear how sequences of foreclosure events (e.g., the issuance of a notice of default followed by a notice of

we finally limit our data analysis to a 33 percent random subsample of all parcels for computational tractability.

In order to ensure the success of our border-pair identification strategy—namely, our ability to isolate the impact of property tax limitations at state borders from other sources of coincident variation in mortgage distress—we strive to control for other important state-specific policies that may also influence default probabilities. Thus, we follow Ghent and Kudlyak (2011) and Mian et al. (2015) and utilize their designations of states which allow foreclosures to proceed without judicial review (i.e., nonjudicial review) or allow lenders to pursue defaulting borrowers through deficiency judgments (i.e., lender recourse). Data on time-varying state-level property tax limitations are drawn primarily from the Lincoln Institute of Land Policy's "Significant Features of the Property Tax" database (Lincoln Institute of Land Policy and George Washington Institute of Public Policy, 2023).

Table 2 summarizes the set of means, medians, and standard deviations for our key regression variables, based on our main estimation sample. Distressed properties are defined as any property which entered into foreclosure proceedings in a given year, regardless of whether the borrower was able to cure their loan or whether the property was ultimately repossessed by the lender or sold via foreclosure auction or short sale. *Tax Policy Risk* and *Tax Policy Level Diff* are calculated as described in Section 3.3 and measured in thousands of dollars. LTV is imputed as described above and ultimately classified into six discrete categories based on quartiles of the LTV distribution for $LTV < 1.6$ along with a fifth category for $LTV \geq 1.6$, and a sixth category for all properties with unknown LTV. Homeowner tenure, age, and renovation age are categorized in a similar manner.[22] We report values separately for distressed and non-distressed properties, with differences in means reported in the final column of Table 2. All differences in means between groups are statistically significant with p-values uniformly well below 0.001. Distressed properties thus face modestly greater tax policy risk (despite a lower absolute tax price), higher average LTVs[23], and higher effective tax rates. Distressed properties are

trustee sale and/or other foreclosure auction) are treated for purposes of ATTOM's annual tabulations, whereas we only count the first foreclosure event in a sequence of related transactions. Figure A.1 shows the evolution of foreclosure activity in our complete national sample 2006-2016.

[22] Renovation age differs from age insofar as year remodeled differs from year built in the data. Where year remodeled is missing, we assume that it coincides with year built.

[23] The continuous distribution of imputed LTVs points to the existence of large outliers. This issue is mitigated in our analysis by using discrete LTV categories. Median LTVs are of a plausible magnitude.

also significantly less valuable, have short-tenured homeowners, and are modestly older and less recently renovated. All of these characteristics speak to unconditional variation in property- and household-level attributes that may contribute to mortgage distress by affecting either homeowners' incentives for strategic default or their susceptibility to precipitating trigger events.

5 Empirical Strategy

As described above, property tax limitations can have unintended effects on household risk by shifting tax payments from high-consumption states of the world to low-consumption states of the world. By limiting the pro-cyclicality of property tax burdens—and thereby raising property tax liabilities during times of weak macroeconomic conditions relative to what would have occurred in the absence of such limits—there is a potential for tax policy risk to trigger mortgage distress. However, it is an empirical question as to whether these shifts in tax burden are large enough for this risk to have a meaningful effect (and outweigh any possible level effect from these same limitations). Otherwise, households might simply self-insure and use liquidity to smooth out these shifts in the timing of tax burdens. Previous literature suggests that even relatively modest changes in property tax burdens can lead households to financial distress (Anderson and Dokko, 2009; Bradley, 2013; Anderson and Dokko, 2016; Wong, 2020) despite the large costs to households from mortgage distress and foreclosure.

We are interested in whether the unintentional risk effects resulting from property tax limitations are large enough to have real impacts on households through increased mortgage distress and foreclosure. The ideal experiment would randomly assign households different bundles of property tax limitations and compare household outcomes over time in terms of mortgage distress. In practice, however, households are not randomly assigned these limitations, thereby creating the potential for a feedback loop between economic conditions that increase the probability of foreclosure and the enactment of property tax limitations. Another practical hurdle in terms of identifying the effects of tax limitations is the high dimensionality of interactions between types of limits and the stringency thereof.

We use a state-border discontinuity design to dampen the feedback loop between economic conditions and property tax limits. The border design allows us to compare properties that face similar local economic conditions except for being subject to different property tax limitations. This is achieved in our empirical specifications by including border pair ($\times$ year) fixed effects. The maintained assumption underpinning this identification strategy is that—conditional on a wide range of property characteristics—homeowners within a narrowly-defined border pair region would face identical distress probabilities on either side of the state boundary if not for differences in property tax system characteristics that give rise to differing exposure to tax risk.

Concretely, we consider three different types of border pairings: county pairs, as well as 10 km² and 5 km² grid cells. County pairs have the virtue of being commonly used in the literature on account of their convenience and their readily understood administrative boundaries; however, counties may differ substantially in size and population density and, in some cases, represent vast areas of land that are less reasonable to treat as uniform markets. To standardize land area, we therefore use the U.S. National Grid coordinate system to construct either 10 or 5 km² grid cells.[24] We refer collectively to each of these types of border pairings as producing a set of $j = 1, ...J$ grid cells, all of which produce distinct mappings of parcels to grid cells and partition parcels differently with respect to all relevant local taxing authority boundaries.[25] In the following results, we ultimately emphasize those that use the narrowest 5 km² grid cells, but we obtain qualitatively similar results using either county pairs or 10 km² grid cells.

Figure 11 provides an illustration of median property characteristics for the set of all Census tracts located in the six counties along the Michigan-Ohio border as of 2015. The agglomeration of Census tracts in the southeast corner of each subfigure is Toledo, OH, and the state border follows the near-horizontal midsection line of each map. As shown, tracts just north and south of the state border exhibit relatively similar median characteristics, especially in terms of housing prices (11a) and LTV (11c). Outside of the more densely populated areas, foreclosure rates are more heterogeneous (11d), and effective tax rates (11b) unsurprisingly reflect more pronounced county, municipal, and school district influences on statutory millage rates. Nevertheless, we view these illus-

[24]The U.S. National Grid coordinate system divides the world into equal-sized "square" grid cells (100 km²) that are defined independently of jurisdictional boundaries. Distortions to the dimensions of these grid cells due to the earth's curvature are mitigated by zooming in on relatively small grid squares. Insofar as certain parcels are attributed to multiple border pair regions, fixed effects are estimated accordingly. This approach is similar to the 10-mile strips used by e.g., Mian et al. (2015).

[25]See Avenancio-León and Howard (2022) for an in-depth discussion of the role of overlapping governments for property tax purposes.

trations as supporting the general concept of the existence of border-straddling local housing markets. Figure 12 depicts the location of each parcel in our estimation sample for the same six counties at the Michigan-Ohio border along with the approximate latitude-longitude coordinates of the 5 km² grid cells that form the basis of our resulting preferred fixed effects estimation strategy. Interior grid cells are outlined in gray, while the set of border-straddling cells which serve as the source of identifying variation for our primary analyses are highlighted in magenta. The western portion of the Michigan-Ohio border which exhibits relatively greater cross-border differences in tract-level housing market characteristics (Figure 11) is also quite sparsely-populated, as shown in Figure 12, and thereby contributes little to identification.

We use our measure of tax risk described in Section 3 to parsimoniously capture the high dimensionality of interactions among property tax limits. The model produces a single measure of the tax price that encompasses all features of the property tax regime in a given state, which we decompose into tax policy *risk* and level components. Intuitively, *Tax Policy Risk* represents the price that households would be willing to pay to avoid the risk effects resulting from the set of property tax limits in their state. A higher value of tax policy risk is therefore predicted to increase the probability of mortgage distress and foreclosure, regardless of whether this risk is primarily attributable to any specific form of assessment limitations, rate limits, or levy/revenue limits (or any combination thereof).[26]

In order to test this core prediction, we estimate the effect of *Tax Policy Risk* on mortgage distress at the property i year t level using a linear probability model where the outcome variable, $\mathbb{1}(\text{Distressed})_{i,t}$, is an indicator that equals one if property i experiences any form of mortgage distress in year t and zero otherwise:

$$\begin{aligned}\mathbb{1}(\text{Distressed})_{i,t} = \beta_0 + \beta_1 \text{Tax Policy Risk}_{s,t} + \beta_2 \text{Tax Policy Level Diff}_{s,t} \\ + X_{i,t}\beta + Z_{s,t}\beta + \lambda_{j,t} + \varepsilon_{i,t}\end{aligned} \tag{2}$$

The regressor of interest, $\text{Tax Policy Risk}_{s,t}$, varies at the state s year t level, as does $\text{Tax Policy Level Diff}_{s,t}$, which we include only to absorb the effects of residual differences in average property tax *amounts* that may result from the application of tax limita-

[26]We consider an alternative reduced-form model in Appendix E which focuses specifically on the consequences of assessment limitations. This alternative model provides qualitatively similar results but has a less direct interpretation and is unable to account explicitly for correlated tax policy choices.

tions.[27] Our state-border discontinuity design dictates the use of either year and grid cell fixed effects λ_t and λ_j, or grid cell by year pair fixed effects $\lambda_{j,t}$, as denoted above. We augment this design with a vector of property level control variables $X_{i,t}$ to incorporate additional parcel-specific factors related to strategic default incentives and other triggers of mortgage distress. These include controls for LTV, homeowner tenure, the age of the home, and the age of renovations (all represented as categorical variables), along with controls for the current estimated house price and the lagged ETR. $Z_{s,t}$ accounts for other important state policy variables that have been shown elsewhere to affect foreclosure rates (Ghent and Kudlyak, 2011; Mian et al., 2015)—namely, whether states permit lender recourse or non-judicial review.

In later tests, we interact Tax Policy Risk$_{s,t}$ with different time-varying state- and parcel-level characteristics that may affect households' susceptibility to tax risk, and we investigate the contributions of different property tax system features to measured risk.

6 Results

6.1 Main Effects

Table 4 reports our estimates of the effect of property tax risk on the probability of mortgage distress in the current period. The dependent variable is pre-multiplied by 100 such that point estimates from the linear probability model can be interpreted directly as percentage point effects. Column 1 presents the no-controls baseline and encompasses nearly 40 million observations. All other specifications include a full set of controls for LTV, house price, last period's ETR, tenure, and the age of the home and major renovations (if any). We also include policy variables denoting states which allow lender recourse and non-judicial review. Columns 2-4 employ progressively narrower border fixed effects, while columns 5-7 replicate the same sequence of specifications with border by year *pair* fixed effects to account for unobserved time-varying local economic conditions. For brevity, we only report the set of coefficient estimates that relate to property tax risk in Table 4, but the complete set of estimates can be found in Appendix Table A.2.

As shown, greater tax policy risk is associated with a significantly higher probability

[27] Such differences are not a true source of risk and are primarily attributable to differences across states in the average effective tax rates which anchor our simulations. These differences ought to be reflected in house prices and ETRs, both of which are accounted for separately at the parcel level in our analysis.

of mortgage distress across all fixed effect specifications. Only in the most basic specification in column 1 is the effect of tax policy risk negligible. Naturally, this unconditional estimate is susceptible to numerous potential biases. Incorporating controls for LTV, tenure, age, etc., along with different sets of fixed effects yields significantly larger estimated effects of tax policy risk (columns 2-7). In general, whereas the point estimates are decreasing in the size of the regions spanned by our time-invariant border pair fixed effects (columns 2-4), the reverse holds where we allow for time-varying border pair fixed effects (columns 5-7). We consequently emphasize the more conservative—and most narrowly-identified—estimates presented in column 7, and we use 5 km² grid cell $\times$ year fixed effects in all subsequent tests.[28]

The coefficient on tax policy risk in column 7 of Table 4 constitutes an economically significant impact of risk from property tax limitations on mortgage distress. Increasing tax policy risk by one thousand dollars—equivalent to moving a parcel from e.g., Maryland to Michigan at the height of the Great Recession—is thus estimated to raise the probability of mortgage distress by 0.686 percentage points from a baseline probability (column 1) of 1.196 percent. By way of comparison, the full results for the same specification in Appendix Table A.2 imply that moving from the lowest quintile of the LTV distribution to the highest quintile raises the probability of distress by approximately 2.8 percentage points. Thus, the effect of a thousand dollar increase in tax risk is roughly one quarter as large as the effect of being severely underwater. More modestly, a one standard deviation increase in tax risk ($343) has an effect on the probability of distress that is roughly one third larger than that of owning a home in disrepair (i.e., homes that have not been renovated in at least 59 years).

6.2 Heterogeneity

We extend our preferred specification from column 7 of Table 4 to test whether certain time-varying market-level or parcel-level characteristics affect homeowners' susceptibility to property tax risk. Concretely, we consider the interaction of tax policy risk with state-level unemployment rates; the existence of state-level property tax deferral

[28] Narrowing our estimation sample to only include parcels within 5 miles of state borders (*N* equals approximately 8.5 million observations) produces slightly larger and more precise point estimates of the effect of tax policy risk for the specifications involving either 10 km² or 5 km² grid cell $\times$ year fixed effects. This is unsurprising given our identification strategy, which leverages within variation in border-straddling regions. Results are available from the authors upon request.

programs for low-income taxpayers; zip code-level federal income tax itemization rates; tract-level race indicators; and owner-specific cumulative housing price growth and LTV. We present the main effects of tax policy risk along with the relevant interaction effects in Figures 13 and 14 and Table 5. Complete results including uninteracted covariates and a full set of interactions with the other state policy control variables are provided in Appendix Table A.3. Columns (1) and (10) of Appendix Table A.3 correspond to Figures 13 and 14, respectively. Columns (2)-(9) correspond to the like-numbered specifications in Table 5.

Figure 13 depicts marginal effects (with 95% confidence intervals) from a model in which tax policy risk is interacted with a cubic polynomial in unemployment to test the proposition that the consequences of risk may be amplified during periods of weaker macroeconomic performance and dampened during good times. As shown, the point estimates in Figure 13 are broadly consistent with this prediction; however, the marginal effects are too imprecisely estimated to draw more rigorous conclusions, and the partial effect of tax policy risk is only statistically differentiable from zero near the average in-sample unemployment rate of 6.5 percent.[29]

Programs that allow homeowners to defer their property tax obligations during periods of financial hardship ought to mitigate the negative effects of countercyclical tax burdens. In practice, 25 of the lower-48 states plus the District of Columbia have some form of state-level property tax deferral program in place. The vast majority of these programs, however, are restricted to low-income seniors and disabled homeowners, and a small number apply exclusively to active military. None of these groups can be separately identified in our data, and given the small proportion of potential beneficiaries of these programs in the population, it is unsurprising that we find no statistically significant differential effect of tax policy risk in states with such tax deferral programs in place (results not shown). In column (2) of Table 5, we focus instead on the much narrower subset of states (N=3) that allow property tax deferral based on low income eligibility criteria alone (i.e., without further restrictions on age, disability, or military status). Taken literally, the point estimate on the interaction of tax policy risk with $I[TaxDeferral = 1]$ is consistent with an attenuated role of risk in places where low-income homeowners

[29]The unemployment rate rarely dipped below 5 percent outside of the years 2006-2007 and 2015-2016 in our estimation sample. Taken literally, our point estimates imply a negative overall partial effect of tax risk during these periods of low unemployment, but these estimates–as well as those at the top end of the unemployment rate distribution–are associated with especially wide confidence intervals.

have the option to smooth their tax payments over time, but this negative differential effect remains imprecisely estimated.

