The Impact of Property Taxation and Tax Limitations on Mortgage Distress: A Decomposition of Risk and Level Effects *

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Abstract

Property tax limitations reduce the inherent pro-cyclicality of property taxes and expose households to greater risk of mortgage distress. We develop a novel measure of tax policy risk using an Arrow-Debreu framework to price property tax regimes' consumption smoothing features and obtain simulated measures of risk that capture all of the key characteristics of states' property tax systems. We simultaneously account for the effects of these policies—including all applicable tax limitations, effective tax rates, and reassessment frequency—on the overall level of taxation. Using a state-border discontinuity design and parcel-level data for residential properties across the continental U.S., we show that a one standard deviation increase in tax policy risk increases the probability of mortgage distress by nearly 30 percent. Variation in the level of taxation due to these same property tax policies is strongly negatively correlated with tax policy risk, and has a somewhat smaller effect on the probability of distress.

Keywords: Property Taxation, Tax Limitations, Risk, Distress, Mortgage Default, Foreclosure.

JEL Classification: H31, H71, G59, K34, R20

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1 Introduction

Property tax payments are an important recurring cost of homeownership. Recent studies point to how these costs can lead to financial distress, such as when the source of changes in tax obligations are less salient (Bradley, 2013), when the timing of tax payments coincides with periods of reduced liquidity (Anderson and Dokko, 2009, 2016), or when reassessments cause property tax liabilities to jump following a period of housing price appreciation (Hayashi, 2020; Wong, 2020). Against this backdrop, all but three U.S. states have implemented some type of property tax limitations (Anderson, 2006). These policies are intended to reduce intertemporal variation in property tax liabilities by limiting the growth rate of the tax base, tax rates, or their product. Voters may also hope to constrain local governments' budgets (O'Sullivan et al., 1995a), yet evidence regarding the effects of these limitations on the average *level* of property taxation is far from conclusive (Dye and McGuire, 1997; Eliason and Lutz, 2018). Less obvious is the fact that these policies may also make property taxes less pro-cyclical (Lutz, 2008) by shifting the timing of liabilities relative to economic conditions (i.e., by imposing higher tax obligations during bad times and lower taxes during good times).

Pro-cyclicality in property tax liabilities provides consumption-smoothing insurance to homeowners; reduced pro-cyclicality therefore introduces *risk*. The latter risk represents an unintended consequence of property tax limitations. In this paper, we are the first to model the effects of property tax system characteristics on *risk*—separate from the *level* of taxation—and we show that this unintended risk effect exposes homeowners to a substantially higher probability of mortgage distress. Moreover, our results suggest that this risk effect outweighs the benefit from any potential countervailing level effect when it comes to mortgage distress.

As a point of departure, we first confirm results in Hayashi (2020) and Wong (2020) using a border-discontinuity design and show that observed parcel-level changes in annual property tax liabilities have a significant positive effect on mortgage distress. We then extend this analysis with two key innovations. First, we calculate level and risk components for any given stream of tax payments. Intuitively, the level component corresponds to the certainty equivalent tax payment amount, and the risk component captures the contemporaneous correlation between tax payments and consumption. This decomposition allows us to study the effects of the timing and the amount of tax liabilities on mortgage distress separately. Crucially, the risk component captures the insight that property tax payments, while never pleasant, are more burdensome in times of low consumption and illiquidity. We formalize this idea with an Arrow-Debreu framework.

Our second innovation is a tax simulation, which replaces the use of realized tax payments observed in the data. We simulate tax payment streams under states' different property tax system characteristics while holding economic conditions, household consumption, and property transaction histories fixed. Our simulation has two advantages. First, the policy space is inherently high-dimensional given states' ability to choose among different types of tax limitations and the stringency thereof, the frequency of mandated reassessments, and the level of effective tax rates needed to achieve local governments' revenue objectives. The simulation allows us to collapse this high-dimensional policy space into a single tax payment stream that incorporates each of these features, including potentially important interactions between these. Second, the simulation ensures that cross-sectional differences in tax payments across states come solely from differences in tax policies. This is a big advantage compared to using observed tax payments, which can be influenced by homeowners' endogenous decisions.

We next combine our two key innovations—the decomposition of tax payments into risk and level components using an Arrow-Debreu framework and our property tax simulation—to calculate *Tax Policy Risk* by state and policy year as our main variable of interest. We simulate tax payments according to each states' full set of applicable policies along with counterfactual tax payments assuming no tax limitations and annual reassessments. We then decompose these actual and counterfactual "no-policy" simulated tax payments into risk and level components. The difference between actual and counterfactual simulated risk amounts represents the difference in property tax risk that is due solely to states' chosen tax limitation and reassessment regimes policies, which we term *Tax Policy Risk*. *Tax Policy Risk* can be interpreted as the insurance premium that homeowners would be willing to pay to avoid the heightened risk resulting from counter-cyclical features of states' property tax regimes. We show that property tax limitations of all types result in greater *Tax Policy Risk*. This is most pronounced for assessment limitations such as those implemented under California's Proposition 13, which typically impose that assessed values grow at a pre-specified annual rate anchored to ordinary inflation, even when housing prices are falling. Similarly, we also calculate the difference between the level components of our actual and counterfactual simulated tax payments and denote this difference as the *Tax Policy Level*.

For our main analysis, we estimate the impact of *Tax Policy Risk* on the probability of mortgage distress while separately controlling for the influence of property tax regime characteristics on the overall level (*Tax Policy Level*) and effective rate of property taxation.

We employ data from both ATTOM Data Solutions and Zillow (ZTRAX) covering property tax assessment, realty transaction, loan, and foreclosure records at the parcel level throughout the continental U.S. for the period 2006-2016. These data allow us to control for loan-to-value ratios (to account for strategic default incentives and to benchmark our effect sizes), along with a host of other parcel- and neighborhood-specific characteristics. We exploit a state border discontinuity design consisting of either county pair or 10 square kilometer (km^2) U.S. National Grid (USNG) cells that straddle state borders, and we focus on properties located within 10 km of state borders. We use these border pairs and a within estimator to control for time-varying unobservable local market conditions, including labor or housing market shocks. Conditional on observables—including other key state-level policy differences (Ghent and Kudlyak, 2011; Mian et al., 2015; O'Malley, 2021)—our identifying assumption is that properties on either side of the state border within the same border pairs are identical except for differences in *Tax Policy Risk*. 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 increase in *Tax Policy Risk* raises the probability of mortgage distress by approximately 30 percent (0.43 percentage points), while a one standard deviation increase in the level (certainty equivalent) property tax amount raises the probability of distress by roughly 23 percent. By way of comparison, the effect of a one standard deviation increase in *Tax Policy Risk* is roughly one quarter as large as the increase in probability of distress that we estimate in relation to moving between the third and fourth quintiles of the loan-to-value distribution (i.e., from an LTV of 0.6-0.91 to 0.91-1.6). Given that tax policy risk and level amounts are strongly negatively correlated (e.g., because levy limits tend to depress average property tax liabilities while simultaneously increasing risk), states' tax regimes will generally produce smaller net effects on distress overall. Indeed, our estimate of the simple effect of changes in annual tax liability—which reflects both risk and level effects, including the influence of endogenous variation in tax payments—is close to the combined impact of a one standard deviation increase in *Tax Policy Risk* coupled with a one standard deviation decrease in *Tax Policy Level*.

These on-average results mask important heterogeneity related to the timing of shocks and homeowners' pre-existing susceptibility to financial distress. We document that the effects of *Tax Policy Risk* and *Tax Policy Level* are generally increasing with regional unemployment rates, as well as with homeowners' loan-to-value ratios and their duration of ownership. These effects are also substantially amplified in predominantly Black neighborhoods, consistent with other findings regarding minority households' greater vulnerability to housing distress (e.g., Reid et al. (2017)).

Our paper is the first of its kind to focus on the risk emanating from property tax limitations and other key features of state property tax systems. In doing so, we develop a new measure of tax policy risk that can be applied to other contexts. We also develop a property tax simulation that can be used to study other types of interactions and consequences of these policies. We then take these innovations to a rich parcel-level dataset with expansive geographic coverage, and we leverage a border discontinuity design to quantify the distinct impacts of tax risk and level amounts on an extreme form of financial hardship—mortgage distress. We show that property tax limitations, though ostensibly intended to protect homeowners from facing excessive tax liabilities, have the unintended consequence of triggering a higher probability of mortgage distress by exposing households to increased tax obligations precisely when economic conditions are otherwise weak. Our paper thus highlights the trade-off between *Tax Policy Risk* and *Tax Policy Level*, which has been absent in the policy discussion and academic debate to date.

A clear policy implication of our results is that tax deferral programs may offer an effective means of mitigating risk for the most vulnerable homeowners. Existing state tax deferral programs impose highly restrictive eligibility requirements, and we are unable to assert empirically whether such programs are indeed effective. Nevertheless, allowing tax deferral under broader conditions would have the virtue of offering targeted (i.e., low cost) relief without requiring changes to states' other tax system characteristics (assuming these already reflect voter preferences).

Our paper combines insights from important literatures on mortgage distress, property taxation, and tax risk. Previous literature has shown that differences in government policies can create divergent incentives and pressures related to mortgage distress. Regulations governing 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) thus have important effects on mortgage default rates. More generally, policies that increase the cost of foreclosure for either borrowers or lenders are associated with fewer delinquencies and defaults. 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 changes 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.

Regardless of the cause, mortgage 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 as a result of property tax limitations may also dampen housing investment and economic growth.

An extensive 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 consider the ramifications of variation in saliency of particular features of property tax regimes (Bradley, 2013, 2017, 2018; Cabral and Hoxby, 2012; Hayashi, 2014). 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).

All of these aforementioned studies (and the literature on property taxation more broadly) can be categorized as either evaluating the effects of individual provisions (e.g., assessment limits, reassessment frequency), or the effects of individual states' unique *combination* of provisions. We add to this literature by studying how property tax provisions *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 across the entire U.S.

Finally, we also contribute to a growing literature on exposure to risk as a key aspect of tax policy. Early work focused on the risk exposure of state and local governments (Groves and Kahn, 1952; Dye and McGuire, 1991; Dye and Merriman, 2004; Bruce et al., 2006; Cornia and Nelson, 2010; Clemens, 2012; Cornia et al., 2017). More recent work has shown that tax revenue volatility increased in the 2000s due to capital gains realizations and tax policy changes (Dadayan and Boyd, 2009; Lutz et al., 2011; Chernick et al., 2014; Seegert, 2015, 2016; Cashin et al., 2018). We add to this literature by focusing on individuals' exposure to tax policy risk, which connects to a literature on automatic stabilizers and tax policy insurance (Follette and Lutz, 2011; Dolls et al., 2012; Bargain et al., 2013; Dauchy et al., 2021).