Specifications (3)-(4) of Table 5 investigate the role of property tax deductibility from federal income tax liability. Federal income tax deductibility of state and local taxes (unrestricted during our period of analysis) implies that the federal government serves as a risk sharing partner in households' property tax obligations in proportion to taxpayers' marginal tax rates, such that itemization may reduce taxpayers' exposure to tax policy risk. At the same time, itemization is more likely among high income taxpayers living in high cost of living areas, which may otherwise influence households' susceptibility to property tax risk. Accordingly, we flag parcels located in zip codes with above-median itemization rates and above-median average adjusted gross income (AGI) separately, and we test for differential effects of tax policy risk across both groups. Individually, high itemization rates (3) and high AGI (not shown) are each associated with weaker effects of tax policy risk on the probability of housing distress. As shown in (4), however, the dampening effect of tax deductibility is swamped by the degree of protection from tax policy risk that is afforded by high income. Though still negative, the differential effect of tax policy risk among households in high itemization rate areas is thus not significantly different from zero after accounting for the separate influence of high AGI.

Prior literature indicates that minority households face significantly higher effective tax rates (Avenancio-León and Howard, 2022), mortgage interest rates (Gerardi et al., 2023) and other mortgage costs (Ambrose et al., 2020), and are more "vulnerable to adverse economic shocks" (Bayer et al., 2016) and housing distress than white homeowners (Reid et al., 2017). We extend these considerations to investigate whether tax policy risk may impose further disproportionate costs in predominantly minority areas using tract-level data from the 2010 American Community Survey. We distinguish parcels according to whether these are located in majority white, majority black, majority Latino (all races), or majority Asian Census tracts and present the corresponding interactions with tax policy risk in specifications (5)-(8) of Table 5, respectively. Consistent with the prior literature, residents of predominantly white (black) neighborhoods face significantly lower (higher) baseline rates of housing distress. More importantly, whereas households in predominantly white neighborhoods also face more muted effects of tax policy risk, the reverse holds in majority black areas, the result being that the effect of tax policy risk is more than 50 percent larger in the latter minority areas. A similar pattern—albeit imprecisely estimated—holds for majority Latino areas, whereas the point estimate of the differential effect for Asian neighborhoods is negative.[30]

Finally, turning to parcel-level characteristics, we document first that—albeit limited to a relatively small subsample of observations—the effects of tax risk are partially mitigated among homeowners who have experienced substantial housing price appreciation since buying their homes (Table 5, specification 9), and vice versa for homeowners who have experienced housing price declines. The accumulation of housing wealth hence serves as a partial buffer from tax policy risk. Second, the marginal effects depicted in Figure 14 reveal that households in the top quintile of the LTV distribution incur the largest effects of tax risk on mortgage distress, while those with unknown LTV amounts—which presumably includes a substantial proportion of homeowners without mortgages—face the smallest such effects. Strategic motives for mortgage delinquency and default are thus amplified in states whose combined property tax system characteristics result in greater tax risk.

7 Conclusion

Using parcel-level panel data for the near universe of residential properties located within 20 miles of all U.S. state borders and a comprehensive measure of property tax risk that reflects states' full complement of property tax system characteristics, we confirm that tax policy risk has a pronounced effect on mortgage distress. Thus, despite reducing intertemporal variation in property tax liabilities, property tax limitations have the perverse effect of increasing risk for homeowners during market downturns, and we show that this increase in risk constitutes a significant trigger event for mortgage distress. Moreover, these effects are reinforced among homeowners facing otherwise stronger strategic incentives for default due to being underwater on their mortgage loans, and vice versa.

Tax policy risk is hence a fundamental aspect of property tax systems throughout the U.S., even in regimes that were ostensibly devised to protect homeowners from rising tax obligations. Missing from consideration is the role that counter-cyclical tax adjustments may play in amplifying household financial distress during periods of weak macroeco-

[30]Majority white, black, Latino, and Asian Census tracts account for 83.4, 10.7, 2.5, and 0.1 percent of all observations in our estimation sample, respectively. It is therefore unsurprising that the estimates of differential tax policy risk effects in the latter two groups suffer from weak statistical precision.

nomic performance and whether targeted measures to protect vulnerable homeowners during market downturns may be warranted.

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Figure 1: State Assessment Limitation Regimes (2016)

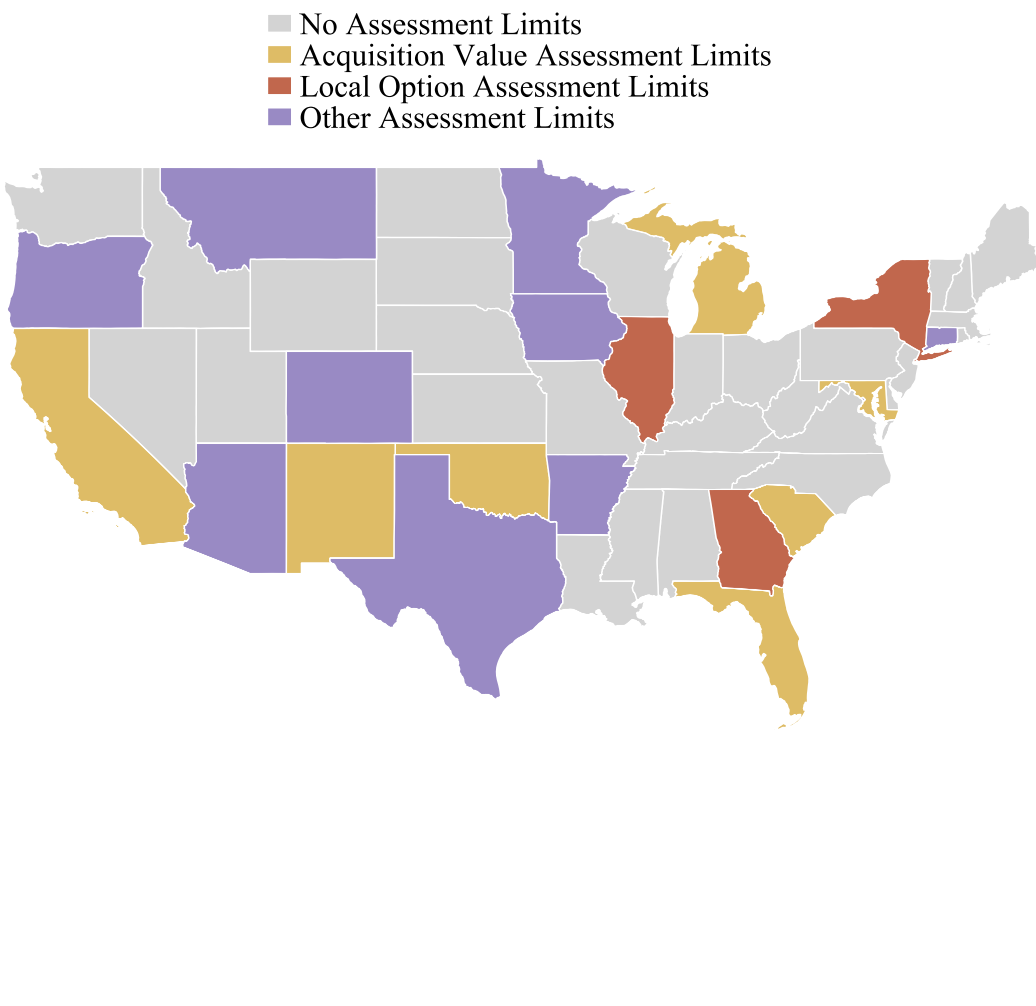
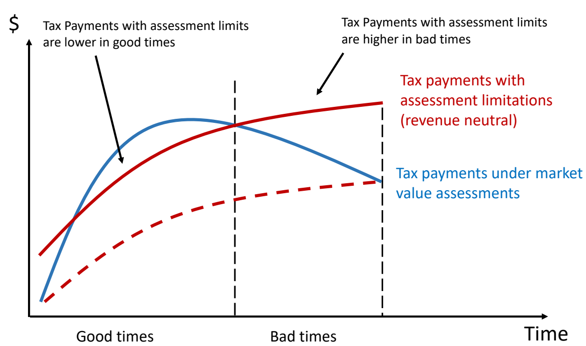
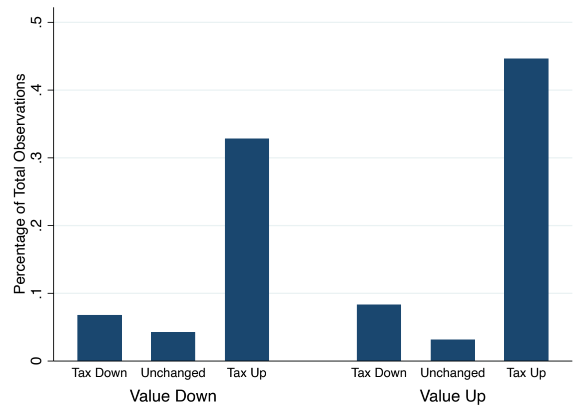


Figure 2: Taxable Values versus Assessed Market Values

(a) Framework for shifting tax payments



(b) Histogram of tax payments



(c) Example of tax payments in California

(d) Example of tax payments in Nevada

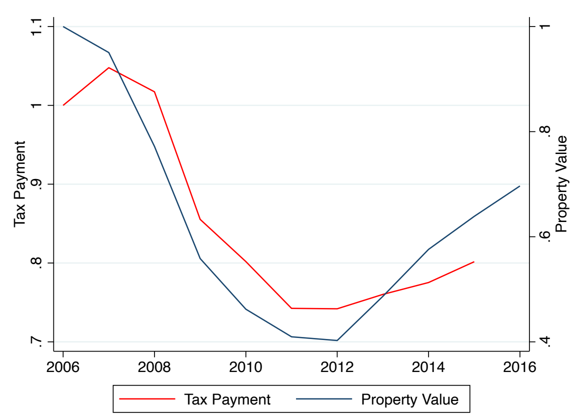


Figure 3

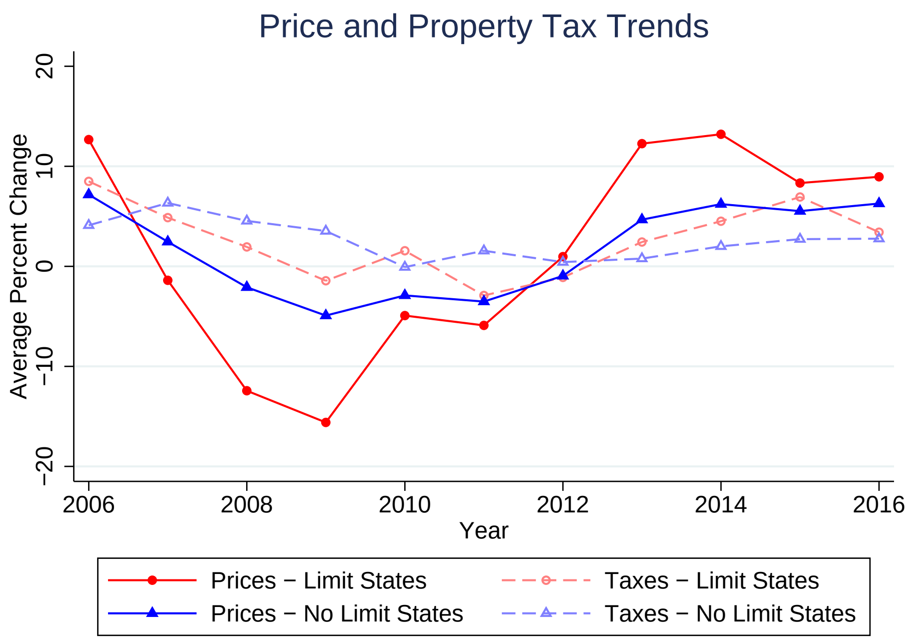


Figure 4

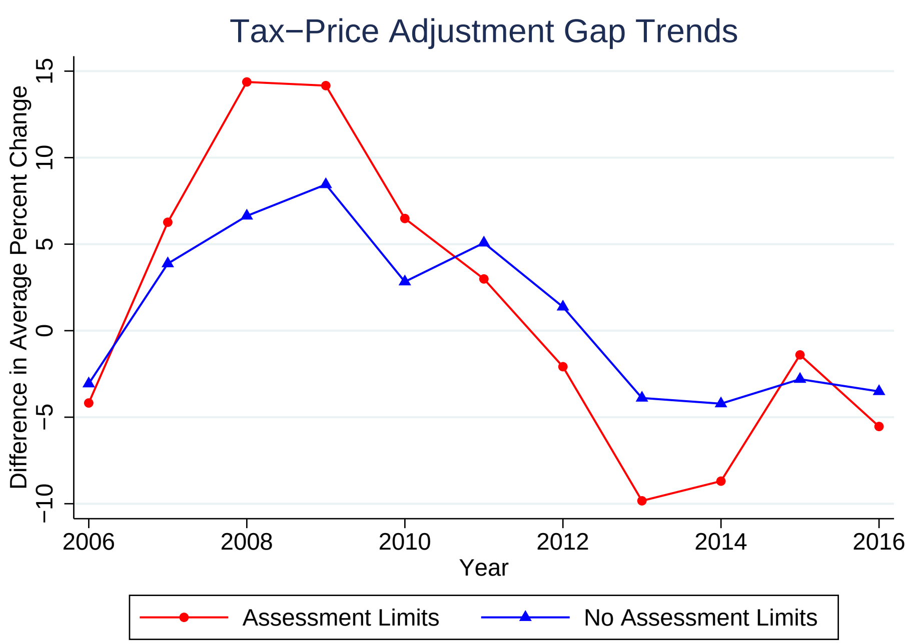
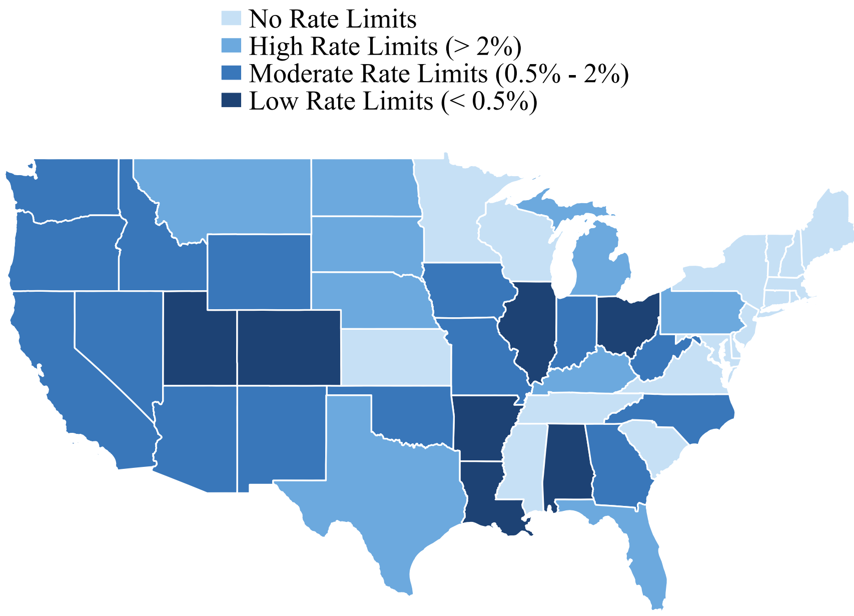


Figure 5: State Rate Limitation Regimes (2016)



To ensure comparability across states, statutory millage rate caps are translated into percentages of fair market value using applicable assessment ratios.