The remainder of the paper is structured as follows. Section 2 describes our data and the construction of key regression variables. Section 3 lays out the core structure of our empirical strategy, and Section 4 applies this strategy to extend the basic findings from the literature regarding the effect of changes in tax payments on mortgage distress. Section 5 introduces the Arrow-Debreu decomposition of tax liabilities into risk and level components, describes the mechanics of property taxation and tax limitations and incorporates these into our property tax simulation, and formally defines *Tax Policy Risk* and *Tax Policy Level*. Section 6 presents our main empirical results regarding the effects of tax policy risk and level amounts on mortgage distress, including a discussion of heterogenous effects and mechanisms. Section 7 concludes.

2 Data

Data collection We combine data from ATTOM Data Solutions and ZTRAX (Zillow, 2018) into a comprehensive panel of parcel-level data for the period 2006-2016 to ensure the broadest possible coverage for our analysis. These data encompass the universe of property tax assessment information and purchase, loan, and foreclosure transaction records spanning the continental U.S. 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—if the former are missing—street address and zip code. This allows 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.[1]

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.

We also collect information on property tax and other state-specific policies that influence default probabilities. 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). Data on judicial review come from Ghent and Kudlyak (2011) and Mian et al. (2015). These data designate which states 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).

Loan to value We augment these data by calculating annual property values and loan balances that allow us to construct loan-to-value ratios (LTV) to account for potential strategic default incentives. 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.[2] We calculate annual loan balances from initial loan amounts by using additional data from the Federal Housing Administration on average national monthly interest rates and average state-level annual rates. With these data, we 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.[3] Taking the ratio of im-

[1]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.

[2]For details regarding how we calculate annual property values based on two complementary techniques—an imputation method and a machine learning hedonic estimation method—see Appendix A.

[3]Initial interest rate information is infrequently populated in either ATTOM or ZTRAX and typically

puted loan balances to property values yields our desired time-varying parcel-specific estimates of LTV, which we subsequently classify into discrete intervals.

Geocoding and other restrictions 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. We restrict our estimation sample to those parcels that are no more than 10 km from the nearest state border. 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 10 km^2 grid cells accordingly.

We exclude from our initial sample all homes that (i) are ever valued in excess of $5 million or less than $1000 in an arm's-length transaction, (ii) are newly built or substantially remodeled, (iii) have effective property tax rates that fall below the 1st percentile or above the 99th percentile of the relevant state distribution, or (iv) 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. These criteria are described in greater detail in Appendix B. Broadly speaking, their intent 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.[4]

We also exclude data from ten price non-disclosure states due to insufficient transaction information. The lack of consistent data in these states make it difficult to estimate our hedonic pricing model or to implement our border pair fixed effects analysis in a credible manner. 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 price information also dictates the exclusion of all but four political subdivisions of Missouri.[5] Figure E.1a describes the geographic distribution of parcels in our final estimation sample that contribute to identification

only for adjustable rate mortgages. Term information is more consistently recorded, but it is 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.

[4]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. The owners of such properties commonly face distinct mortgage financing environments, either as developers, flippers, or buyers of builder-financed homes.

[5]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.

(i.e., where we have complete information for parcels on opposite sides of a state border within border-straddling regions). Observation counts are aggregated to the county level for visibility.

Analysis dataset The complete ATTOM-ZTRAX dataset consists of approximately 390 million parcel-year observations with non-missing property values distributed throughout the continental U.S., of which over 50 million are located within 10 km of a state border. Our initial border sample represents approximately $1.25 trillion in total property value and $16.1 billion in property tax liabilities as of 2016 and encompasses nearly 650,000 foreclosure events over the period 2006-2016.[6]

Table 1 summarizes the set of means, medians, and standard deviations for our key regression variables. Distressed properties are defined as any property that 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* are calculated as described in Section 5.4 below and measured in thousands of dollars. Unless otherwise specified, we employ *standardized* versions of both throughout our analyses for ease of interpretation. These are calculated to have in-sample average values of 0 and standard deviations of 1. The loan-to-value ratio (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 ≥ 1.6, and a sixth category for all properties with unknown LTV. The latter category includes most mortgage-less homeowners. Homeowner tenure, age, and renovation age are similarly categorized into logical bins.[7]

We report values separately for distressed and non-distressed properties, with differences in means reported in the final column of Table 1. All differences in means between groups are statistically significant, with p-values uniformly well below 0.001. Distressed properties are thus significantly less valuable and face higher effective tax rates (despite

[6]Our full sample for the continental U.S. captures 8.1 million foreclosure events, 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. Furthermore, it is not clear how sequences of foreclosure events (e.g., the issuance of a notice of default followed by a notice of 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 E.2 shows the evolution of foreclosure activity in our complete national sample 2006-2016.

[7]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.

lower overall tax bills), and they experience larger year-over-year changes in tax liability. At the same time, distressed properties face modestly lower simulated *Tax Policy Risk* but higher (less negative) simulated reductions in tax amounts (*Tax Policy Level*). Distressed properties also exhibit significantly higher average LTVs,[8] have shorter-tenured homeowners, and are modestly older and less recently renovated. Finally, they are also disproportionately located in lower income, less educated, younger, and larger minority share neighborhoods. All of these characteristics speak to unconditional variation in property-, household-, and neighborhood-level attributes that may contribute to mortgage distress by affecting either homeowners' incentives for strategic default or their susceptibility to precipitating trigger events.

3 Empirical Strategy

Our core empirical strategy consists of estimating the effect of property taxation on mortgage distress at the parcel level using a linear probability model featuring a rich set of controls and a state border discontinuity design. The outcome variable, $\mathbb{1}(\text{Distressed})_{i,t}$, is an indicator variable denoting whether or not property i experiences any form of mortgage distress in year t:

$$\mathbb{1}(\text{Distressed})_{i,t} = \alpha + ZTax_{s,t}\beta + X_{i,t}\gamma_i + X_{k,t}\gamma_k + Z_{s,t}\gamma_s + \lambda_{j,t} + \varepsilon_{i,t}. \quad (1)$$

The dependent variable in all specifications is pre-multiplied by 100 such that point estimates can be interpreted directly as percentage point effects. $ZTax$ denotes different tax measures. Initially, this is simply the percent change in annual tax payments observed in the data, as we detail in the next section. In Section 6, we use our simulated measures of *Tax Policy Risk* and *Tax Policy Level*. In all cases, $ZTax$ is expressed in standard deviations around the mean.

We incorporate additional parcel-specific factors related to strategic default incentives and other triggers of mortgage distress, denoted as the vector of property level controls, $X_{i,t}$. 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. $X_{k,t}$ accounts for "neighbor-

[8] The continuous distribution of imputed LTVs points to the existence of large outliers. Despite our efforts to screen such cases, these are most likely due to instances where multiple loan transactions in a series are treated as additive rather than sequential. This issue is mitigated in our analysis by using discrete LTV categories. Median LTVs are of a plausible magnitude.

hood" k zip code-level or tract-level demographic controls, including measures of average income, age-specific population, racial composition, and educational attainment. $Z_{s,t}$ 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.

We use a state border discontinuity design to dampen the potential feedback 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 regimes. This is achieved in our empirical specifications by including a combination of either year and border pair fixed effects, λ_t and λ_j, or border $\times$ year *pair* fixed effects $\lambda_{j,t}$, as denoted above. 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 liability or risk.

Concretely, we consider two different types of border pairings: county pairs and 10 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 use the U.S. National Grid coordinate system to construct 10 km² grid cells.[9] These border pairings produce 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. In the following results, we ultimately emphasize those that use the 10 km² grid cells, but we obtain qualitatively similar results using the broader county pairs or 15 km² grid cells (unreported).

In Figure 1, we illustrate 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

[9]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 Mian et al. (2015), for example, but produces more narrowly delineated border pair regions.

just north and south of the state border exhibit relatively similar median characteristics, especially in terms of housing prices (1a) and LTV (1c). Outside of the more densely populated areas, foreclosure rates are more heterogeneous (1d), and effective tax rates (1b) unsurprisingly reflect more pronounced county, municipal, and school district influences on statutory millage rates. Nevertheless, these illustrations support the general concept of border-straddling local housing markets. In Figure 2, we depict the location of each parcel in our estimation sample for the same six counties at the Michigan-Ohio border along with the corresponding 10 km² grid cells. 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 1) is also quite sparsely populated, as shown in Figure 2, and thereby contributes little to identification.

4 Property Tax Payments and Mortgage Distress

We first demonstrate our empirical strategy by applying it to a basic, yet instructive, question: how do changes in annual property tax payments affect mortgage distress? This analysis allows us to benchmark our initial estimates against other studies by Hayashi (2020) and Wong (2020) on this topic. After establishing this baseline result, we extend the analysis with our Arrow-Debreu decomposition and property tax simulation, which we elaborate on in Sections 5.1 and 5.3, respectively.

We use a standardized measure of the percent change in annual tax obligations, $\%\Delta$Tax, as our main explanatory variable to estimate Equation (1). This encompasses all tax changes due to either rate changes or reassessment—with or without limitations—but excludes reassessments triggered by sales or renovations. For reference, we observe an average year-over-year change in annual tax liabilities of 3.5 percent over our sample period, with a standard deviation of 17.3.

In columns 1-3 of Table 2, we report results based on our border-discontinuity design using county pair fixed effects. We begin in Column 1 with fixed effects only, and we proceed by incorporating our full set of property and demographic controls (Column 2) and year-fixed effects (Column 3). In Columns 4-6, we repeat the same specifications, with the narrower 10 km² grid cell fixed effects. In Columns 7-8, we extend the border fixed effects strategy from Columns 4-5 by allowing local market effects to be time-varying (i.e., using 10 km² grid cell $\times$ year pair fixed effects). The point estimates from the county pair and 10 km^2 grid cell fixed effect specifications are similar in magnitude. The effects of %ΔTax are more precisely estimated where we employ the narrowly defined 10 km^2 grid cell fixed effects, which yield 4740 unique border-straddling regions (versus 947 county pairs). Narrowing the source of identifying variation further to within border-year *pair* yields a larger point estimate in Columns 7-8.