Figure 6: State Levy/Revenue Limitation Regimes (2016)

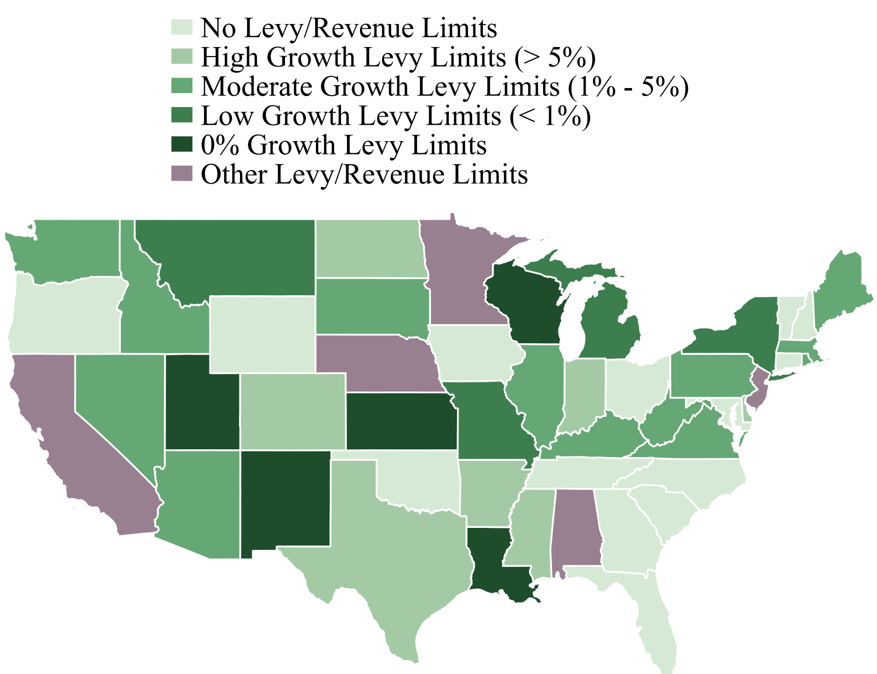
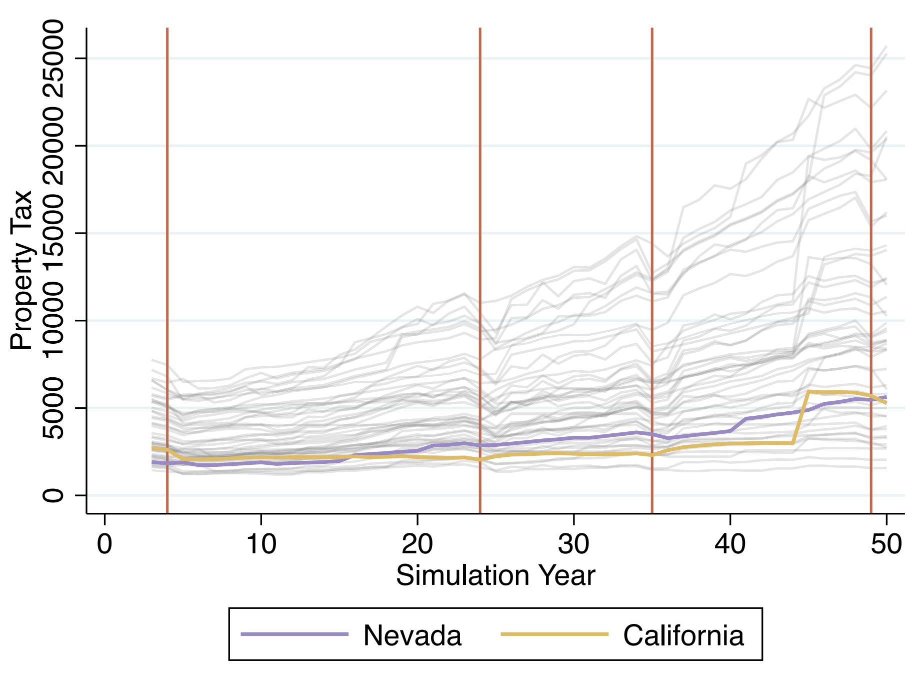
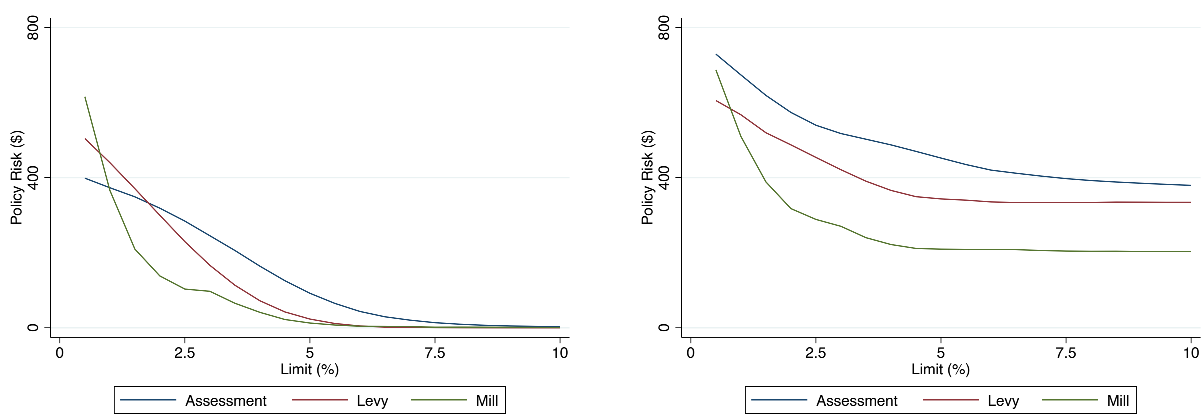


Figure 7: **Simulated Property Tax Bills**



Different lines depict the evolution of states' simulated property tax bills of the same property as a function of state-specific policies for the same economy and transaction process. Red vertical lines denote recession years in the simulation.

Figure 8: **Simulated Policy Risk Attributable to Individual Policies**



(a) (b)

Different lines depict the dollar amount of policy risk associated with each policy. Other policies are turned off in panel (a) and are set to median value in the sample in panel (b).

Figure 9: **Policy Risk by States**

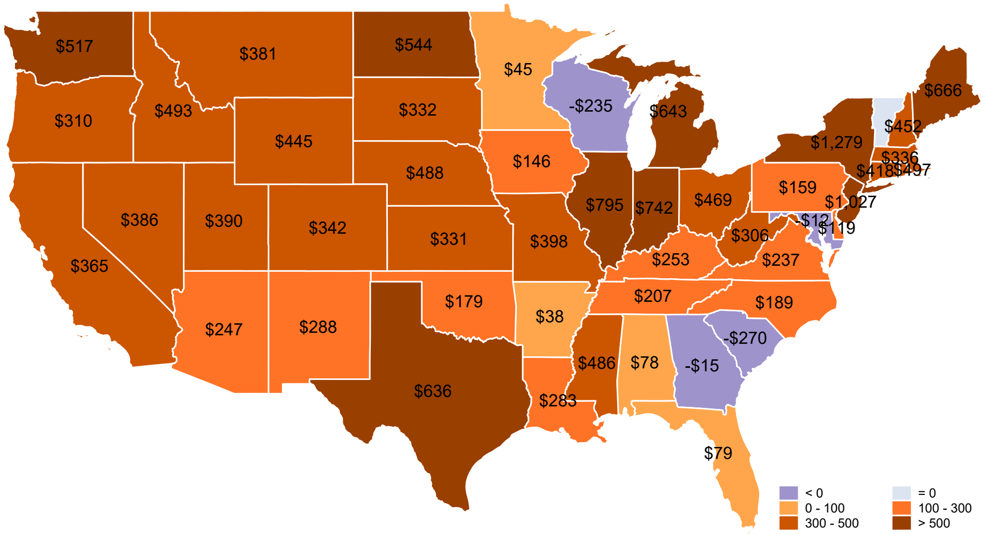


Figure 10: **Policy Risk by States – Rescaled**

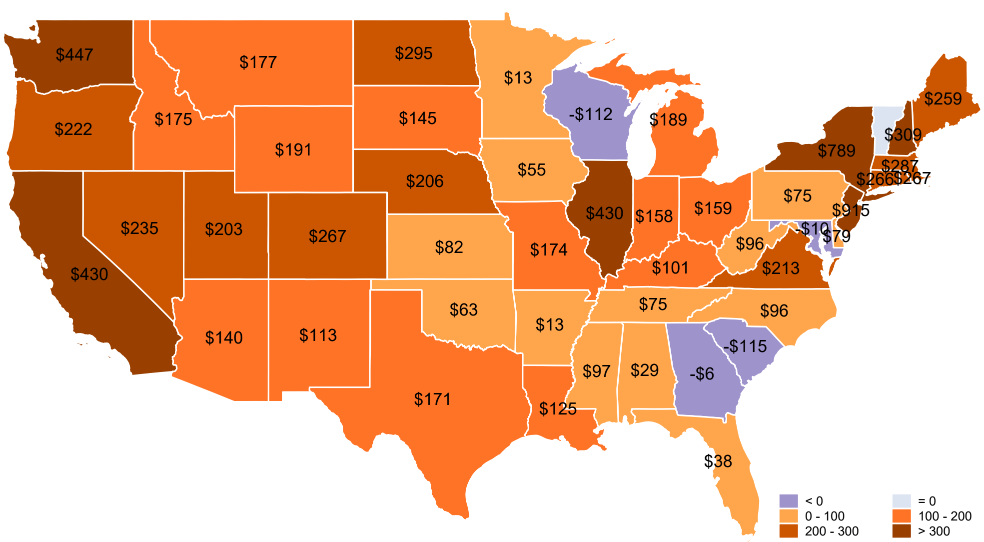
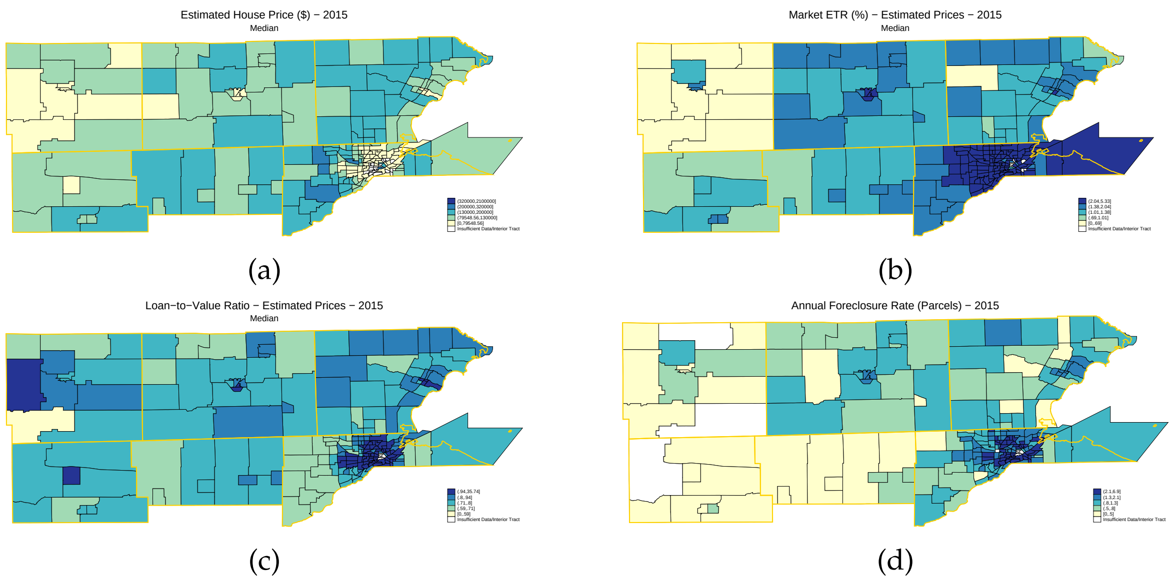
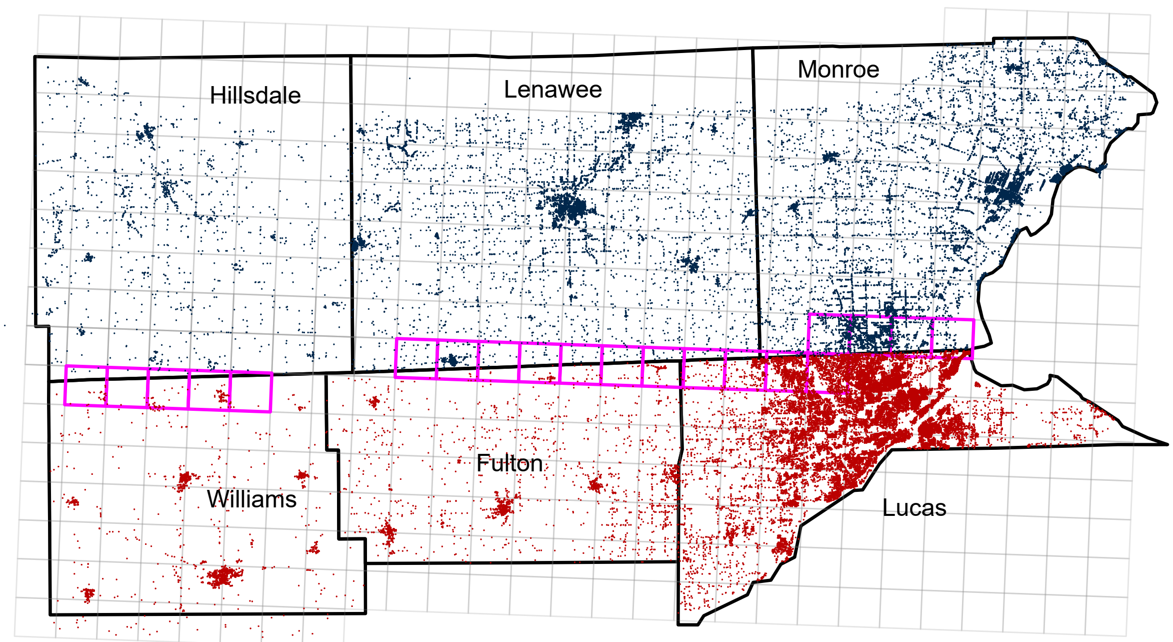


Figure 11: Local Housing Market Characteristics Across State Borders: MI-OH



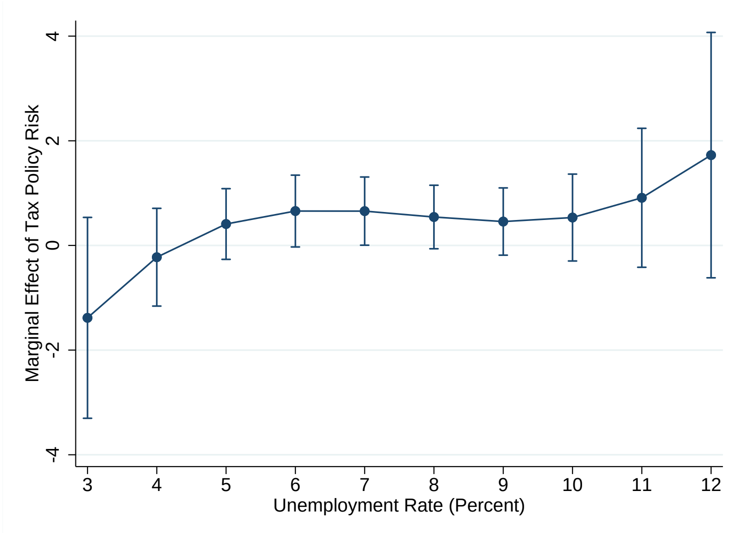
Maps each show median property characteristics for the set of all Census tracts located in the six counties at the Michigan-Ohio border. The state border follows the near-horizontal midsection line. The tight cluster of tracts in the southeast corner of the map is Toledo, OH, just south of the state border.

Figure 12: Parcels and 5 km² Grid Cells: MI-OH



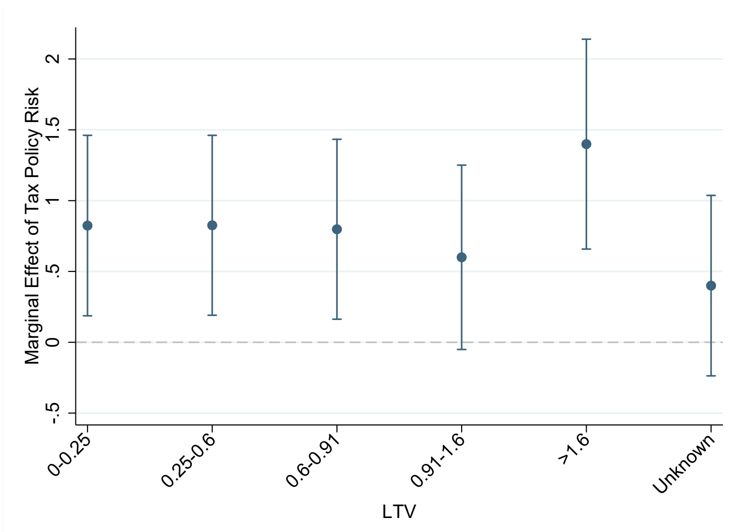
Blue (red) points denote all unique parcel locations in our estimation sample for Michigan (Ohio) along the states' shared border. Border-straddling 5 km² grid cells that contain parcels in both states are outlined in magenta based on the latitude-longitude coordinates of included parcels, while interior cells and border-straddling cells that contain parcels from only one state appear outlined in gray.

Figure 13: Marginal Effects of Tax Risk as a Function of Unemployment



Marginal effects of tax risk are estimated from a model featuring interactions of tax risk with a cubic function of state-year average unemployment rates.

Figure 14: Marginal Effects of Tax Risk as a Function of Parcel-Level LTV



Marginal effects of tax risk are estimated from a model featuring interactions of tax risk with categorical LTV indicators by approximate LTV quintile and a sixth category for parcels with unknown LTV.

Table 1: State Policy Variables (2016)

State	Assessment Limitations	Other Assess Limits	Levy Limits	Rate Limits	Revenue/Spend Limits	Truth in Taxation	Lender Recourse	Non-Judicial Review	Appraisal Frequency
AL			x	x			x	x	1
AR		x	x	x			x	x	5
AZ		x	x	x	x	x		x	1
CA	x			x	x			x	-[a]
CO		x	x	x	x		x	x	2
CT		x	x				x		5
DC		x	x	x			x	x	1
DE			x	x		x	x		-
FL	x			x		x	x		1
GA		x		x		x	x	x	1
IA		x		x					2
ID				x			x	x	1
IL			x	x			x		4
IN			x	x			x		4
KS			x				x		-
KY			x	x		x	x		4
LA			x	x			x		4
MA			x	x			x		5
MD	x					x	x		3
ME			x		x		x		-
MI	x		x	x	x		x	x	1
MN			x		x			x	1
MO			x	x		x	x	x	2
MS			x				x	x	4
MT			x	x				x	2
NC				x				x	8
ND			x	x		x			1
NE			x	x	x		x	x	1
NH							x	x	-
NJ			x		x		x		-
NM	x		x	x	x		x		1
NV			x	x			x	x	5
NY		x	x				x		4
OH			x	x			x		6
OK	x			x			x	x	1
OR		x		x				x	1
PA			x	x			x		-
RI			x				x	x	9
SC	x			x			x		5
SD			x	x			x		1
TN			x				x	x	6
TX		x	x	x		x	x	x	3
UT			x	x		x	x	x	5
VA			x			x	x	x	4
VT							x		1
WA			x	x	x			x	6
WI			x		x				1
WV			x	x			x	x	1
WY				x			x	x	6

[a] California only reassesses properties upon sale. Conditional on sale, however, appraisal frequency is implicitly annual.

Table 2: Summary Statistics

Variable	I[Distress]=0			I[Distress]=1			
	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.
Tax Policy Risk ($000s)	0.359	0.275	0.343	0.355	0.281	0.320	-0.004
Tax Policy Level Diff ($000s)	-10.150	-4.100	14.359	-9.713	-4.419	12.973	0.437
LTV	1.57	0.63	77.41	2.06	0.92	51.66	0.50
Price ($)	251188	177433	276850	185844	140078	184123	-65344
Lagged ETR (%)	1.48	1.17	1.35	1.64	1.25	1.47	0.16
Tenure	11.2	9	10.3	8.3	6	8.1	-2.9
Age	48.4	44	32.7	48.7	45	33.7	0.3
Renovation Age	42.6	37	33.9	43.7	38	34.8	1.2
Observations	22,966,629			332,836			

Table 3: Mechanisms

Dependent variable: *Tax Policy Risk*$_{s,t}$	Levy limit	Rate limit	Assess. limit	Combined
	(1)	(2)	(3)	(4)
$\mathbb{1}$(Levy Limit)$_{s,t}$	198.360***			104.585***
	(30.165)			(29.028)
$\mathbb{1}$(Rate Limit)$_{s,t}$		143.079***		254.382***
		(28.552)		(32.042)
$\mathbb{1}$(Assess. Limit)$_{s,t}$			336.171***	325.451***
			(59.092)	(53.447)
F-statistic	43.242	25.112	24.803	39.407
Adj. R-Square	0.089	0.053	0.142	0.308
Observations	432	432	432	432

The dependent variable is our measure of *Tax Policy Risk* (see Section **??**) which varies at the state-year level. Levy, rate, and assessment limits are defined in Section 2. This table excludes nondisclosure states and includes New York City and Washington DC. Significance levels are designated as *** $p<0.01$, ** $p<0.05$, and * $p<0.1$. Standard errors (in parentheses).

Table 4: Mortgage Distress and Tax Policy Risk

$Y = Pr(Distressed_t = 1), Y \in \{0, 100\}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Tax Policy Risk	0.072	1.224*	1.420***	1.527***	1.272**	1.210*	0.686**
	(0.100)	(0.630)	(0.527)	(0.364)	(0.568)	(0.629)	(0.319)
Tax Policy Level Diff		0.021*	0.018**	0.019***	0.030**	0.023**	0.007
		(0.012)	(0.009)	(0.006)	(0.013)	(0.012)	(0.007)
	$\ddots$	$\ddots$	$\ddots$	$\ddots$	$\ddots$	$\ddots$	$\ddots$
Constant	1.196***						
	(0.070)						
Fixed Effects:							
County pair		x					
10 km² grid			x				
5 km² grid				x			
Year		x	x	x			
County pair × Year					x		
10 km² grid × Year						x	
5 km² grid × Year							x
Observations	38,842,845	23,322,707	23,322,453	23,321,476	23,322,132	23,317,199	23,299,066
R-squared	0.000	0.017	0.018	0.019	0.020	0.023	0.027

Significance levels are designated as *** $p<0.01$, ** $p<0.05$, and * $p<0.1$. Standard errors (in parentheses) are clustered by 5 km² grid cell. For brevity, only main effects are shown. Specifications (2)-(7) include controls for LTV, house price, lagged ETR, tenure, age, and renovation age, as well as indicators for recourse and non-judicial review states. Complete results for the set of specifications involving grid cell FE are reported in Appendix Table A.2.

Table 5: Mortgage Distress and Tax Policy Risk - Heterogenous Effects

$Y = Pr(Distressed_t = 1), Y \in \{0, 100\}$	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Tax Policy Risk	0.717**	0.829**	0.788**	0.949***	0.769**	0.781**	0.812**	2.718***
	(0.324)	(0.323)	(0.336)	(0.312)	(0.306)	(0.338)	(0.337)	(0.935)
I[TaxDeferral=1]	0.405							
	(1.946)							
I[TaxDeferral=1]	-0.602							
× Tax Policy Risk	(3.718)							
I[HighItemizationRate=1]		-0.165	-0.086					
		(0.133)	(0.137)					
I[HighItemizationRate=1]		-0.220*	-0.047					
× Tax Policy Risk		(0.127)	(0.138)					
I[HighAGI=1]			-0.185**	-0.100	-0.177**	-0.196**	-0.186**	
			(0.089)	(0.074)	(0.087)	(0.092)	(0.091)	
I[HighAGI=1]			-0.195**	-0.161**	-0.188**	-0.204**	-0.242***	
× Tax Policy Risk			(0.093)	(0.070)	(0.081)	(0.085)	(0.089)	
I[MajorityWhite=1]				-0.707***				
				(0.165)				
I[MajorityWhite=1]				-0.181**				
× Tax Policy Risk				(0.091)				
I[MajorityBlack=1]					0.565***			
					(0.160)			
I[MajorityBlack=1]					0.391***			
× Tax Policy Risk					(0.126)			
I[MajorityLatino=1]						-0.180		
						(0.255)		
I[MajorityLatino=1]						0.287		
× Tax Policy Risk						(0.187)		
I[MajorityAsian=1]							-0.216	
							(0.328)	
I[MajorityAsian=1]							-0.033	
× Tax Policy Risk							(0.362)	
% Δ_{T-0} Price								0.0004***
								(0.000)
% Δ_{T-0} Price								-0.0001**
× Tax Policy Risk								(0.000)

Appendix A Simulation Procedure

This section describes the detailed procedure for our simulation. The simulation captures two aspects of property tax policy risk – (1) how tax policy affects property tax payments and (2) how such payments interact with household consumption. Therefore, we first simulate the underlying economy, which consists of a panel of aggregate consumption shock, individual consumption shock, and property value. We then calculate the tax payments with and without the tax limits policy. Finally, we price the risk of tax payment and isolate the risk price of the tax limits policy.

• **Simulate the Economy Process**

We build an underlying economy process that consists of 500 properties (denoted by i) with 50 years of history (denoted by z). We first simulate the aggregate consumption shock series. We collect the aggregate consumption data from 1997 to 2020 from the Bureau of Labor Statistics. We assume the consumption growth follows an AR(1) process and estimate the following:

$$g_{s,t} = \beta_1 + \beta_2 g_{s,t-1} + \epsilon_{s,t},$$

where $g_{s,t}$ is the growth of the personal consumption expenditure (linecode = 1) for state s in year t. In addition, we separately model a recession process that follows Poisson distribution. We assume that recessions happen once every 15 years on average and that the aggregate consumption growth decline by 6% during recessions. Put together, we simulate the aggregate consumption shock as the following:

$$\hat{g}_z = \begin{cases} \bar{g} & \cdots \text{ if } z = 1 \\ \hat{\beta}_1 + \hat{\beta}_2 \hat{g}_{z-1} & \cdots \text{ if } z > 1 \end{cases}$$

$$\tilde{g}_z = \hat{g}_z + \hat{\sigma}_\epsilon \tilde{x}_1 - 0.06 \cdot \tilde{x}_2$$

where $\tilde{g}_t$ is the simulated aggregate consumption growth in year t, $\tilde{x}_1$ is a random variable that follows a standard normal distribution, and $\tilde{x}_2$ is a random variable that follows a Poisson distribution with $\lambda = 1/15$.

We then simulate the individual consumption shock. Following Pischke (1995), we make a conservative assumption that individual consumption shock is on average 10 times as volatile as the aggregate consumption shock. We simulate the individual consumption shock as the following:

$$\tilde{g}_{i,z} = (\tilde{g}_z - \bar{g})\tilde{a}_i + \bar{g},$$

where $\tilde{a}_i$ is a person-specific amplifier that takes the value of a random variable that follows a normal distribution with a mean of 10, i.e., on average the individual consumption shock is 10 times as volatile as the aggregate consumption shock. We also truncate the individual consumption shock at -0.8 with the assumption that it is unlikely that a person loses more than 80% of her total wealth in one year. This helps avoid extreme values and produces qualitatively similar results compared to not having this truncation.

We next simulate the inflation process. We collect inflation data from 1997 to 2020 from the Bureau of

Labor Statistics and estimate the following equation:

$$f_t = \beta_3 + \beta_4 g_{i,t} + \epsilon_t$$

where f_t is the inflation in year t. We simulate the inflation process as the following:

$$\tilde{f}_z = \hat{\beta}_3 + \hat{\beta}_4 \tilde{g}_z + \hat{\sigma}_\epsilon \tilde{x}_3$$

where $\tilde{x}_3$ is a random variable that follows a standard normal distribution.