Under the most narrowly identified specification in Column 8, a one standard deviation increase in the size of this tax change (i.e., a 17.3 percent increase in tax liability, or $590) thus implies a 0.06 percentage point increase in the probability of distress or 4.2 percent. Equivalently, this implies that a $1,000 increase in annual tax liabilities raises the probability of distress by 7.2 percent. For comparison, Hayashi (2020) finds that a $1,000 increase in annual tax payments results in a 0.1 percentage point (5.6 percent) increase in the probability of mortgage default due to property reassessments in Maryland. Wong (2020) extends a similar analysis to nine states and reports that a $1000 increase in annual property tax payments due to countywide reassessment is associated with a 0.67 percentage point (15 percent) increase in the probability of 30-day mortgage delinquency, 11 months after the onset of increased escrow payments.[10] Our finding of a 7.2 percent increase in the probability of mortgage distress resulting from a $1000 increase in annual tax obligations is thus of a comparable magnitude to related work, despite important differences in our research design and the breadth of data coverage employed in our analysis.

Examining the effect of changes in tax payments on mortgage distress nevertheless neglects two important considerations. First, the preceding analysis does not allow drawing a distinction between increases in tax liability that occur during market booms when the marginal utility of consumption is relatively low, versus market downturns, when the marginal utility of private consumption is relatively high and households may already be more susceptible to liquidity shocks (e.g., due to job loss). This represents a source of risk that is distinct from simple level effects. Second, tax payments are affected by factors beyond tax policy alone. These include both exogenous and endogenous influences that may impact taxpayers' assessed values or their applicable tax rates (e.g., local economic conditions, investments in home renovations, whether to use a home as a primary residence, etc.). It is, therefore, difficult to pinpoint the effects of specific policies by focusing on changes in tax payments. We address the first deficiency of the previous

[10] A direct comparison of effect sizes is complicated by the fact that Wong (2020) focuses exclusively on mortgage-holding households with tax escrow accounts, whereas our sample consists of all homeowners, including those without mortgages. The unconditional probability of mortgage delinquency reported by Wong (2020) is roughly 2.7 times higher than the probability of distress that we observe in our sample.

analysis with an Arrow-Debreu decomposition in Section 5.1 and the second deficiency with a tax simulation in Section 5.3.

5 Modeling Tax Policy Risk and Levels

5.1 Arrow-Debreu Decomposition

People generally dislike paying taxes, dislike paying higher taxes, and especially dislike paying higher taxes in bad times when the economy is slowing. In this section, we introduce an Arrow-Debreu framework to enable the decomposition of a stream of tax liabilities into separate level and risk components. This framework is inherently well suited to capture people's dislike of paying higher taxes in bad times, when the marginal utility of private consumption is high, and we define our measure of tax risk accordingly. This decomposition is especially pertinent because—as we discuss in detail in the next section—property tax limitations tend to introduce a tradeoff between these. Attempts to smooth government revenues and mitigate unpredictable swings in tax payments inevitably shift tax liabilities intertemporally relative to the state of the economy.[11]

The key insight to tax risk is that an individual's perceived tax burden depends on both their tax liability (how much they have to pay) and on economic conditions *when* they have to pay. We capture this insight by calculating tax risk as a weighted sum of tax liabilities, where liabilities in bad economic times are weighted more than in good times, net of the certainty equivalent payment amount (i.e., the level effect). Two tax schedules that produce the same total liability will impose different tax burdens if the timing of those payments relative to the state of the economy differs. A tax schedule that requires higher payments in good times and lower payments in bad times will thus impose a lower tax burden than another schedule that requires 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 macroeconomic conditions (e.g., recessions, geopolitical unrest, etc.).

Arrow-Debreu (AD) security prices provide a straightforward way to weight tax liability in order to calculate tax risk. AD state-contingent securities capture the value of an asset paying an additional dollar in a given state of the world. Consider the following

[11] In a different context, progressivity of the federal income tax acts as an automatic stabilizer by reducing taxpayers' total tax bills and marginal tax rates in bad times and raising these during good times (Dauchy et al., 2021). As discussed in Section 5.2, property tax limitations (and to a lesser extent, infrequent reassessments) do the opposite.

example with two states of the world—good and bad—that occur with equal probability. Suppose 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 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 when consumption is otherwise lower, and vice versa in the good state of the world. This merely follows from diminishing marginal utility. 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 ($1 = 0.2 \times 1 + 0.8 \times 1$). Equivalently, the payment stream is weighted by 0.2 in good times and 0.8 in bad times. By extension, a security that pays \$2 in good times and \$0 in bad times would have a price of \$0.4 ($= 0.2 \times 2$), while a security that pays \$2 in bad times and 0 in good times would have a price of \$1.6 ($= 0.8 \times 2$). Both securities have an expected payoff of \$1 but have very different prices. The security that pays out in bad times is worth more than the security that pays out in good times. AD securities, therefore, capture the key insight that the pattern of payments matters.

We apply the same Arrow-Debreu framework to price the risk of tax payments that likewise "pay off" in good or bad times. 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 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:

Limits	Good Times	Bad Times	Expected	Std. Dev.	Arrow-Debreu Price ($\mathbb{P}$)	CE Price ($\mathbb{C}$)	Risk Price ($\mathbb{R}$)
None	4	1	2.5	1.5	1.6 ($= 0.2 \times 4 + 0.8 \times 1$)	2.5	-0.9
Loose	3	2	2.5	0.5	2.2 ($= 0.2 \times 3 + 0.8 \times 2$)	2.5	-0.3
Strict	2	3	2.5	0.5	2.8 ($= 0.2 \times 2 + 0.8 \times 3$)	2.5	0.3

The expected payment is the same in all three limit regimes, \$2.5. The difference in regimes appears in the standard deviation *and* the timing of payments. The standard deviation of tax payments is highest in the no-limit example, at 1.5. The standard deviation of tax payments with the loose and strict limits are the same, at 0.5. However, despite the standard deviation being the same with loose and strict limits, the timing of the payments leads to different risk prices.

We calculate the AD prices for these three property tax limit regimes and decompose them into a certainty equivalent price that captures the level effect and a risk price. The AD prices weight the payment in good times by 0.2 and payments in bad times by 0.8 (from the example above). This leads to AD prices ($\mathbb{P}$) of 1.6, 2.2, and 2.8 in the no limit, loose limit, and strict limit property tax regimes, respectively.

We calculate the certainty equivalent price ($\mathbb{C}$) by considering the price if taxpayers 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 ($\mathbb{R}$) is the difference between the total AD price and the certainty equivalent price. This risk price, therefore, captures only differences in the timing of tax payments.[13]

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

[13] To see this point, consider the scenario where tax liability is \$8 (instead of \$4) in the no limit regime in good times and tax liability is \$5 (instead of \$1) in bad times. In this case, the expected payment would be \$6.5, the AD price would be \$5.6, and the certainty equivalent price would be \$6.5, yet the risk price would remain the same as before at -\$0.9. This reflects the fact that in both cases, tax payments are \$3 more in the good state of the world.

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 limit 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. Volatility reflects only the variability of the tax liabilities, whereas our risk measure considers the timing of tax liabilities relative to property owners' consumption patterns—i.e., the comovement between these. The no-limit regime has higher volatility (as measured by the standard deviation) but is less risky than the strict-limit regime because property owners pay more taxes when they earn more, and vice versa.

In sum, the Arrow-Debreu framework allows us to decompose property tax liabilities into a certainty equivalent price ($\mathbb{C}$) and a risk price ($\mathbb{R}$). The foregoing decomposition of tax liabilities under stylized no-limit, loose-limit, and strict-limit scenarios illustrates the importance of the timing of tax payments. In the next section, we describe the essential features of state property tax systems in the U.S., and we discuss how different types of tax limitations may lead to more or less counter-cyclical tax obligations. These details anchor our approach to simulating realistic property tax liabilities, and we decompose the resulting liabilities to obtain our key variables of interest in Section 5.4.

5.2 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. 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 that may apply and extend beyond property taxes by encompassing other sources of state and local tax revenue. In practice, as shown in Table 3, 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.[14]

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. This variation dictates the details of our property tax simulation in Section 5.3.

5.2.1 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.[15] As reported in the last column of Table 3, 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-

[14]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 characteristics 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, with mixed results (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.

[15]Without pre-existing rate limitations, assessment ratio designations are wholly arbitrary as rates could merely be adjusted 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 York, Pennsylvania, etc.).[16] 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 5.3.

5.2.2 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.[17] 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 3, 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 E.3 depicts the geographic distribution of these different types of assessment limitation regimes.

During housing market downturns, California's Proposition 8 amendment stipulates that properties' taxable values may temporarily fall below their "factored base year

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

[17] 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.

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).[18] 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 3a illustrates a hypothetical version of this scenario. The red dashed line depicts the evolution of tax payments subject to assessment limitations, while the solid blue line represents tax payments under market value assessments. The solid red line mirrors the dashed red line, albeit assuming a higher effective tax rate so as to maintain revenue neutrality between the market value and assessment limitation regimes (i.e., assuming no level effect of assessment limitations). As shown, tax payments increase at a slower rate in good times (increasing home prices) under assessment limitations, yet they continue to increase in bad times (decreasing home prices) so long as taxable values remain below market values. The risk 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.

[18] 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.

In Figure 3b, we show that the hypothetical situation given in Figure 3a is not unusual. This panel plots the proportion of parcel-year observations in our sample that saw their tax liability decrease, remain unchanged, or increase while their property value went down or up. The most common scenario—roughly 45% of the time—is for tax payments to increase as market values increase. However, the second most common scenario is for tax payments to increase while market values are falling, occurring roughly 35% of the time.

Figure 3c provides additional 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) over the period 2006-2016 than homes in other states (solid blue), both during the initial market downturn and the subsequent run-up. Meanwhile, tax 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 3d, 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.[19]

5.2.3 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.[20] Elsewhere, rate limits are instead set on a statewide basis as a percentage of fair market value, without specifying each taxing jurisdictions' allowed rate, or they restrict mil-

[19]We investigate the reduced form effects of assessment limitations and the tax-price adjustment gap on mortgage distress in Appendix E. Larger tax-price adjustment gaps are responsible for significantly higher probabilities of distress.

[20]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 had a state-wide rate limit of 35 ($= 5 + 15 + 15$) mills.

lage rate *growth*.[21] Figure E.4a 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.[22] Insofar as rate limits are ever binding, this is more likely to occur when property values are falling if local jurisdictions attempt 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 taxable 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 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. On the other hand, in places where revenue requirements adjust at least partially to economic conditions, and assessed value adjustments exhibit downward stickiness, rate limits may instead bind with lower probability during market downturns (i.e., because of the combination of inflated assessed values and reduced revenue requirements) and thereby induce more counter-cyclical fluctuations in tax liability. The net effect of rate limitations on the overall pro-cyclicality of property tax obligations is thus an empirical question, the answer to

[21]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.