Lastly, we simulate the change in value of the property. We use Case-Shiller Home Price Index to calculate the year-over-year change in property value, h_t, and estimate the following equation:

$$_t = \beta_5 + \beta_6 g_{s,t} + \beta_7 f_t + \epsilon_t$$

In addition, we assume that on average property value declines by 0% during recessions. We simulate the change in property value as the following:

$$h_{i,z} = \hat{\beta}_5 + \hat{\beta}_6 \tilde{g}_z + \hat{\beta}_7 \tilde{f}_z + \hat{\sigma}_\epsilon \tilde{x}_4 - 0.3 \cdot \tilde{x}_2$$

where $\tilde{x}_4$ is a random variable that follows a standard normal distribution.

We then simulate the initial values of the 500 properties to follow a normal distribution with a mean of 300,000 and a standard deviation of 50,000 but not lower than 1,000. With initial values and the changes in value of properties, we obtain a full panel of property values.

Finally, we also simulate the transaction status of the property. We assume that each property has a 7% probability of being sold in any given year, consistent with the average turnover rate in our data for the period 2006-2016.

- **Calculate the Property Tax**

We next calculate two property tax payments for each property i in (simulation) year z in the simulated economy – one payment with the tax limit policy in state s in (real) year t and one without. Before applying the tax limits, we make three adjustments with respect to heterogeneous property value across states, downward stickiness, and infrequent reassessment. First, we re-scale the property value by the median transaction value of properties in the border counties of state s in year t. We use the border counties for re-scaling to be consistent with our empirical design. Second, we empirically observe downward stickiness in the assessed value of properties. We capture this feature in the assessment value in the following way: if the change in property value, $h_{i,z}$, is positive, the value in the next year changes (grows) by $h_{i,z}$; but if the change is negative, there is a 30% chance that the value in the next year stays the same and a 70% chance that the value in the next changes (declines) by $h_{i,z}$. Lastly, for states that do not have assessment limit and do not reassess the property value every year, we process the assessment value in one of the two ways: (1) if the state has a fixed reassessment frequency greater than 1, we code the assessment value such that it updates once every fixed number of years, i.e., in non-assessment years the value is the last assessed value; (2) if the state does not mandate a fixed reassessment frequency, we assume each property has a 10% chance of being reassessed and updated to current market value.

We apply assessment limit on the taxable value. If the assessment value next grows too fast and would exceed the assessment limit, the taxable value is set such that it grows at exactly the assessment limit. Most states have a fixed assessment limit but some states (FL, CA, and MI) have a dynamic assessment limit, usually the lower of the CPI (simulated as f_z) and a fixed number. For states that have the pop-up feature, we reset the taxable value to market value every time the property is transacted and apply the assessment limit rule to the property throughout the tenure of the new owner.

We apply levy limit in the following way. We use the taxable value and the effective tax rate (ETR) we empirically observed in state s year t to calculate a property tax for each property i in simulation year z. We then assume that the state has a complementary taxation policy – the state has a revenue growth target of g_z, the aggregate consumption growth. However, if the state has a levy limit and the aggregate consumption growth exceeds the limit, the revenue target is set at the levy limit. The state then adjusts the mill rate such that the tax revenue next year meets the revenue target. When the property market is too hot, the state reduces the mill rate such that the total tax revenue grows in line with the aggregate consumption growth. When the property market crashes, the state increases the mill rate to compensate for the smaller tax base.

We then apply mill rate limit. When the state wants to raise the mill rate during recessions, it has to comply with the mill rate limit. If the state would like to raise the mill rate that exceeds the limit, it is allowed to raise the mill rate at the mill rate and the revenue target will not be met. This process yields a dynamically determined mill rate taking into consideration of levy limit and mill rate limit.

We then calculate the final property tax, $q_{s,t,i,z}$, for property i in simulation year z with the tax limit policy of state s in year t to be the product of the taxable value and the dynamic mill rate. We also calculate a counterfactual property tax without any tax limit policy, $q'_{s,t,i,z}$, to simply be the market value times the ETR observed empirically.

• **Price Property Tax and Isolate Policy Risk**

For each property i in year z, we calculate the Arrow-Debreu price of the property tax during the entire tenure of the property. We assume a CRRA utility with a risk aversion of 3.5. The pricing kernel for property i in year z is:

$$p_{i,z} = 1/g_{i,z}^{3.5}$$

Note that the pricing kernel is not state-policy specific (i.e., it has no s and t subscript).

Denote the tenure of property i in year z as $T_{i,z}$. Throughout the tenure, the AD price of the property tax for property i in simulation year z under the policy in state s and year t:

$$\mathbb{P}_{s,t,i,z} = \sum_{y=z-T_{i,z}}^{z} p_{i,y} q_{s,t,i,y}$$

We further decompose the AD price of the property tax into a certain-equivalent component:

$$\mathbb{C}_{s,t,i,z} = \sum_{y=z-T_{i,z}}^{z} p_{i,y} \bar{q}_{s,t,i,y}$$

where $\bar{q}_{s,t,i,y}$ is the average property tax payment throughout the tenure, and a risk component:

$$\mathbb{R}_{s,t,i,z} = \sum_{y=z-T_{i,z}}^{z} p_{i,y} (q_{s,t,i,y} - \bar{q}_{s,t,i,y})$$

Note that by construction, $\mathbb{P}_{s,t,i,z} = \mathbb{C}_{s,t,i,z} + \mathbb{R}_{s,t,i,z}$. We also apply the same pricing kernel to the counterfactual property tax without policy, $q_{s,t,i,z}$, and obtain the counterfactual version of $\mathbb{P}'_{s,t,i,z}$, $\mathbb{C}'_{s,t,i,z}$, and $\mathbb{R}'_{s,t,i,z}$. The property tax risk induced by tax limits policy, or policy risk, is then:

$$\Delta\mathbb{R}_{s,t,i,z} = \mathbb{R}_{s,t,i,z} - \mathbb{R}'_{s,t,i,z}$$

We then drop two types of observations from the simulated panel of properties that could potentially cause inaccuracies for the simulation. We first drop the first 20 years of the simulation (i.e., $z < 20$) because all properties are hard-coded to be transacted in year 1, which may cause unintended results. By the simulation year 20, most properties have at least "naturally" been transacted once before, which mitigates the potential unintended interactions. Second, we also drop observation with which the tenure of the property is greater than 15 years (i.e., $T_{i,z} > 15$) to avoid potential outliers driving the simulation results.

Finally, we average across the remaining observations in the simulated property panel to obtain one value, $\Delta\mathbb{R}_{s,t}$, that captures the tax policy risk for state s in year t. We repeat the process 1,000 times and take the average across iterations to avoid effects from any particular realization of the simulated economy. This final value is the main independent variable of interest for the empirical analysis.

Appendix B Variable Definitions

Notation	Description
i	An index that denotes property or property owner.
z	An index that denotes year in the simulation.
s	An index that denotes state.
t	An index that denotes year.
$p_{i,z}$	The pricing kernel for property owner i in year z.
π_t	The state probability of the world in year t.
$C_{i,t}$	The consumption of property owner i in year t.
$q_{s,t,i,z}$	The tax payment of property owner i in simulation year z under the policy in state s in year z.
$\mathbb{P}_{s,t,i,z}$	The Arrow-Debreu price of property taxes during the entire tenure of property owner i in simulation year z under the policy in state s in year z.
$\mathbb{C}_{s,t,i,z}$	The certainty equivalent of property taxes during the entire tenure of property owner i in simulation year z under the policy in state s in year z.
$\mathbb{C}'_{s,t,i,z}$	The counterfactual of $\mathbb{C}_{s,t,i,z}$, i.e., the certainty equivalent without any tax limit policy.
$\mathbb{R}_{s,t,i,z}$	The property tax risk during the entire tenure of property owner i in simulation year z under the policy in state s in year z.
$\mathbb{R}'_{s,t,i,z}$	The counterfactual of $\mathbb{R}_{s,t,i,z}$, i.e., the property tax risk without any tax limit policy.
$\Delta\mathbb{R}_{s,t,i,z}$	The difference between $\mathbb{R}_{s,t,i,z}$ and $\mathbb{R}'_{s,t,i,z}$, i.e., the property tax risk during the entire tenure of property owner i in simulation year z under the policy in state s in year z.
$\Delta\mathbb{R}_{s,t}$	The simple average of $\Delta\mathbb{R}_{s,t,i,z}$ over i and z, i.e., the tax policy risk of state s in year t.
$\mathbb{1}(\text{Distressed})_{i,t}$	An indicator that equals one if property i experiences any form of mortgage distress in year t and zero otherwise.
Tax Policy Risk$_{s,t}$	The same as $\Delta\mathbb{R}_{s,t}$, i.e., the tax policy risk of state s in year t.

Continued on next page

Table A.1 – continued from previous page

Variable Definitions	Description
$\mathbb{1}(\text{Levy Limit})_{s,t}$	An indicator that equals one if state s has a levy limit in year t and zero otherwise.
$\mathbb{1}(\text{Rate Limit})_{s,t}$	An indicator that equals one if state s has a millage rate limit in year t and zero otherwise.
$\mathbb{1}(\text{Assessment Limit})_{s,t}$	An indicator that equals one if state s has an assessment limit in year t and zero otherwise.
Levy Limit$_{s,t}$	The level of levy limit in state s in year t.
Rate Limit$_{s,t}$	The level of millage rate limit in state s in year t.
Assessment Limit$_{s,t}$	The level of assessment limit in state s in year t.

Appendix C Machine Learning Hedonic Estimation

We use a machine learning process to infer the market value of a property using its characteristics and location. The machine learning procedure is able to impute a market value of the property without prior arm's-length transaction using only information of the property. We predict the property values census tract by census tract using the following procedure.

For each (focal) census tract, we start with all properties in the focal tract and append all properties in the next adjacent census tract. 10% of the sample is reserved for validation and 90% is used for training. With all the information available on transaction price (prediction target) and property characteristics (prediction input, including number of rooms, lot size, zip code, existence of fireplace, etc.), we use a ensemble method with gradient boosting regression tree. The method is able to select information for the best fit taking into account of non-linear relations and interactions. We specifically use the histogram-based gradient boosting regression tree method to natively handle missing values and categorical values to improve the efficiency of the process.[31]

After obtaining the prediction output from the gradient boosting regression tree, we regulate potential outliers with a simple censoring procedure. We apply this censoring procedure as a preemptive measure because our context is potentially more prone to producing outlier predictions due to certain input fields being poorly populated. The censoring procedure is as follows: for each property we run a simple regression but only using observations with prediction output that is within the 25th and 75th percentile range:

$$\mathrm{Y} = \beta_0 + \beta_1 \mathrm{Year}$$

where Y is the prediction from the gradient boosting regression tree. We calculate $\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 \mathrm{Year}$ for *all* observations. We then censor the predicted value at $\hat{Y} * (1 \pm 10\%)$ if the predicted value is outside of [90%, 110%] range surrounding $\hat{Y}$. Very rarely does the predict get censored. Lastly, we record the mean squared error with the preferred model.

We then add the next adjacent census tract to the sample and repeat the process. The iterative process is done with the following tradeoff in mind. The more census tracts we include in the sample to predict the focal tract, the more information we are using, which improves the prediction quality. However at the same time, the more census tracts we include in the sample, the further-away properties we are using to

[31] For more details, see the documentation of the histogram-based gradient boosting method at: https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.HistGradientBoostingRegressor.html.

predict properties in the focal tract, i.e., the relevance of the information goes down and prediction quality could decrease. For each census tract, we repeat the process until the sample has 20,000 transactions. We then pick the iteration that has the lowest mean square error, which usually bottoms between 5,000 to 10,000 transactions.

The prediction we obtained using this process is therefore parameter-optimized and sample-optimized. We apply this process to all census tracts in our sample to obtain a machine-learning prediction for market value of properties.

Appendix D Sample Construction

Our core dataset starts from the universe of parcel-level administrative assessor data on tax and property characteristics obtained from ATTOM Data Solutions for the continental U.S. for the period 2006-2016, and we match these data based on ATTOM's unique property identifiers to all available data on housing and loan transactions from ATTOM's recorder datafiles, along with indicators of all foreclosure-related events over the corresponding period.[32]

We group sale and loan transactions falling within 60 days of each other and treat the latest date within each such series as the relevant transaction date. Accordingly, we alternately sum relevant loan amounts (e.g., as appropriate for "piggyback" mortgages) or record only the latest loan transaction in a series, depending on the characteristics of the parties to a given sequence of loan transactions. In the case of multiple distinct transactions or transaction series (i.e., separated by more than 60 days) occurring within the same calendar year, we preserve only the latest arm's length transaction of the year while flagging any distressed transactions that might have occurred earlier in the year.[33]

We apply a parallel set of procedures to format the universe of parcel-level data from Zillow (ZTRAX) over the same 2006-2016 period and similarly link all available assessment and transaction data (sales, loans, and foreclosures) on the basis of Zillow's unique property identifiers. Constructing a concordance of ATTOM and Zillow's proprietary identifiers in order to validate and complement the ATTOM data using ZTRAX proceeds in three steps. We prioritize merging property records using a combination of legal parcel numbers (i.e., those assigned by local tax assessors) and zip code. Due to frequent inconsistencies in parcel number formatting, we implement an extensive list of county-specific pre-processing to improve the ATTOM-ZTRAX match rate; nevertheless, this leaves a large number of unmatched parcels, either due to inaccurate or missing parcel numbering or missing zip code information. We consequently repeat the procedure by parcel number plus street address (i.e., to catch failed matches due to missing zip codes) and again by street address plus zip code.

Due to the importance of our state-border identification strategy, we drop all observations from the merged ATTOM-ZTRAX concordance of property identifiers which do not include sufficient information for geocoding (i.e., due to missing latitude/longitude coordinates or–where unavailable–missing or incom-

[32]These latter data were formerly assembled by RealtyTrac, the then-leading provider of foreclosure information in the U.S.

[33]Where not explicitly designated in the transaction data, we also flag related party transactions as those involving sellers and buyers with the same last names, quit claim deeds, or flagged as exempt from transfer taxes. Any remaining related-party transactions are likely excluded due to restrictions on exceptionally low transaction prices, as discussed below.

plete street address or zip code information). We geocode all other addresses using ArcMap 10.7.1/10.8.1 using a U.S. address dual ranges locator to obtain latitude, longitude, and U.S. National Grid coordinates and to calculate parcel distances to state borders.

Where property characteristic data are missing from ATTOM at the parcel-year level, we first attempt to interpolate these from previous and subsequent years of (unchanged) non-missing data. Where this approach is infeasible (e.g. because earlier or later years of data are unavailable), we attempt to use matched data from ZTRAX provided that these imply unchanged property characteristics. Where ATTOM and ZTRAX data conflict, we defer exclusively to ATTOM. Unless otherwise explicitly identified in the assessor data, we infer home remodelings from discrete changes in key property characteristics (i.e., square footage, number of rooms, bedrooms, or bathrooms) provided that lot size remains unchanged.

Prior to imputing annual house prices or loan balances in the merged data, we exclude all transactions featuring purchase prices of less than $1000 or more than $5 million, and we exclude short-term loans (i.e. loans with due dates less than 12 months from origination). We also ignore re-recorded deeds or loan transfers between lenders. We apply the same restrictions to sale prices for our machine learning hedonic estimation procedure. To the extent that the imputation or hedonic estimation procedures yield prices outside of these bounds, we exclude such parcels from the analysis for the entire sample period (regardless of the number of years for which this happens).

We apply multiple layers of additional restrictions to our final estimation sample based on extreme or implausible ETRs, changes in annual tax liability or changes in assessed values. These proceed in steps and are designed to avoid applying blanket exclusions that would risk affecting parcels in certain states and/or certain types of homeowners more strongly than others due to state-specific property tax and assessment practices. Thus, we start by excluding observations with ETRs in excess of 100% or inferior to 0.01% using ETRs constructed from either imputed or estimated house prices, which represent approximately 0.5% of all observations with non-missing ETR information. Such extreme values are implausible regardless of state property tax practices. Next, we drop all observations whose ETRs fall below the 1st percentile or above the 99th percentile of each state's respective ETR distribution, based on ETRs constructed from imputed prices, estimated prices, or assessed values (grossed up to full market value according to state assessment ratios). With respect to changes in annual tax liabilities, we drop all parcels for which the percent change in liability fell outside the 5th through 95th percentile within state-year-tenure-homestead status *provided that* the change also exceeded 10% in absolute value *and* either assessment ratios, ETRs, or assessed values also exhibited extreme changes from the prior year (i.e., in the top or bottom 5% of their respective distributions). Alternatively, we drop all parcels for which the percent change in tax liability fell outside the 1st through 99th percentiles within state-year-tenure-homestead status if the change in tax amount exceeded either 100% on the upside or -50% on the downside. Lastly, we drop any remaining parcels that saw their assessed values rise by more than 345% or fall by more than -65% year-over-year.[34]

For computational reasons, we use only a 33.3% random subsample of parcels (located within 20 miles of a state border) that survive the above sample restrictions. Of these, we exclude from our analysis all parcels in price non-disclosure jurisdictions (i.e., ID, KS, LA, MS, MT, NM, ND, TX, UT, WY, and all but four counties in MO) due to insufficient price information for reliable imputation or hedonic estimation, and we omit new construction and newly-renovated properties (i.e., built or remodeled within the last two years) on account of the difficulty in interpreting changes in assessed value and tax liability over the course of (re)construction. Our baseline (unconditional) estimation sample thus consists of 38,842,845 parcel-year observations, which is reduced to approximately 23.3 million parcel-year observations once we condition on the availability of data on imputed or estimated house prices and ETRs.

Figure A.2 characterizes the geographic distribution of unique parcels in the latter final estimation sample. Darker shaded border counties denote areas with a higher density of observations. As shown, the highest concentration of observations arises among states east of the Mississippi River and along the U.S. west coast and southwest. Sparsely populated border areas coupled with price non-disclosure imply that our analysis necessarily omits large parts of the U.S. mountain west.

[34] These figures correspond to less than 1% of values at either end of the distribution for state border counties.

Appendix E Assessment Limits and the Tax-Price Gap

As we show in Section **??**, assessment limitations contribute more to tax risk than any other type of tax limit. This is not entirely surprising given the discussion in Section 2.2 about how assessment limitations can give rise to rising tax obligations during periods of declining home prices, and this is reflected in the divergence between tax-price adjustment gaps for assessment limitation states versus other states, as depicted in Figure 4.

In this section, we investigate to what extent assessment limits affect property tax liabilities at the parcel level and how the resulting spread between the growth in tax payments and home values ultimately affects mortgage distress. In contrast to the measure of tax policy risk used for our primary analyses, the tax-price adjustment gap lacks a clean economic interpretation, and we cannot use it to readily address the effect of interactions among different features of states' property tax regimes, or the stringency thereof. Nevertheless, we view this exercise as providing additional reduced-form evidence of the importance of tax limitations for households' financial well-being.

Concretely, our analysis proceeds in three steps. First, we confirm that assessment limitations affect tax liabilities in a predictable manner as a function of homeowner tenure and the state of the economy. Next, we show that assessment limitations are associated with higher probabilities of mortgage distress under certain conditions. Finally, we demonstrate that when tax liabilities grow at a faster rate than housing values and the tax-price gap is growing (e.g., during a market downturn in assessment limitations states), this contributes to an increased probability of distress. For each of these tests, we employ similar methods and data as used in our main analyses.

Our first empirical specification consists of testing how changes in housing prices affect property tax liabilities as a function of whether those properties are subject to assessment limitations and the number of years elapsed since the last change of ownership (i.e., Tenure). In particular, we expect the percent change in annual tax liability, $\%\Delta Tax$, to be generally less responsive to changes in market values, $\%\Delta Price$, in states with assessment limits and for new homeowners in assessment limitation states to experience relatively large increases in tax liability due to taxable value uncapping. To test these stylized facts, we use the following estimating equation

$$
\begin{aligned}
\%\ \Delta\ \text{Tax}_{i,t} = {} & \beta_0 + \beta_1 \mathbb{1}(\text{AssessmentLimit})_{s,t} + \beta_2 \%\ \Delta\ \text{Price}_{i,t} \\
& + \beta_3 \mathbb{1}(\text{AssessmentLimit})_{s,t} \times \%\ \Delta\ \text{Price}_{i,t} \\
& + \theta^k \mathbb{1}(\text{Tenure})_{i,t} + \gamma^k \mathbb{1}(\text{Tenure})_{i,t} \times \mathbb{1}(\text{AssessmentLimit})_{s,t} \\
& + \rho^k \mathbb{1}(\text{Tenure})_{i,t} \times \%\ \Delta\ \text{Price}_{i,t} \\
& + \delta^k \mathbb{1}(\text{Tenure})_{i,t} \times \mathbb{1}(\text{AssessmentLimit})_{s,t} \times \%\ \Delta\ \text{Price}_{i,t} \\
& + X_{i,t}\beta + \lambda_{j,t} + \varepsilon_{i,t},
\end{aligned}
\tag{A.1}
$$

where an observation is a property i in year t, and property i is in a state s and grid cell j. Tenure is a categorical variable given by a vector of indicator variables which denote different durations of ownership. Due to the nature of assessment limits, the effect of the limits can differ based on how long an owner has had the property, which we capture with the interaction terms and vector of coefficients δ^k. $X_{i,t}$ is a vector of property-specific control variables, which consists of the lagged ETR and estimated house price. All specifications include grid cell by year pair fixed effects $\lambda_{j,t}$ to implement our border discontinuity design.

Results from this first-stage test are shown in Table A.4. As shown in column 1, properties in assessment limitation states experience larger changes in annual property tax obligations overall—roughly 0.5 percentage points larger—than their counterparts in adjacent no-limit states, while the rate at which changes in house prices are passed through to tax obligations in all states is considerably less than 1. This pair of results likely points to the fact that tax assessments tend to adjust slowly or infrequently in all states, including those with notional market value assessment regimes.[35] As a result, the combination of taxable value uncapping for newly sold properties along with regular capped taxable value adjustments–neither of which are closely tied to changes in home prices–evidently translate to larger average changes in annual tax obligations in states with acquisition value assessment limits. In column 2, we allow for changes in house prices to be passed through to tax liability at a different rate in assessment limitation states, and we further break down the average rate of property tax increases in these states as a function of homeowner tenure. Relative to homeowners with at least 6 years of tenure (i.e., the omitted category), new homeowners in assessment limitation states experience tax increases that are approximately 5 percentage points greater, on average, consistent with a relatively modest "pop-up tax" due to taxable value

[35] As noted in the last column of Table 1, a large number of states only reappraise property every four years or more, and some, like Pennsylvania, have no fixed schedule for doing so.

uncapping during this time period. Furthermore, changes in house prices are passed through to property taxes at similar rates in states with and without assessment limitations *on average*. However, as shown in column 3, this latter effect masks the fact that longer-tenured homeowners in assessment limitation states experience significantly attenuated (if not reversed) changes in tax liability in relation to housing prices relative to new homeowners, consistent with the discussion in Section 2.2 of asymmetric tax adjustments.

Next, we evaluate the reduced form effect of assessment limitations on the probability of mortgage distress at the property i and year t level, which we estimate as a linear probability model:

$$\begin{aligned}
\mathbb{1}(\text{Distressed})_{i,t} = {} & \beta_0 + \beta_1 \mathbb{1}(\text{AssessmentLimit})_{s,t} + \beta_2 \mathbb{1}(\Delta \text{ Price} < 0)_{i,t} \\
& + \beta_3 \mathbb{1}(\text{AssessmentLimit})_{s,t} \times \mathbb{1}(\Delta \text{ Price} < 0)_{i,t} + \theta^k \mathbb{1}(\text{Tenure})_{i,t} \\
& + \gamma^k \mathbb{1}(\text{Tenure})_{i,t} \times \mathbb{1}(\text{AssessmentLimit})_{s,t} \\
& + \rho^k \mathbb{1}(\text{Tenure})_{i,t} \times \mathbb{1}(\Delta \text{ Price} < 0)_{i,t} \\
& + \delta^k \mathbb{1}(\text{Tenure})_{i,t} \times \mathbb{1}(\text{AssessmentLimit})_{s,t} \times \mathbb{1}(\Delta \text{ Price} < 0)_{i,t} \\
& + \beta_2 \mathbb{1}(\text{NonJudicial Review})_{s,t} + \beta_3 \mathbb{1}(\text{Recourse})_{s,t} \\
& + X_{i,t}\beta + Z_{i,t}\beta + \lambda_{j,t} + \varepsilon_{i,t},
\end{aligned} \tag{A.2}$$

We again allow for the effect of assessment limitations to differ according to homeowner tenure, and we allow these effects to differ further depending on whether house prices decreased from the prior period to capture possible asymmetric effects. We augment our vector of controls $X_{i,t}$ to incorporate additional factors related to strategic default incentives and proxies for trigger events, exactly as in equation Appendix A in Section 5.

As shown in the first column of Table A.5, long-tenured homeowners (i.e., the reference category) in assessment limitation states are significantly less likely to experience mortgage distress (conditional on LTV, age, etc.), though this effect is at least partially offset among short-tenured homeowners or homeowners of unknown tenure. Meanwhile, a reverse pattern with respect to tenure and mortgage distress appears to hold in states without assessment limitations, and the contrast between these sets of results as a function of tenure likely reflects the impact of taxable value uncapping for new homeowners in states with assessment limitations. The results in column 1 also imply that falling house prices contribute to a higher probability of distress, without any statistically significant difference between states with or without assessment limits. With a full set of interactions between assessment limit, tenure, and directional price change indicators (column 2), we note that whereas new homeowners are at significantly lower risk of distress in states without assessment limits (and even more so when prices are falling), new and short-tenured homeowners are at significantly higher risk of distress in assessment limitation states (especially when house prices are falling). Overall, the set of homeowners who face the greatest increase in risk of mortgage distress are the subset of homeowners in assessment limitation states during market downturns who have been in their homes 2-5 years—long enough to have potentially enjoyed a few years of capped taxable growth prior to the downturn but not so long as to have accumulated a significant tax reduction relative to what market values would dictate.

Finally, in order to investigate the role of asymmetric tax adjustments more directly, we replicate the preceding analysis of mortgage distress replacing the indicator for falling house prices with a measure of the property-specific tax-price adjustment gap discussed in Section 2.2. Having demonstrated above that assessment limitations affect changes in annual property tax obligations in predictable ways, this is akin to a sort of "second-stage" analysis. Defined as the difference between the percent change in annual tax liability and the percent change in house price, $\Delta Tax - PriceGap$ incorporates the primary mechanism through which assessment limits may induce property tax liabilities to deviate from what would occur under annual market value based assessments. Absent any changes in statutory tax rates, this variable should equal zero under a system of annual market value based assessments, and non-zero values hence represent the extent to which changes in property tax liabilities deviate from such a regime.

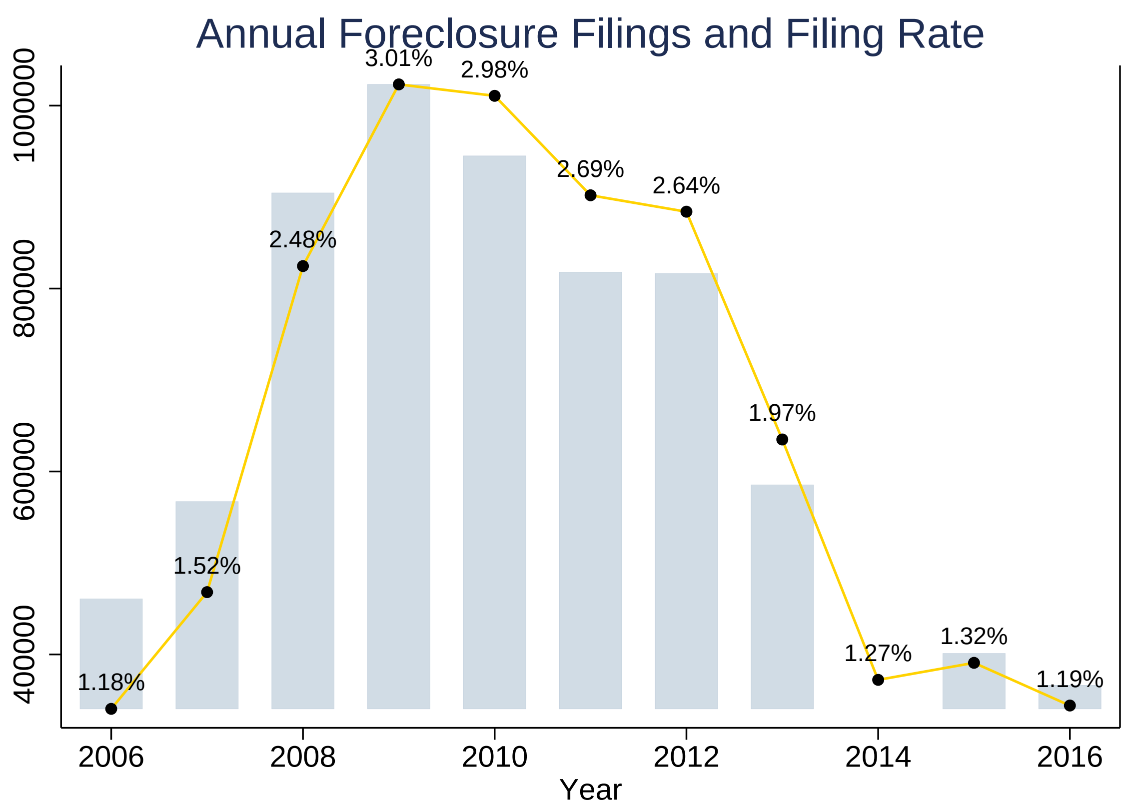
As shown in column 1 of Table A.6, larger tax-price gaps are responsible for a higher probability of mortgage distress everywhere, but this effect is significantly more pronounced in assessment limitation states and virtually twice as large. Furthermore, this effect is again largest for the 25 percent of homeowners who have been in their homes 2-5 years, and more than twice as large for those in assessment limitation states (column 2). Otherwise, assuming zero tax-price gap, new homeowners are generally at lowest risk of distress in states without assessment limits, with gradually increasing risk for longer-tenured homeowners thereafter, but this pattern is largely reversed in assessment limitation states, presumably due to the outsized role of taxable value uncapping and subsequent capped taxable value growth.