[22]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 state as if it does not have a rate limit at all (e.g., Alabama, Arkansas, Georgia, etc.) or we 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%.)

which may well vary as a function of interactions with other tax system characteristics.[23]

5.2.4 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.[24] Figure E.4b 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". These are widely used outside of the Southeast, with broad geographic variation in limit stringency.

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

[23] Brosy and Ferrero (2021) present evidence for the period around the Great Recession that is broadly consistent with the former characterization of rate limits as inducing more pro-cyclical tax obligations. Rate adjustments to changes in housing prices are attenuated in states with rate limits (of any type), while aggregate assessed values appear to adjust symmetrically—if at all—to both housing price increases and decreases. These tests do not, however, account for the potential confounding influence of correlated tax regime characteristics nor variation in the stringency of these limitations.

[24] 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).

not otherwise limit taxable value growth.[25] 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.

5.2.5 The Effect of Property Tax Limitations on Distress

For illustration, we demonstrate the effect of individual property tax limitations on distress. This naive analysis fails to capture the interactions that are critical to understanding the effect of these policies on distress. We classify limitations as a simple indicator variable and report a range of point estimates and 95% confidence intervals in Figure 4. We report the effect of assessment limits (Panel a), levy limits (Panel b), rate limits (Panel c), and revenue/expenditure limits (Panel d). The top and bottom estimates in each subfigure correspond to the specifications in columns 7 and 8 of Table 2. We provide three additional specifications consisting of intermediate sets of covariates.

The effects of levy, rate, and revenue/expenditure limits are insignificant at a 5 percent significance level in the full specification. Levy and rate limits have marginally significant positive effects, whereas assessment limits appear to have a relatively large negative effect on distress. Unsurprisingly, the effects of individual types of property tax limitations are hence largely uninformative when viewed in isolation.

There are several limitations to this reduced-form analysis. First, these isolated effects fail to account for the interactions of these limitations and conflate potentially-correlated tax system characteristics. Second, these effects do not hold fixed economic conditions. Finally, much like the analysis of changes in annual tax liability, these estimates conflate the effect of limitations on the level of property tax liabilities with their effects on the degree of intertemporal variation in tax payments and the comovement of tax payment amounts with the state of the world: i.e., risk.

We overcome these limitations by turning to our property tax simulation and pricing the resulting tax policy risk.

[25] 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).

5.3 Property Tax Policy Simulation

Our property tax simulation captures the policy effect of property limitations and their interactions with other key tax system characteristics (i.e., average effective millage rates for new homeowners and reassessment frequency). Whereas observed property tax liabilities reflect the effects of both tax policies and economic conditions, our simulation allows us to calculate tax payments while holding economic conditions fixed, thereby isolating policy effects at the state-year level.[26]

We construct a panel of 500 simulated properties (indexed by i) over 50 simulation years (indexed by z). We capture economic conditions through each property's market value, whether it transacts in 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. The market value of the property (from the Case-Shiller Index) and the aggregate and individual consumption growth (from the Consumer Expenditure Survey) are always kept the same such that variation across states is solely attributable to differences in property assessment and tax policies. We then obtain the assessed value of properties by applying each state's reassessment policy.[27] We apply the tax policy of state s in year t (where policy year is indexed by t and simulation year is indexed by z) 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 5, 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) subject to the same economic shocks but differ-

[26]We do not generally 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. The only exceptions that we make are for the five counties that make up New York City and Cook County, IL, which encompasses the city of Chicago.

[27]In states where reassessment does not occur annually, we censor the data according to the reassessment policy; i.e., the assessed value of the property is the market value of the property when it was last reassessed. We also observe that even among states with annual reassessments and no assessment limitations, assessed values do not adjust annually, i.e., assessed values are sticky. Importantly, assessed values are only 70% as likely to be adjusted downward when housing prices are falling as they are to be adjusted upward during periods of rising prices. In other words, assessed values are more sticky downward. Based on this observation, we impose that only 70% of properties that are otherwise due for reassessment (based on state policies) are in fact reassessed to market value when housing prices are falling, and the remaining 30% of properties have their assessed values fixed at the prior year's level.

ent states' tax policies, as of 2016 (i.e., $t = 2016$). Vertical lines indicate simulated 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 relatively strict rate and levy limits in the case of Nevada, and rate, assessment, and revenue/expenditure limits for California. A key distinction between the two tax systems is that California's assessment limitation regime triggers taxable value uncapping upon sale—hence the spike in property tax liability for California property at year 45. Meanwhile, despite relatively infrequent market value reassessments, Nevada's combined levy and rate limits lead to a more stable evolution of property tax liabilities compared to California. Simulated property tax liabilities track simulated property values more closely in Nevada (with a growth rate correlation of 0.13) than in California (with a growth rate correlation of only 0.05).

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

5.4 Tax Policy Risk

In this section, we obtain our key variables of interest, *Tax Policy Risk* and *Tax Policy Level*, by applying the Arrow-Debreu decomposition from Section 5.1 to the tax payments derived from our property tax simulation. We provide a detailed description of the characteristics of *Tax Policy Risk* and demonstrate how individual property tax limitations and their interactions drive variation in *Tax Policy Risk* and *Tax Policy Level*.

5.4.1 Definition

We calculate the risk price, $\mathbb{R}_{i,z,s,t}$, for the series $q_{i,z,s,t}$, i.e., for each property owner (indexed by i) at any point in the simulation (index by z) in each simulation (indexed by state s and year t). To do so, we first calculate the total price and the certainty equivalent as follows:

$$\mathbb{P}_{i,z,s,t} = \sum \frac{q_{i,z,s,t} \times p_{i,z}}{N}, \tag{2}$$

$$\mathbb{C}_{i,z,s,t} = \sum \frac{q_{i,z,s,t}}{N} \times \sum \frac{p_{i,z}}{N}, \tag{3}$$

where N is the number of years since the property owner bought the property. The pricing kernel, $p_{i,z}$, up- or down-weights the tax liability in bad or good times and is simulated for each property owner and kept the same across simulations.[28] We calculate the total price and certainty equivalent throughout the tenure of ownership; i.e., the $q_{i,z,s,t}$ series goes back to the last transaction year in the simulation, which allows us to capture the risk experienced by each property owner. The risk price of property i in simulation year z in simulation s, t is therefore

$$\mathbb{R}_{i,z,s,t} = \mathbb{P}_{i,z,s,t} - \mathbb{C}_{i,z,s,t}. \tag{4}$$

$\mathbb{R}_{i,z,s,t}$ measures how much homeowner i in state s in year t would be willing to pay in simulation year z to pay only the time-invariant certainty equivalent $\mathbb{C}_{i,z,s,t}$ component of their property tax bills over their duration of ownership. We take the mean across properties and simulation years 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 for which we assume no tax limitations and annual reassessments.[29] The increase in tax risk attributable to states' combined tax policy characteristics, which we define as *Tax Policy Risk*, is therefore:

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

$\textit{Tax Policy Risk}_{s,t}$ is the amount that property owners in state s in year t would be willing to pay to do away with the combined tax limitation policies due to risk considerations. In other words, $\textit{Tax Policy Risk}_{s,t}$ is the additional insurance premium homeowners would be willing to pay for consumption smoothing purposes due to the existence of tax limitations. We similarly calculate *Tax Policy Level* as the difference in certainty equivalent components of the overall tax price in the actual and counterfactual policy environments ($\mathbb{C}_{s,t} - \mathbb{C}'_{s,t}$).

5.4.2 Tax Policy Risk Characteristics

Figure 6a shows how *Tax Policy Risk* differs across states. *Tax Policy Risk* is the amount of money (averaged across policy years 2006-2016) that the owner of a $300,000 home would be willing to pay to eliminate all consumption risk from property tax limitations and/or

[28]See Appendix C for calibration details.

[29]The counterfactual risk price is not just a constant (as it is indexed by s, t) because the effective tax rate and the mean property value for each state-year are different. As a result, we calculate the counterfactual specific to each state-year.

infrequent reassessments. A higher *Tax Policy Risk* indicates a higher consumption risk induced by property tax limitations. The numbers shown on the map are *Tax Policy Risk* standardized to a mean of 0 and a standard deviation of 1 for ease of comparison with *Tax Policy Level*. There is considerable variation across states, from a high of $1,120 (or 2.30 standard deviations above the mean) in New York to a low of -$232 (or -1.76 standard deviations below the mean) in South Carolina. These estimates indicate that New York's property tax regime adds considerable risk while South Carolina's property tax regime provides some insurance.

Figure 6b shows how *Tax Policy Level* varies by state, defined as the difference between the certainty equivalent amount of taxes paid with and without property tax limitations imposed. A higher *Tax Policy Level* indicates a higher level of property tax liability, or lower property tax savings, under the actual tax regime in the state relative to the no-policy counterfactual. The numbers shown on the map are standardized to a mean of 0 and a standard deviation of 1 for ease of comparison with Tax Policy Risk. In Figure 6a, a darker color indicates a higher *Tax Policy Risk*, and in Figure 6b, a darker color indicates a lower *Tax Policy Level*. We see that the shading of the colors in Figures 6a and 6b is similar, indicating a negative correlation between *Tax Policy Risk* and *Tax Policy Level*. A regression of *Tax Policy Risk* on *Tax Policy Level* based on 2016 values (standardized) yields a coefficient of -0.84. See Figure E.5. In other words, policies that tend to reduce the level of homeowners' tax liability also introduce more risk for taxpayers, and vice versa.