As noted in Section 2.2 and documented in Figure 4, the average Δ Tax-Price Gap in assessment limitation states peaked at nearly 15 percentage points in 2008 and 2009. Rescaling the overall partial effect of the tax price gap for homeowners in assessment limitation states who have resided in their homes 2-5 years by this average 15 percentage point amount translates to an implied increase in the probability of distress of approximately 0.29 percentage points.[36] For comparison, homes with an LTV of 91 to 160

[36]i.e., $(0.008 + 0.011) * 15 = 0.285$

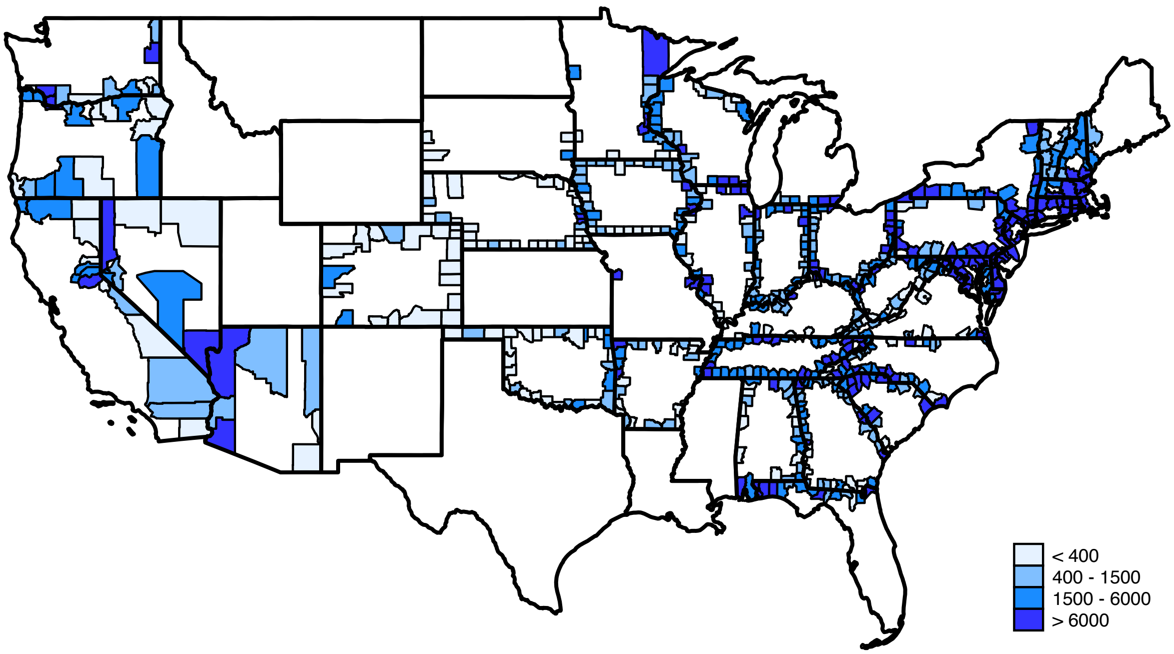
percent or more are estimated to face a 2.2 to 2.9 percentage point increase in the probability of distress relative to those with an LTV of less than 25 percent. Living in a heavily outdated home (last renovated 60 or more years ago) increases the probability of distress by roughly 0.15 percentage points, presumably due to a higher risk of unanticipated repairs. As such, during the worst of the Great Recession, the average short-tenured homeowner in assessment limitation states saw an increased likelihood of mortgage distress as a result of asymmetric tax adjustments of a comparable magnitude to nearly twice the effect of owning a home in disrepair, or one tenth as large as the effect of being severely underwater on one's mortgage. These effect sizes are comparable to those obtained in relation to the average increase in tax policy risk due to assessment limitations, as discussed in Section 6.

Figure A.1: Trends in National Foreclosure Activity



Foreclosure activity reflects only the first foreclosure event in a sequence of distressed transactions for our initial (national) sample of linked property tax assessment, realty transaction, loan, and foreclosure data.

Figure A.2: In-Sample Distribution of Unique Parcels



Observation counts refer to the number of unique parcels in the main estimation sample, aggregated by border county.

Table A.2: Mortgage Distress and Tax Policy Risk

$Y = Pr(Distressed_t = 1), Y \in \{0, 100\}$	(3)	(4)	(6)	(7)
Tax Policy Risk	1.420***	1.527***	1.210*	0.686**
	(0.527)	(0.364)	(0.629)	(0.319)
Tax Policy Level Diff	0.018**	0.019***	0.023**	0.007
	(0.009)	(0.006)	(0.012)	(0.007)
LTV				
0.25 - 0.6	-0.091***	-0.079***	-0.085***	-0.074***
	(0.018)	(0.015)	(0.018)	(0.015)
0.6 - 0.91	0.612***	0.622***	0.615***	0.624***
	(0.028)	(0.021)	(0.028)	(0.021)
0.91 - 1.6	2.270***	2.258***	2.232***	2.213***
	(0.057)	(0.039)	(0.055)	(0.038)
> 1.6	2.901***	2.861***	2.854***	2.822***
	(0.110)	(0.076)	(0.104)	(0.071)
Unknown	-1.528***	-1.555***	-1.568***	-1.597***
	(0.053)	(0.033)	(0.055)	(0.034)
Price	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Lagged ETR	0.047***	0.038***	0.047***	0.036***
	(0.008)	(0.005)	(0.006)	(0.005)
Tenure				
< 2 years	-0.883***	-0.897***	-0.897***	-0.913***
	(0.055)	(0.034)	(0.056)	(0.035)
2-5 years	-0.064**	-0.078***	-0.069**	-0.082***
	(0.032)	(0.021)	(0.035)	(0.022)
Unknown	1.550***	1.579***	1.610***	1.643***
	(0.079)	(0.047)	(0.081)	(0.048)
Age				
10-19 years	-0.475***	-0.445***	-0.458***	-0.425***
	(0.056)	(0.040)	(0.053)	(0.033)
20-59 years	-0.445***	-0.400***	-0.436***	-0.394***
	(0.057)	(0.037)	(0.055)	(0.032)
60-99 years	-0.329***	-0.313***	-0.266***	-0.240***
	(0.065)	(0.041)	(0.060)	(0.035)
>99 years	-0.135*	-0.087*	-0.086	-0.032
	(0.073)	(0.048)	(0.070)	(0.042)
Unknown	-0.090	-0.094	-0.162	-0.178
	(0.137)	(0.131)	(0.141)	(0.133)
Renovation Age				
11-32 years	-0.067***	-0.059***	-0.033*	-0.021
	(0.023)	(0.015)	(0.019)	(0.013)
33-59 years	-0.020	-0.015	-0.004	0.002
	(0.026)	(0.017)	(0.022)	(0.015)
> 59 years	0.242***	0.212***	0.219***	0.174***
	(0.034)	(0.022)	(0.031)	(0.021)
Unknown	-0.584***	-0.591***	-0.401***	-0.389***
	(0.126)	(0.127)	(0.131)	(0.130)
I[Recourse=1]	-0.012	0.244	0.000	0.044
	(0.143)	(0.179)	(0.176)	(0.264)

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	(3)	(4)	(6)	(7)
I[NonJudicialReview=1]	-0.372	-0.156**	-0.357	-0.035
	(0.228)	(0.075)	(0.289)	(0.085)
Fixed Effects:				
10 km² grid	x			
5 km² grid		x		
Year	x	x		
10 km² grid × Year			x	
5 km² grid × Year				x
Observations	23,322,881	23,321,903	23,317,620	23,299,465
R-squared	0.018	0.019	0.023	0.027

Significance levels are designated as *** $p<0.01$, ** $p<0.05$, and * $p<0.1$. Standard errors (in parentheses) are clustered by 5 km² grid cell.

Table A.3: Mortgage Distress and Tax Policy Risk - Heterogenous Effects

$Y = Pr(Distressed_t = 1), Y \in \{0, 100\}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Tax Policy Risk	-9.377*	0.717**	0.829**	0.788**	0.949***	0.769**	0.781**	0.812**	2.718***	
	(5.114)	(0.324)	(0.323)	(0.336)	(0.312)	(0.306)	(0.338)	(0.337)	(0.935)	
Tax Policy Level Diff	0.004	0.008	0.007	0.006	0.009	0.009	0.007	0.007	0.041*	0.005
	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.023)	(0.007)
$UnempRate$	2.915									
	(2.105)									
$UnempRate^2$	-0.459									
	(0.318)									
$UnempRate^3$	0.024									
	(0.015)									
$UnempRate$	4.069*									
× Tax Policy Risk	(2.164)									
$UnempRate^2$	-0.537*									
× Tax Policy Risk	(0.292)									
$UnempRate^3$	0.023*									
× Tax Policy Risk	(0.013)									
I[TaxDeferral=1]		0.405								
		(1.946)								
I[TaxDeferral=1]		-0.602								
× Tax Policy Risk		(3.718)								
I[HighItemizationRate=1]			-0.165	-0.086						
			(0.133)	(0.137)						
I[HighItemizationRate=1]			-0.220*	-0.047						
× Tax Policy Risk			(0.127)	(0.138)						
I[HighAGI=1]				-0.185**	-0.100	-0.177**	-0.196**	-0.186**		
				(0.089)	(0.074)	(0.087)	(0.092)	(0.091)		
I[HighAGI=1]				-0.195**	-0.161**	-0.188**	-0.204**	-0.242***		
× Tax Policy Risk				(0.093)	(0.070)	(0.081)	(0.085)	(0.089)		
I[MajorityWhite=1]					-0.707***					
					(0.165)					
I[MajorityWhite=1]					-0.181**					
× Tax Policy Risk					(0.091)					
I[MajorityBlack=1]						0.565***				
						(0.160)				
I[MajorityBlack=1]						0.391***				
× Tax Policy Risk						(0.126)				
I[MajorityLatino=1]							-0.180			
							(0.255)			
I[MajorityLatino=1]							0.287			
× Tax Policy Risk							(0.187)			
I[MajorityAsian=1]								-0.216		
								(0.328)		
I[MajorityAsian=1]								-0.033		
× Tax Policy Risk								(0.362)		

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
% Δ_{T-0} Price									0.0004***	
									(0.000)	
% Δ_{T-0} Price									-0.0001**	
$\times$ Tax Policy Risk									(0.000)	
LTV $\times$ Tax Policy Risk										
0 - 0.25										0.824**
										(0.325)
0.25 - 0.6										0.826**
										(0.324)
0.6 - 0.91										0.798**
										(0.324)
0.91 - 1.6										0.600*
										(0.332)
$>$ 1.6										1.399***
										(0.378)
Unknown										0.400
										(0.325)
I[Recourse=1] $\times UnempRate$	-5.051**									
	(1.968)									
I[NonJudicialReview=1] $\times UnempRate$	-0.023									
	(1.257)									
I[Recourse=1] $\times UnempRate^2$	0.717**									
	(0.284)									
I[NonJudicialReview=1] $\times UnempRate^2$	0.015									
	(0.189)									
I[Recourse=1] $\times UnempRate^3$	-0.034**									
	(0.013)									
I[NonJudicialReview=1] $\times UnempRate^3$	-0.001									
	(0.009)									
I[Recourse=1] $\times$ I[TaxDeferral=1]		-0.726								
		(1.245)								
I[NonJudicialReview=1] $\times$ I[TaxDeferral=1]		-								
		-								
I[Recourse=1] $\times$ I[HighItemizationRate=1]			-0.187	-0.152						
			(0.116)	(0.121)						
I[NonJudicialReview=1] $\times$ I[HighItemizationRate=1]			-0.068	-0.002						
			(0.093)	(0.091)						
I[Recourse=1] $\times$ I[HighAGI=1]				-0.075	-0.146**	-0.116	-0.160**	-0.168**		
				(0.078)	(0.064)	(0.076)	(0.082)	(0.080)		
I[NonJudicialReview=1] $\times$ I[HighAGI=1]				-0.052	-0.099	-0.079	-0.076	-0.079		
				(0.065)	(0.063)	(0.070)	(0.073)	(0.071)		
I[Recourse=1] $\times$ I[MajorityWhite=1]					0.040					
					(0.151)					
I[NonJudicialReview=1] $\times$ I[MajorityWhite=1]					-0.042					
					(0.087)					
I[Recourse=1] $\times$ I[MajorityBlack=1]						0.121				
						(0.136)				

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
I[NonJudicialReview=1] × I[MajorityBlack=1]						-0.001				
						(0.109)				
I[Recourse=1] × I[MajorityLatino=1]							0.185			
							(0.201)			
I[NonJudicialReview=1] × I[MajorityLatino=1]							0.361*			
							(0.200)			
I[Recourse=1] × I[MajorityAsian=1]								-		
								-		
I[NonJudicialReview=1] × I[MajorityAsian=1]								0.676*		
								(0.372)		
I[Recourse=1] × % Δ_{T-0} Price									-0.0003***	
									(0.000)	
I[NonJudicialReview=1] × % Δ_{T-0} Price									-0.0004***	
									(0.000)	
I[Recourse=1] × LTV										
0.25 - 0.6										0.048
										(0.044)
0.6 - 0.91										0.049
										(0.054)
0.91 - 1.6										0.166*
										(0.092)
$>$ 1.6										0.502***
										(0.154)
Unknown										-0.129
										(0.084)
I[NonJudicialReview=1] × LTV										
0.25 - 0.6										0.107***
										(0.033)
0.6 - 0.91										0.033
										(0.044)
0.91 - 1.6										0.148*
										(0.078)
$>$ 1.6										0.245*
										(0.136)
Unknown										-0.442***
										(0.076)
LTV										
0.25 - 0.6	-0.074***	-0.074***	-0.072***	-0.072***	-0.068***	-0.069***	-0.073***	-0.073***	0.351***	-0.153***
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.031)	(0.051)
0.6 - 0.91	0.624***	0.624***	0.626***	0.626***	0.628***	0.628***	0.624***	0.624***	0.165***	0.575***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)	(0.028)	(0.063)
0.91 - 1.6	2.213***	2.213***	2.211***	2.208***	2.206***	2.208***	2.207***	2.207***	1.338***	2.081***
	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.038)	(0.034)	(0.106)
$>$ 1.6	2.822***	2.822***	2.812***	2.808***	2.795***	2.799***	2.810***	2.811***	2.563***	2.074***
	(0.071)	(0.071)	(0.071)	(0.071)	(0.070)	(0.071)	(0.071)	(0.071)	(0.071)	(0.180)
Unknown	-1.597***	-1.597***	-1.599***	-1.601***	-1.606***	-1.608***	-1.600***	-1.600***	-0.723***	-1.174***
	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.034)	(0.041)	(0.092)