Table 4 reports how much each of the different types of tax limitations contribute *ceteris paribus* to our simulated values of *Tax Policy Risk* and *Tax Policy Level*. Both measures are again standardized for interpretability. We include indicator variables denoting the application of particular tax limits in a given state-year (i.e., $\mathbb{1}(\text{Levy Limit})_{s,t}$, $\mathbb{1}(\text{Rate Limit})_{s,t}$, and $\mathbb{1}(\text{Assessment Limit})_{s,t}$), and each specification features controls $X_{s,t}$ for appraisal frequency and effective tax rates, along with year fixed effects, λ_t. This specification is given by

$$\begin{aligned} \textit{Tax Policy Risk/Level}_{s,t} =& \beta_0 + \beta_1 \mathbb{1}(\text{Levy Limit})_{s,t} + \beta_2 \mathbb{1}(\text{Rate Limit})_{s,t} \\ &+ \beta_3 \mathbb{1}(\text{Assessment Limit})_{s,t} + \beta X_{s,t} + \lambda_t + \varepsilon_{s,t}. \end{aligned} \tag{5}$$

As shown in Column 1 of Table 4, *Tax Policy Risk* increases with all three types of limits, on average. *Tax Policy Risk* thus increases by 0.33 standard deviations in states with levy limits, 0.74 standard deviations in states with rate limits, and 0.82 standard deviations in states with assessment limits and yearly reassessments. In contrast, property tax *amounts* decrease with levy and rate limits and increase with assessment limits. In Column 2 of Table 4, we report that *Tax Policy Level* decreases by 0.63 standard deviations in states with levy limits and 1.06 standard deviations in states with rate limits. The level of property taxes increases with assessment limits by 1.79 standard deviations. This last finding is consistent with the mixed empirical evidence regarding whether or not assessment limits dampen property tax payments overall, and may partly reflect localities' ability to raise millage rates to overcome lower assessments.

Specification (5) accounts for 74 percent of the variation in *Tax Policy Risk* and 60 percent of the variation in *Tax Policy Level*. This is unsurprising given the design of our property tax simulations. The remaining unexplained variation is attributable to interactions and non-linearities among these features.

Figure 7 shows how *Tax Policy Risk* (vertical axis) changes as we relax different property tax limits (i.e., raise the corresponding allowable growth rate or effective statutory tax rate) (horizontal axis). In Panel (a), we consider individual types of property tax limits in isolation, with all other limitations turned off. With stricter limits (closer to 0 along the horizontal axis), policy risk is between \$500 and \$400. As the respective limit thresholds increase, and become less strict, policy risk decreases from all three types of limitations. Policy risk thus approaches zero for rate limits near 5%, levy limits near 5.5% annual growth, and assessment limits near 8% annual growth, as these caps gradually become non-binding. Panel (b) shows how these effects are dependent on the existence of other limitations by repeating the previous exercise, albeit with other property tax limitations set to their median in-sample stringency level. Unsurprisingly, *Tax Policy Risk* is shifted upwards across the board as a result, but Figure 7b also highlights the fact that when implemented alongside other limitations, assessment limits always yield the highest risk for a given level of limit stringency. We describe a brief validation exercise for our measure of *Tax Policy Risk* at the conclusion of Appendix C, which further emphasizes the role of assessment limitations and confirms a positive association between our simulated risk measure and average parcel-level risk prices in the data.

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 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.

Having developed the foregoing methodology, we are finally in a position to test our core research question: namely, whether property tax limitations and other countercyclical features of state property tax systems contribute to a higher probability of mortgage distress by increasing households' exposure to tax risk.

6 Tax Policy Risk and Mortgage Distress

6.1 Empirical Specification

We address concerns about the reduced form analyses in Sections 4 and 5.2.5 by re-estimating the same specifications with our newly developed measures of *Tax Policy Risk* and *Tax Policy Level*. These measures distinguish explicitly between risk and level effects while consistently accounting for all relevant property tax regime characteristics across states. These enable us to isolate tax policy influences while keeping economic conditions fixed. Moreover, unlike changes in observed tax liability, homeowners' endogenous choices cannot affect these measures.

Intuitively, *Tax Policy Risk* represents the average amount that households would be willing to pay to avoid the risk effects resulting from the set of property tax limits in their state. Conditional on *Tax Policy Level*, 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).

In order to test this core prediction, we replicate the set of specifications shown in Table 2, replacing $ZTax$ in (1) with standardized measures of our key explanatory variables, *Tax Policy Risk*$_{s,t}$ and *Tax Policy Level*$_{s,t}$. Our risk measure of interest, *Tax Policy Risk*$_{s,t}$, varies at the state s year t level, as does *Tax Policy Level*$_{s,t}$, which we include to absorb the effects of differences in average property tax amounts that may result from the application of tax limitations. In later tests, we interact *Tax Policy Risk*$_{s,t}$ and *Tax Policy Level*$_{s,t}$ with different time-varying state-, neighborhood, and parcel-level characteristics that may affect households' susceptibility to tax risk.

6.2 Main Estimates

As shown in Table 5, *Tax Policy Risk* has a statistically significant positive effect across all specifications at the 10 percent level.[30] Just as in the previous reduced form results, the most narrowly identified specifications involving 10 km^2 grid cell $\times$ year pair fixed effects (Columns 7-8) yield the largest point estimates. Based on the estimates reported in Column 8, a one standard deviation increase in *Tax Policy Risk* raises the probability of mortgage distress by 0.44 percentage points, or approximately 30 percent. By way of comparison, the full results for the same specification (Table E.3) imply that moving between the third and fourth quintiles of the known LTV distribution (i.e., from an LTV of 0.6-0.91 to 0.91-1.6) raises the probability of distress by approximately 1.6 percentage points. Thus, the effect of a one standard deviation increase in *Tax Policy Risk* is roughly one-quarter as large as the effect of crossing the threshold to being underwater. More modestly, a one standard deviation increase in *Tax Policy Risk* raises the probability of distress by roughly seventy percent more than owning a home in disrepair (i.e., a home that has not been renovated in at least 60 years and hence presumably at greater risk of facing unanticipated repair costs).

The results in Table 5 imply a large increase in mortgage distress due to tax policy risk, holding fixed the effect of policy characteristics on the certainty equivalent level of taxation. The latter level effects likewise increase the probability of mortgage distress, albeit by a somewhat smaller amount; i.e., a one standard deviation increase in *Tax Policy Level* raises the probability of mortgage distress by 0.33 percentage points, or roughly 23 percent. Both risk and level effects underlie the overall effects attributable to changes in annual property tax amounts in Section 4. Insofar as the effects of *Tax Policy Risk* and *Tax Policy Level* are negatively correlated—as documented in Section 5.4—states' tax regimes will have smaller net effects on distress overall. However, the important point here is that property tax *risk* has a uniquely detrimental effect on financially vulnerable households, *above and beyond whatever benefit various tax policies may produce in terms of dampening the overall level of taxation*. With the exception of Hayashi (2020), the financial ramifications of policies which introduce counter-cyclical variation in property tax obligations have been entirely ignored.

[30]For brevity, we only report the set of coefficient estimates that relate to property tax risk and levels in Table 5. Complete estimates can be found in Table E.3.

6.3 Heterogeneous Effects

We extend our preferred specification from column 8 of Table 5 to test whether certain time-varying market-level or parcel-level characteristics affect homeowners' susceptibility to property tax risk and levels. Concretely, we consider the interaction of *Tax Policy Risk* and *Tax Policy Level* with state-level unemployment rates, the existence of state-level property tax deferral programs for low-income taxpayers, zip code-level federal income tax itemization rates, tract-level race indicators, and owner-specific LTV and tenure. Panels (a)-(d) of Figure 8 summarize the implied marginal effects of *Tax Policy Risk* and *Tax Policy Level* over the relevant distributions of unemployment, majority race, LTV, and tenure, respectively. Complete results, including uninteracted covariates and the full set of relevant interactions, are provided in Table E.4.

Figure 8a depicts marginal effects (with 90% confidence intervals) from a model in which *Tax Policy Risk* and *Tax Policy Level* are 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. As shown, the point estimates in Figure 8a are broadly consistent with this prediction, although the marginal effects are too imprecisely estimated to draw more rigorous conclusions about what happens in the tails of the unemployment rate distribution. Overall, the partial effects of both *Tax Policy Risk* and *Tax Policy Level* appear to peak when unemployment is between 6 and 8 percent, near the average in-sample unemployment rate of 6.5 percent.[31]

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 Black, majority Latino (all races), or majority white (+ Other) Census tracts. Figure 8b reports the implied overall partial effects of *Tax Policy Risk* and *Tax Policy Level* by racial group. Consistent with the prior literature, residents of predominantly Black neighborhoods face significantly higher baseline rates

[31]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.

of mortgage distress (Table E.4, Column 2). More importantly, households in predominantly Black neighborhoods face significantly larger effects of *Tax Policy Risk* and *Tax Policy Level*, the result being that both effects are approximately three times larger in majority Black areas than in majority white areas. Majority Latino areas, on the other hand, do not appear to suffer differentially from tax risk or level effects.[32]

Finally, turning to parcel-level characteristics, we first document that households in the third and fourth quintiles of the LTV distribution—around the threshold for being underwater—incur the largest effects of *Tax Policy Risk* on mortgage distress (Figure 8c). Limiting the analysis to the subset of observations with known LTV (which presumably excludes a substantial proportion of homeowners without mortgages) yields uniformly larger point estimates of the effects of both *Tax Policy Risk* and *Tax Policy Level*, and these effects are monotonically increasing across the bottom four LTV quintiles (Figure E.7). Strategic motives for mortgage delinquency and default are thus amplified in states whose combined property tax system characteristics result in greater *Tax Policy Risk*. Equivalently, tax risk constitutes a stronger trigger for mortgage distress when homeowners are already confronted with being underwater.

Second, we show that the foregoing LTV heterogeneity is not an artifact of newer homeowners being more susceptible to tax policy risk. In fact, as depicted in Figure 8d, longer-tenured homeowners (i.e., households who have owned their homes for more than 5 years) exhibit the largest partial effects of both *Tax Policy Risk* and *Tax Policy Level*. This is likely attributable to the fact that the risk consequences of assessment limits, for instance, only manifest themselves after households have owned their homes long enough to experience an initial divergence between their market values and taxable values.

In unreported tests, we also investigate whether programs that allow homeowners to defer their property tax obligations during periods of financial hardship are able to mitigate the negative effects of counter-cyclical 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

[32]Majority white, Black, and Latino Census tracts account for 76.3, 15.9, and 3.1 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 group suffer from weaker statistical precision.

unsurprising that we find no statistically significant differential effect of *Tax Policy Risk* or *Tax Policy Level* in states with such tax deferral programs in place. Focusing 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 apparent restrictions on age, disability, or military status), we obtain point estimates that are consistent with substantial (i.e., complete) attenuation of the effects of *Tax Policy Risk* and *Tax Policy Level* where low-income homeowners have the option to smooth their tax payments over time, but these negative differential effects remain imprecisely estimated.

Similarly, we also 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 based on data from the IRS's Statistics of Income tables, and we test for differential effects of *Tax Policy Risk* and *Tax Policy Level* across both groups. Taken together, areas with high itemization rates or high AGI do not exhibit significantly weaker effects of tax risk or levels on mortgage distress.[33] Given our border discontinuity design and lack of data on parcel-specific variation in itemization behavior, incomes, eligibility for tax deferral, etc., it is relatively unsurprising that these tests are underpowered. We defer a narrower investigation of the set of policies and household characteristics that contribute to greater or lesser susceptibility to tax policy risk until such data can be assembled.