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Price	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Lagged ETR	0.036***	0.036***	0.035***	0.034***	0.033***	0.034***	0.034***	0.034***	-0.051***	0.037***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.011)	(0.004)
Tenure										
< 2 years	-0.913***	-0.913***	-0.913***	-0.913***	-0.915***	-0.915***	-0.913***	-0.913***	-1.983***	-0.909***
	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.035)	(0.068)	(0.035)
2-5 years	-0.082***	-0.082***	-0.082***	-0.082***	-0.084***	-0.083***	-0.082***	-0.082***	-0.887***	-0.076***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.057)	(0.022)
Unknown	1.644***	1.643***	1.644***	1.644***	1.647***	1.645***	1.644***	1.644***	23.5343***	1.662***
	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(0.048)	(1.949)	(0.049)
Age										
10-19 years	-0.425***	-0.425***	-0.425***	-0.425***	-0.420***	-0.423***	-0.425***	-0.425***	-0.480***	-0.424***
	(0.033)	(0.033)	(0.033)	(0.033)	(0.032)	(0.032)	(0.033)	(0.033)	(0.049)	(0.033)
20-59 years	-0.393***	-0.394***	-0.393***	-0.393***	-0.383***	-0.387***	-0.394***	-0.393***	-0.191***	-0.393***
	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.032)	(0.049)	(0.032)
60-99 years	-0.239***	-0.240***	-0.242***	-0.243***	-0.226***	-0.232***	-0.242***	-0.242***	0.010	-0.242***
	(0.035)	(0.035)	(0.035)	(0.035)	(0.034)	(0.034)	(0.035)	(0.035)	(0.064)	(0.035)
>99 years	-0.031	-0.032	-0.042	-0.046	-0.027	-0.024	-0.046	-0.043	0.177**	-0.036
	(0.042)	(0.042)	(0.042)	(0.042)	(0.041)	(0.041)	(0.042)	(0.042)	(0.071)	(0.042)
Unknown	-0.177	-0.179	-0.188	-0.190	-0.193	-0.186	-0.192	-0.190	-0.179	-0.183
	(0.133)	(0.133)	(0.132)	(0.133)	(0.133)	(0.133)	(0.133)	(0.133)	(0.352)	(0.133)
Renovation Age										
11-32 years	-0.021	-0.021	-0.020	-0.020	-0.020	-0.019	-0.021	-0.020	-0.092***	-0.022*
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.031)	(0.013)
33-59 years	0.001	0.002	0.003	0.001	0.005	0.004	0.000	-0.001	-0.040	0.000
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.034)	(0.015)
> 59 years	0.173***	0.174***	0.167***	0.166***	0.161***	0.165***	0.168***	0.169***	0.369***	0.175***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.020)	(0.020)	(0.021)	(0.021)	(0.069)	(0.021)
Unknown	-0.389***	-0.389***	-0.389***	-0.389***	-0.388***	-0.389***	-0.388***	-0.387***	-2.147***	-0.380***
	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.130)	(0.366)	(0.130)
I[Recourse=1]	11.8765***	0.089	0.234	0.389	0.316	0.314	0.350	0.351	1.375**	0.145
	(4.356)	(0.276)	(0.302)	(0.321)	(0.370)	(0.298)	(0.299)	(0.300)	(0.580)	(0.269)
I[NonJudicialReview=1]	-0.068	-0.034	0.013	0.041	0.105	0.046	0.067	0.072	-0.424*	0.201*
	(2.654)	(0.086)	(0.100)	(0.108)	(0.126)	(0.106)	(0.104)	(0.104)	(0.255)	(0.107)
Fixed Effects:										
5 km² grid × Year	x	x	x	x	x	x	x	x	x	x
Observations	23,299,066	23,299,066	23,280,123	23,280,004	23,277,205	23,277,205	23,277,205	23,277,205	4,755,129	23,299,066
R-squared	0.027	0.027	0.027	0.028	0.028	0.028	0.028	0.027	0.061	0.028

Significance levels are designated as *** p<0.01, ** p<0.05, and * p<0.1. Standard errors (in parentheses) are clustered by 5 km² grid cell.

Table A.4: Property Tax Effects of Assessment Limitations (≈ 1st Stage)

Y = % Δ Tax	(1)	(2)	(3)
I[AssessmentLimit=1]	0.510***	0.303	0.303
	(0.195)	(0.217)	(0.217)
Tenure			
< 2 years	1.878***	1.027***	1.027***
	(0.078)	(0.056)	(0.056)
2-5 years	-0.033	0.155***	0.154***
	(0.027)	(0.019)	(0.019)
Unknown	-0.025	-0.037	-0.036
	(0.052)	(0.057)	(0.057)
% Δ Price	0.001***	0.002***	0.002***
	(0.000)	(0.000)	(0.000)
I[AssessmentLimit=1] × % Δ Price		0.000	0.001
		(0.000)	(0.001)
Tenure × I[AssessmentLimit=1]			
< 2 years		4.966***	4.958***
		(0.326)	(0.326)
2-5 years		-1.113***	-1.113***
		(0.106)	(0.106)
Unknown		0.057	0.057
		(0.131)	(0.131)
Price	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
ETR_{t-1}	-0.660***	-0.661***	-0.661***
	(0.019)	(0.019)	(0.019)
Tenure × % Δ Price			
> 5 years			0.000
			(0.000)
< 2 years			
2-5 years			0.000
			(0.000)
Unknown			0.000
			(0.000)
Tenure × I[AssessmentLimit=1] × % Δ Price			
> 5 years			-0.002**
			(0.001)
< 2 years			
2-5 years			-0.001
			(0.001)
Unknown			-0.001
			(0.001)
Observations		23,299,480	
R-squared	0.432	0.433	0.433

Significance levels are designated as *** p<0.01, ** p<0.05, and * p<0.1. Standard errors (in parentheses) are clustered by 5 km² grid cell. All specifications include 5 km² grid cell × year fixed effects.

Table A.5: Distress Probabilities and Assessment Limitations (≈ Reduced Form)

$Y = Pr(Distressed_t = 1), Y \in \{0, 100\}$	(1)	(2)
I[AssessmentLimit=1]	-0.851***	
	(0.055)	
I[Δ Price $<$ 0]	0.119***	
	(0.026)	
I[AssessmentLimit=1] $\times$ I[Δ Price $<$ 0]	0.032	
	(0.022)	
Tenure		
$<$ 2 years	-0.907***	-0.791***
	(0.101)	(0.102)
2-5 years	-0.389***	-0.447***
	(0.072)	(0.048)
Unknown	1.553***	1.669***
	(0.152)	(0.139)
Tenure $\times$ I[AssessmentLimit=1]		
$<$ 2 years	0.287***	0.030
	(0.059)	(0.060)
2-5 years	0.436***	0.090***
	(0.053)	(0.034)
Unknown	0.196**	0.015
	(0.077)	(0.067)
Tenure $\times$ I[Δ Price $<$ 0]		
$<$ 2 years		-0.160**
		(0.077)
2-5 years		0.200**
		(0.086)
Unknown		-0.148**
		(0.074)
Tenure $\times$ I[AssessmentLimit=1] $\times$ I[Δ Price $<$ 0]		
$<$ 2 years		0.264***
		(0.057)
2-5 years		0.362***
		(0.070)
Unknown		0.033
		(0.061)
LTV		
0.27 - 0.65	-0.069***	-0.065***
	(0.015)	(0.015)
0.65 - 0.9	0.633***	0.639***
	(0.021)	(0.021)
0.9 - 1.6	2.214***	2.191***
	(0.038)	(0.038)
$>$ 1.6	2.825***	2.809***
	(0.072)	(0.071)
Unknown	-1.602***	-1.589***
	(0.034)	(0.034)
Age		
10-19 years	-0.417***	-0.413***

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	(0.032)	(0.032)
20-59 years	-0.395***	-0.390***
	(0.032)	(0.032)
60-99 years	-0.245***	-0.238***
	(0.035)	(0.035)
>99 years	-0.036	-0.027
	(0.042)	(0.042)
Unknown	-0.185	-0.165
	(0.133)	(0.133)
Renovation Age		
11-32 years	-0.023*	-0.015
	(0.013)	(0.013)
33-59 years	-0.002	0.009
	(0.015)	(0.015)
> 59 years	0.167***	0.177***
	(0.021)	(0.021)
Unknown	-0.385***	-0.380***
	(0.130)	(0.130)
Price	-0.000***	-0.000***
	(0.000)	(0.000)
Lagged ETR	0.036***	0.038***
	(0.005)	(0.005)
I[Recourse=1]	0.134	
	(0.297)	
I[NonJudicialReview=1]	-0.523***	
	(0.100)	
I[Recourse=1] $\times$ I[Δ Price $<$ 0]	-0.015	
	(0.025)	
I[NonJudicialReview=1] $\times$ I[Δ Price $<$ 0]	0.047**	
	(0.018)	
Tenure $\times$ I[Recourse=1]		
$<$ 2 years	-0.075	-0.146*
	(0.080)	(0.078)
2-5 years	0.153**	-0.021
	(0.068)	(0.043)
Unknown	-0.376**	-0.455***
	(0.157)	(0.140)
Tenure $\times$ I[NonJudicialReview=1]		
$<$ 2 years	0.046	-0.026
	(0.076)	(0.077)
2-5 years	0.242***	0.055*
	(0.059)	(0.032)
Unknown	1.182***	0.968***
	(0.126)	(0.093)
Tenure $\times$ I[Recourse=1] $\times$ I[Δ Price $<$ 0]		
$<$ 2 years		0.107
		(0.071)
2-5 years		0.282***
		(0.085)

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Unknown		0.111
		(0.079)
Tenure × I[NonJudicialReview=1] × I[Δ Price < 0]		
< 2 years		0.128**
		(0.056)
2-5 years		0.415***
		(0.083)
Unknown		0.426***
		(0.097)
Observations	23,299,465	
R-squared	0.028	0.028

Significance levels are designated as *** p<0.01, ** p<0.05, and * p<0.1. Standard errors (in parentheses) are clustered by 5 km² grid cell. All specifications include 5 km² grid cell × year fixed effects.

Table A.6: Distress Probabilities and Tax-Price Trends ($\approx$ 2nd Stage)

$Y = Pr(Distressed_t = 1), Y \in \{0, 100\}$	(1)	(2)
Δ Tax Gap	0.006***	0.000
	(0.001)	(0.001)
I[AssessmentLimit=1] $\times \Delta$ Tax Gap	0.003***	
	(0.001)	
Tenure		
$<$ 2 years	-0.939***	-0.874***
	(0.036)	(0.105)
2-5 years	-0.082***	-0.325***
	(0.022)	(0.075)
Unknown	1.694***	1.818***
	(0.050)	(0.172)
Tenure $\times$ I[AssessmentLimit=1]		
$<$ 2 years		0.125**
		(0.058)
2-5 years		0.326***
		(0.049)
Unknown		0.024
		(0.081)
Tenure $\times \Delta$ Tax Gap		
2-5 years		0.008***
		(0.001)
$>$ 5 years		0.005***
		(0.001)
Unknown		0.010***
		(0.001)
Tenure $\times$ I[AssessmentLimit=1] $\times \Delta$ Tax Gap		
$<$ 2 years		0.002
		(0.001)
2-5 years		0.011***
		(0.002)
$>$ 5 years		0.003***
		(0.001)
Unknown		0.010***
		(0.002)
% Δ Price	-0.000	-0.000
	(0.000)	(0.000)
I[AssessmentLimit=1] $\times$ % Δ Price	-0.000	-0.000
	(0.000)	(0.000)
LTV		
0.25 - 0.6	-0.087***	-0.084***
	(0.016)	(0.016)
0.6 - 0.91	0.630***	0.639***
	(0.021)	(0.021)
0.91 - 1.6	2.230***	2.231***
	(0.038)	(0.038)
$>$ 1.6	2.871***	2.882***
	(0.071)	(0.071)

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Unknown	-1.647***	-1.641***
	(0.034)	(0.035)
Age		
10-19 years	-0.426***	-0.423***
	(0.033)	(0.033)
20-59 years	-0.396***	-0.402***
	(0.032)	(0.033)
60-99 years	-0.248***	-0.253***
	(0.036)	(0.036)
>99 years	-0.021	-0.025
	(0.043)	(0.043)
Unknown	-0.155	-0.151
	(0.133)	(0.133)
Renovation Age		
11-32 years	-0.020	-0.016
	(0.013)	(0.013)
33-59 years	-0.001	0.004
	(0.016)	(0.016)
> 59 years	0.152***	0.154***
	(0.020)	(0.020)
Unknown	-0.262**	-0.262**
	(0.129)	(0.129)
Price	-0.000***	-0.000***
	(0.000)	(0.000)
Lagged ETR	0.051***	0.049***
	(0.005)	(0.005)
I[Recourse=1]	-0.097	-0.147
	(0.339)	(0.431)
I[NonJudicialReview=1]	0.032	-0.277***
	(0.087)	(0.104)
Tenure $\times$ I[Recourse=1]		
$<$ 2 years		-0.094
		(0.083)
2-5 years		0.127*
		(0.071)
Unknown		-0.563***
		(0.175)
Tenure $\times$ I[NonJudicialReview=1]		
$<$ 2 years		0.007
		(0.077)
2-5 years		0.200***
		(0.061)
Unknown		1.129***
		(0.130)
I[Recourse=1] $\times$ % Δ Price	0.000	0.000
	(0.000)	(0.000)
I[NonJudicialReview=1] $\times$ % Δ Price	0.000	-0.000
	(0.000)	(0.000)
Observations	22,663,442	
R-squared	0.027	0.028

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Significance levels are designated as *** $p<0.01$, ** $p<0.05$, and * $p<0.1$. Standard errors (in parentheses) are clustered by 5 km^2 grid cell. All specifications include 5 km^2 grid cell $\times$ year fixed effects.