7 Conclusion

Using parcel-level panel data for the near universe of residential properties located within 10 km 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 conclude that *Tax Policy Risk* has a pronounced effect on mortgage distress. This effect is distinct from the level of taxation, *Tax Policy Level*, which has implicitly been the main

[33]Results available from the authors upon request.

focus of a handful of studies to consider the effects of property taxation on financial 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. Assessment limits are responsible for the single largest contribution to *Tax Policy Risk*, but other forms of property tax limitations—as well as infrequent reassessments—likewise play an important role. *Tax Policy Risk* also has disparate impacts on different segments of the population. As in many realms, these effects are borne disproportionately by financially vulnerable residents in minority areas, and they are reinforced among homeowners facing otherwise stronger strategic incentives for default due to being underwater on their mortgages.

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 macroeconomic performance and whether targeted measures to protect vulnerable homeowners during market downturns may be warranted to avert the negative welfare consequences and spillovers associated with mortgage foreclosures. Though existing state-level property tax deferral programs appear to do little to counteract the negative consequences of *Tax Policy Risk*, a narrow expansion of these programs (i.e., beyond low-income seniors) may provide a path forward. We do not address directly the potential gains to local governments from *revenue* smoothing, yet the existence of such gains ought to leave scope for such targeted approaches while leaving voters' preferred property tax regime features otherwise unchanged.

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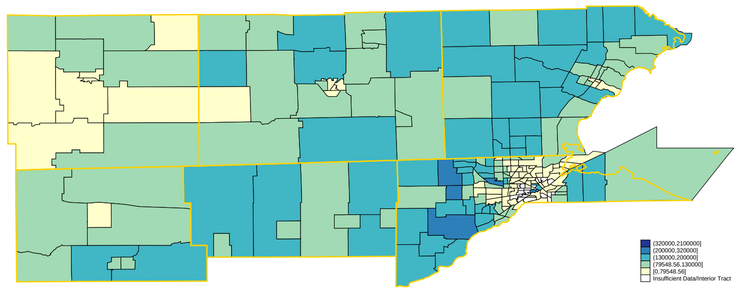
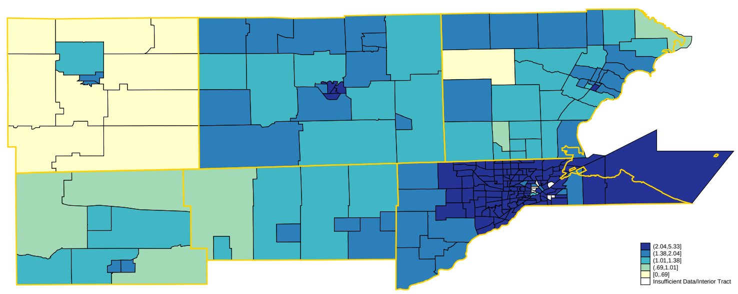
Figure 1: Local Housing Market Characteristics Across State Borders: MI-OH

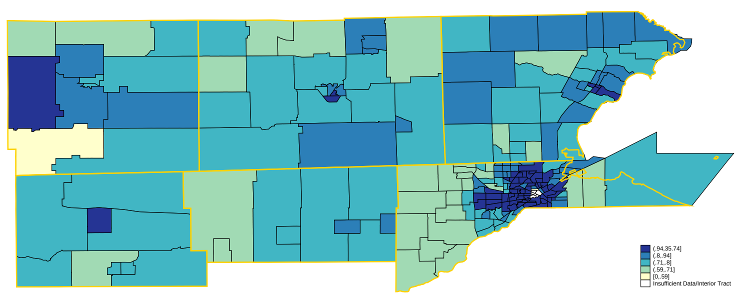
(a) Estimated House Price ($)



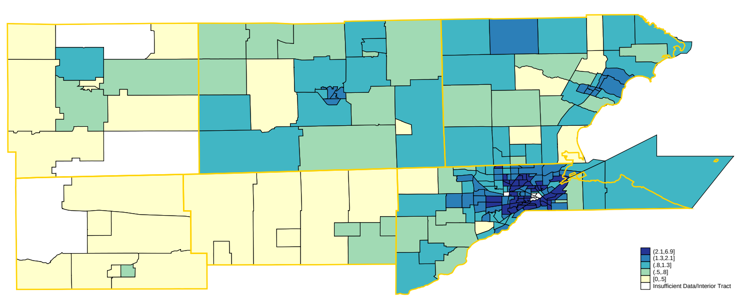
(b) Market ETR (%) - Estimated Prices



(c) Loan-to-Value Ratio - Estimated Prices

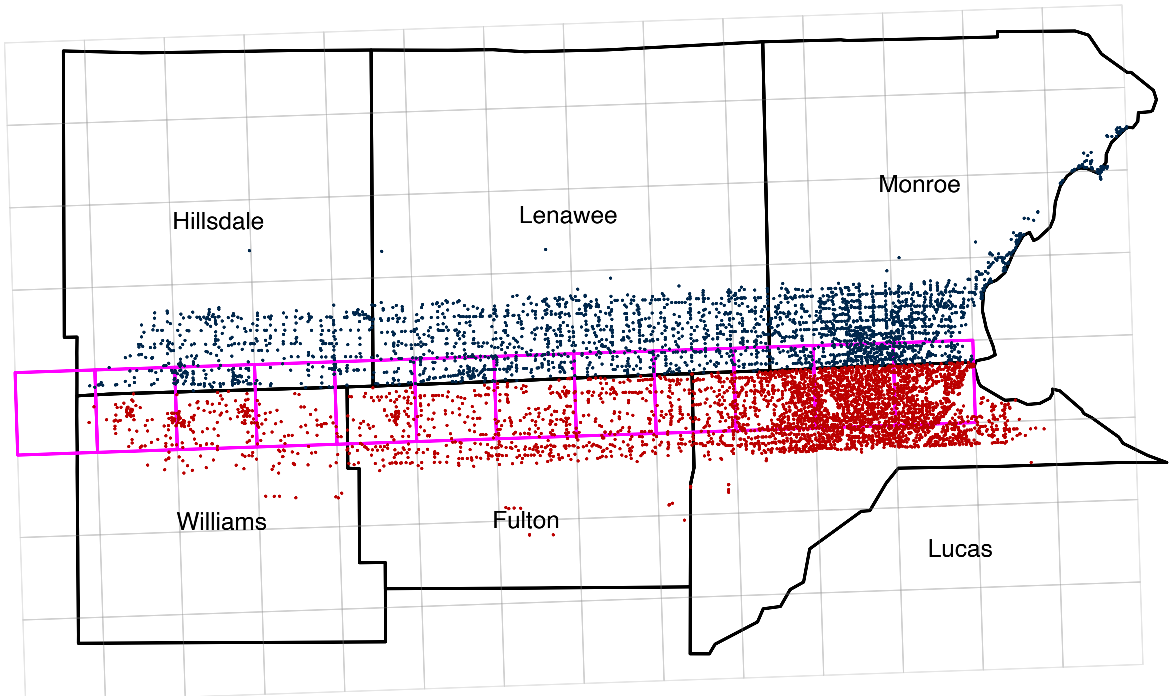


(d) Annual Foreclosure Rate (Parcels)



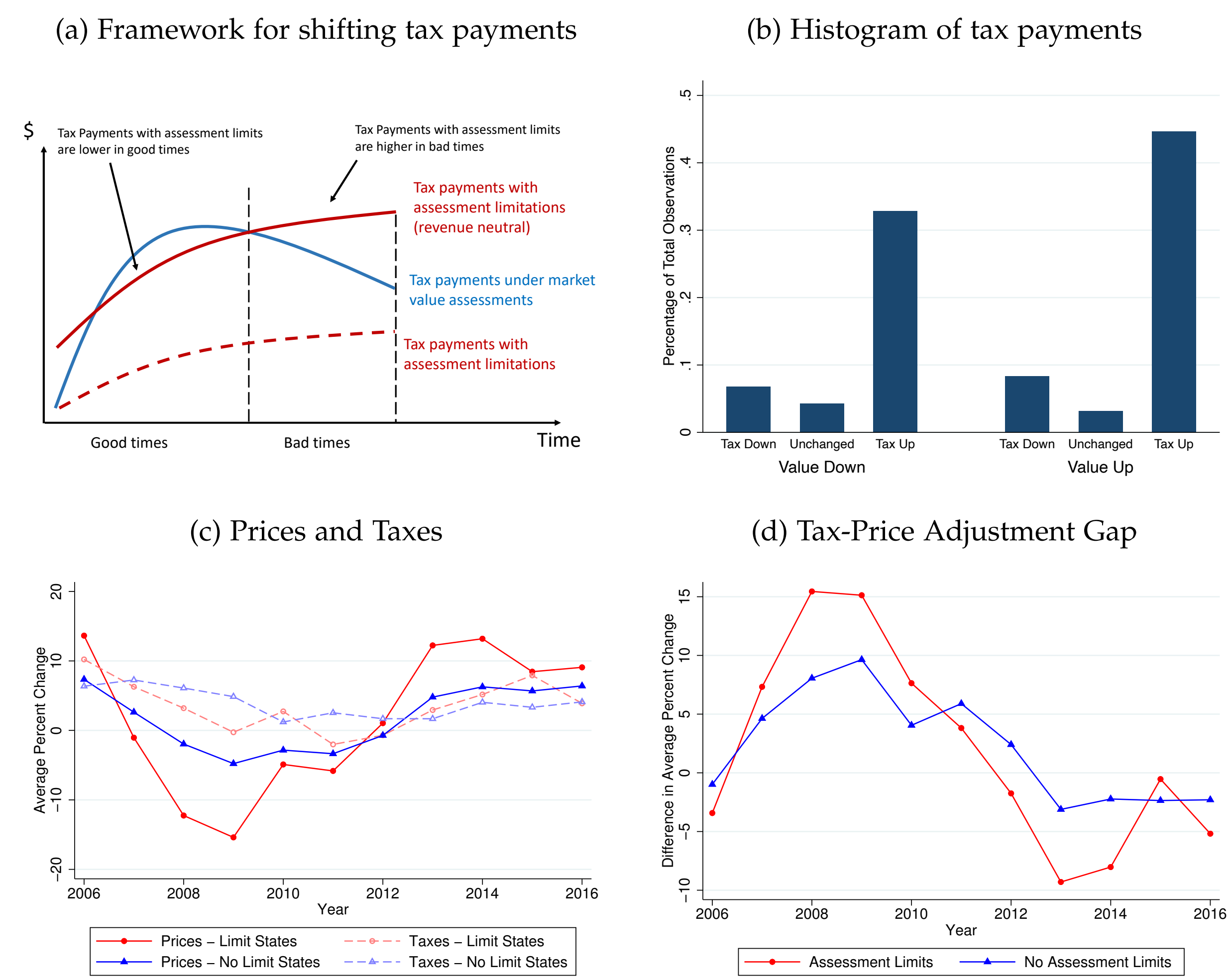
The figure shows median property characteristics in 2015 for all Census tracts located in the six counties at the Michigan-Ohio border. Solid yellow lines are county borders. The state border follows the near-horizontal midsection line. The tight cluster of tracts in the southeast corner of the map is Toledo, OH, just south of the state border.

Figure 2: Properties and 10 km² Grid Cells: MI-OH



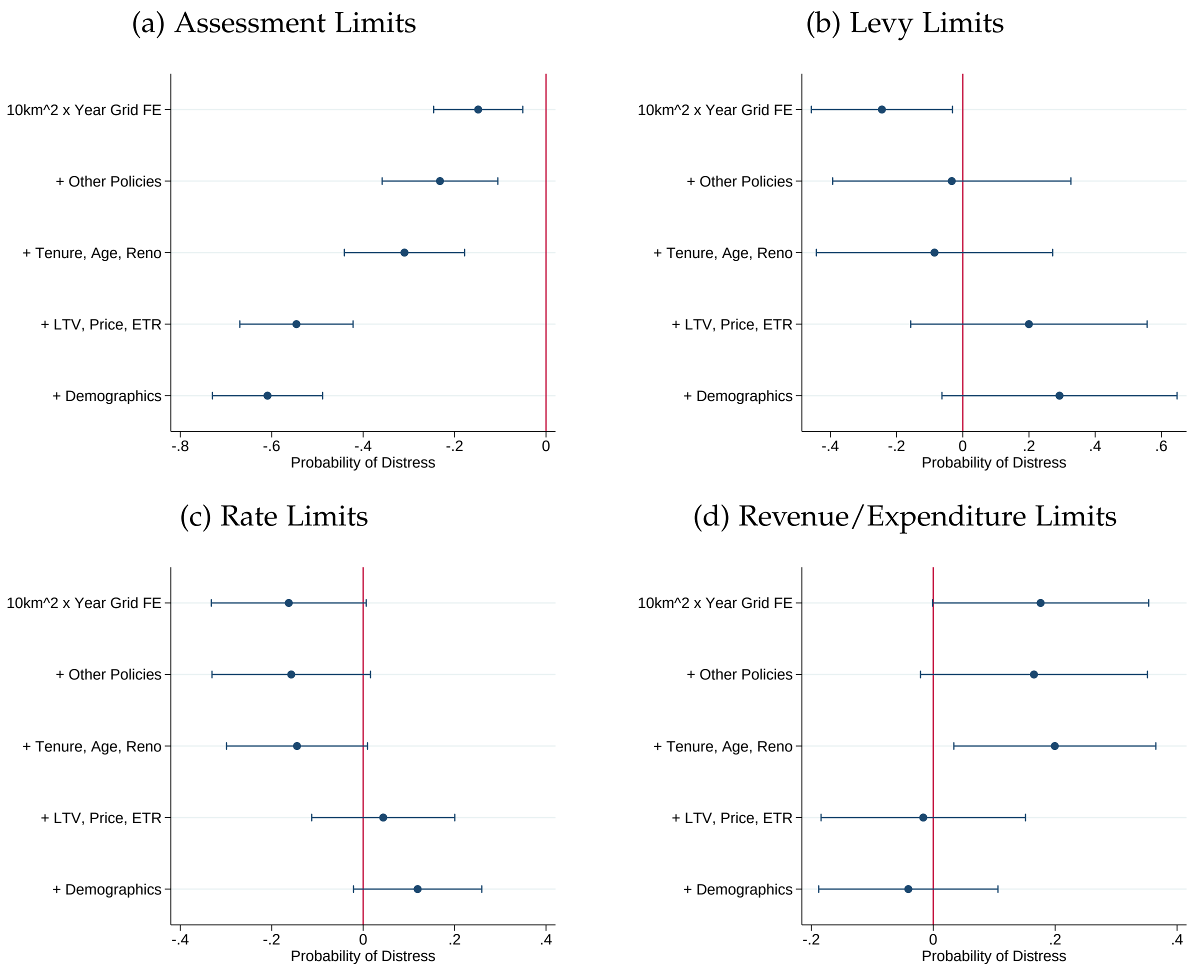
The figure illustrates the grid-based spatial regression discontinuity design with the Michigan-Ohio border as an example. Blue points denote unique properties in the sample in Michigan and red points denote those in the sample in Ohio along the states' shared border. The map is overlaid with 10 km² grid cells identified by the United States National Grid (USNG). Border-straddling grid cells that contain parcels in both states are outlined in magenta. Interior cells and border-straddling grid cells that contain parcels from only one state are outlined in gray.

Figure 3: Housing Prices and Tax Payments



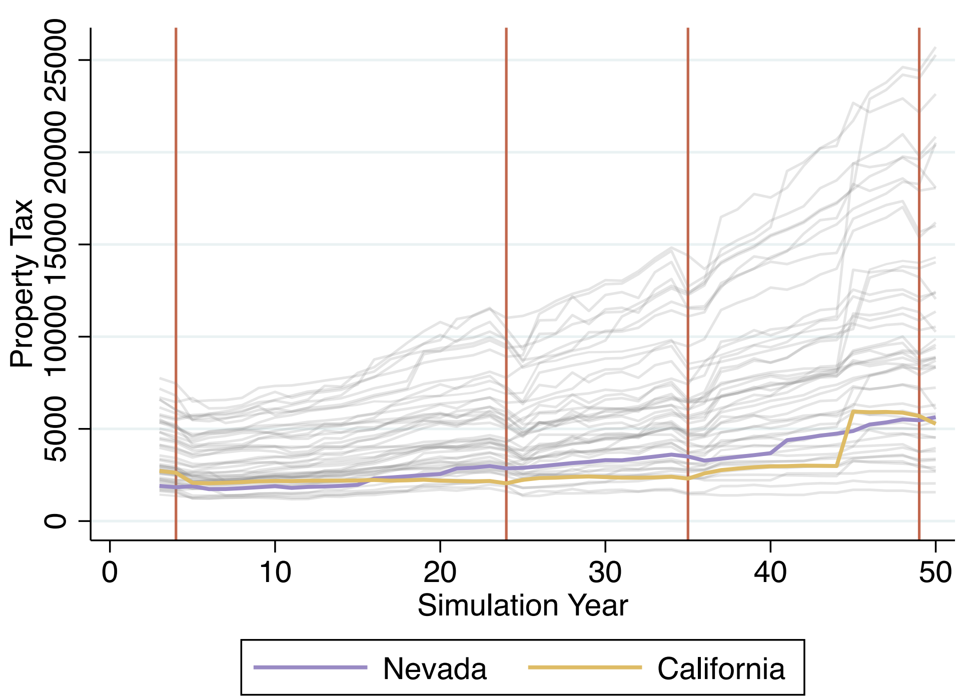
The figure describes the relation between housing prices and property tax payments. Panel 3a illustrates a hypothetical dynamic wherein tax payments may continue to increase even while market values are declining. Panel 3b shows the proportion of instances in which property tax payments fall, remain unchanged, or rise while market values are rising or falling in our estimation sample. Panel 3c plots year-over-year changes in housing prices and property tax payments for states with and without assessment limitations. Panel 3d plots the "tax-price adjustment gap", defined as the percentage change in taxes (dash lines in panel 3c) minus the percentage change in housing price (solid lines in panel 3c).

Figure 4: Mortgage Distress and Property Tax Limitations



The figure depicts reduced-form estimates with 95% confidence intervals of the effects of property tax limitations on mortgage distress, replacing $ZTax$ in Equation (1) with a binary indicator denoting the existence of either assessment limits (Panel a), levy limits (Panel b), rate limits (Panel c), or revenue/expenditure limits (Panel d). From the top, the point estimates depicted in each panel show a progression from the most to least parsimonious specification. The set of controls added at each step are labeled accordingly. Standard errors are clustered by 10 km² grid cell.

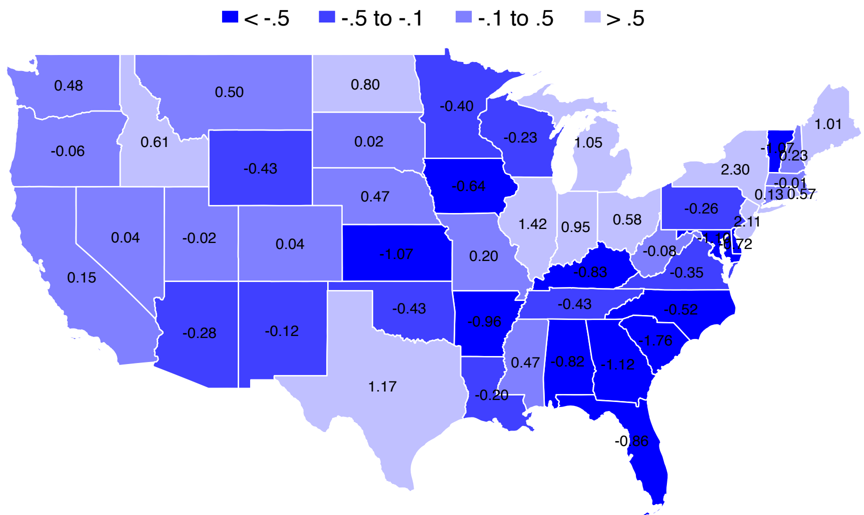
Figure 5: **Simulated Property Tax Bills**



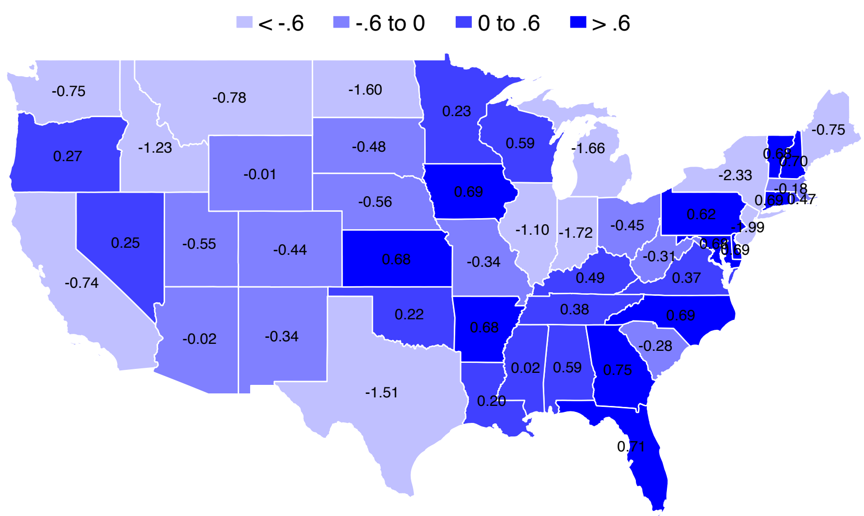
This figure plots the property tax bill for the same simulated property under the same simulated macroeconomic conditions, with the same transaction process, but under different tax regimes across states. Different lines depict the property tax bill under state-specific tax regimes. Red vertical lines denote recession years in the simulation. The purple line represents the property tax bill of the property under the tax regime in Nevada and the yellow line represents that under the tax regime in California. See detailed description of the simulation in Section 5.3 and Appendix C.

Figure 6: **Tax Policy Risk Attributable to Individual Policies**

(a) *Tax Policy Risk*



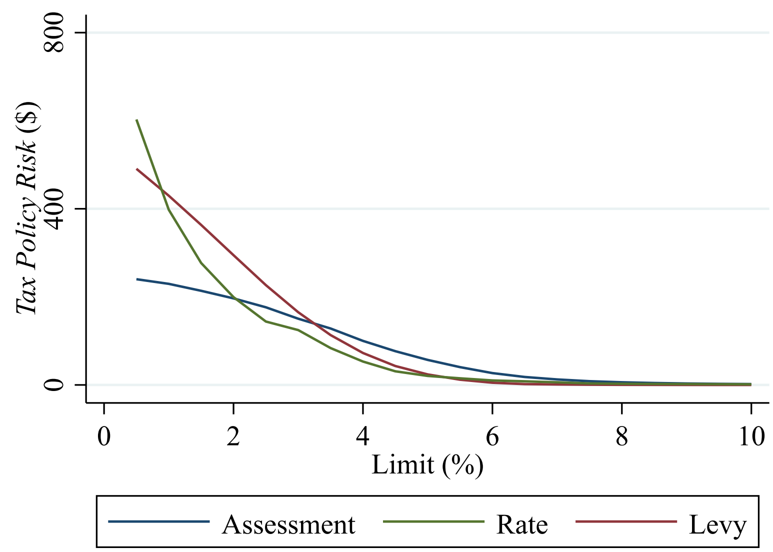
(b) *Tax Policy Level*



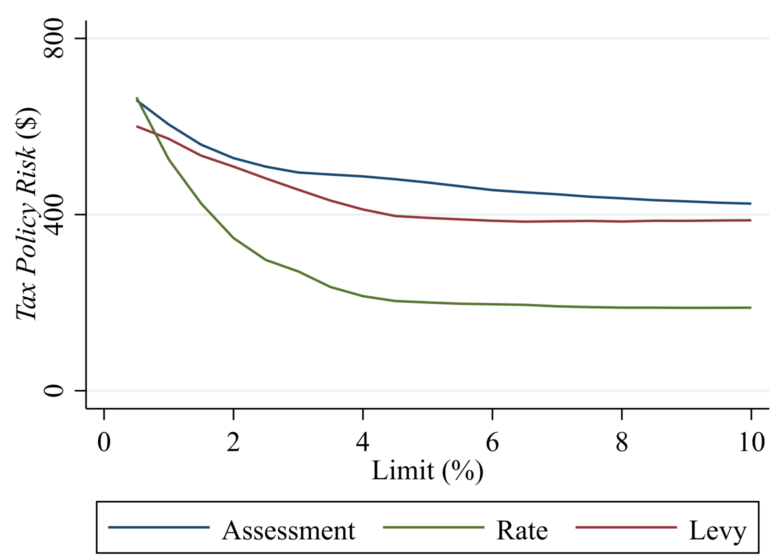
Panel 6a shows *Tax Policy Risk* by state, which represents the amount of money (average across 2006 to 2016) that an owner of a property worth $300,000 would be willing to pay per year to eliminate all risk due to property tax limitations. Panel 6b shows *Tax Policy Level* by state, which represents the net saving per year for an owner of a property worth $300,000 due to property tax limitations. The numbers shown in the figure are standardized to a mean of 0 and a standard deviation of 1. See detailed description of the simulation that produces *Tax Policy Risk* and *Tax Policy Level* in Section 5.3 and Appendix C.

Figure 7: **Tax Policy Risk Attributable to Individual Policies**

(a) Changes absent interactions

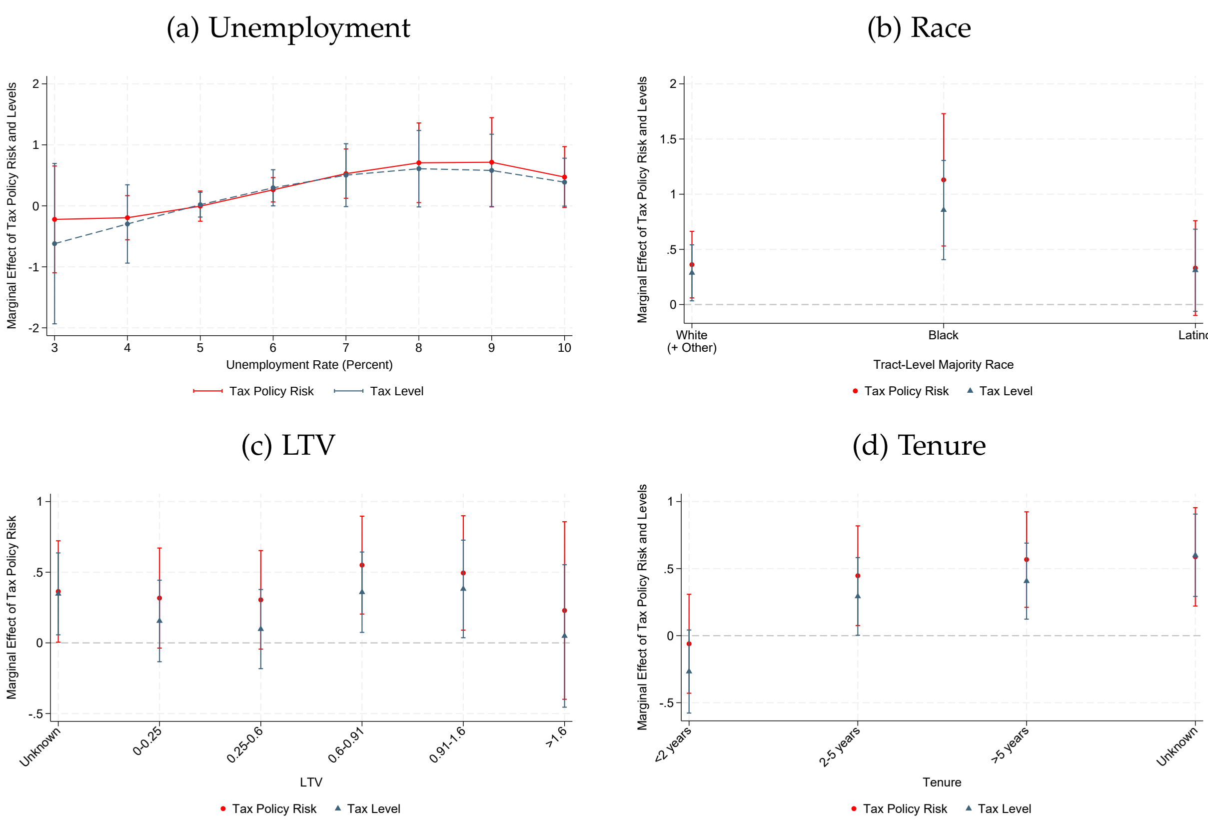


(b) Changes with interactions



This figure shows how assessment limitations, rate limitations, and levy limitations affect *Tax Policy Risk* independently and jointly. Panel 7a plots the dollar amount *Tax Policy Risk* as a function of the corresponding limitation while the other two limitations are turned off. Panel 7b plots the dollar amount *Tax Policy Risk* as a function of the corresponding limitation while the other two limitations are set at the median value across states in the sample. See detailed description of the simulation in Section 5.3 and Appendix C.

Figure 8: **Heterogeneous Effects of *Tax Policy Risk* and *Tax Policy Level* on Mortgage Distress**



Marginal effects are estimated from extensions of Equation 1 featuring interactions of *Tax Policy Risk* and *Tax Policy Level* with (a) a cubic function of state-year average unemployment rates, (b) binary indicators denoting majority race by Census tract, (c) categorical LTV indicators by approximate LTV quintile and a sixth category for parcels with unknown LTV, and (d) categorical indicators of homeowner tenure duration. Complete results are reported in Table E.4. Error bands denote 90% confidence intervals.

Table 1: Summary Statistics

	I[Distress]=0			I[Distress]=1			
Variable	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.
Tax Policy Risk ($000s)	0.355	0.275	0.333	0.351	0.275	0.309	-0.004
Tax Policy Level ($000s)	-9.539	-3.751	14.058	-9.197	-4.086	12.761	0.342
Tax Policy Risk (Standardized)	0.000	-0.238	1.001	-0.011	-0.238	0.930	-0.012
Tax Policy Level (Standardized)	0.000	0.412	1.001	0.024	0.388	0.909	0.024
Price ($000s)	255.048	169.330	298.403	179.093	127.793	195.076	-75.955
Tax ($)	3417.8	1981.4	5391.2	2598.9	1670.0	3350.2	-818.9
Lagged ETR (%)	1.48	1.16	1.36	1.69	1.28	1.53	0.21
Δ Tax ($)	101.2	22.0	880.6	73.3	15.0	603.4	-27.9
%Δ Tax	3.53	1.73	17.26	4.07	1.25	20.23	0.54
%Δ Price	4.76	0.00	162.40	4.26	-1.33	166.99	-0.51
Δ Tax Gap	-1.23	2.83	163.26	-0.19	4.08	168.32	1.04
LTV	1.38	0.63	71.95	1.78	0.93	46.47	0.40
Tenure	11.6	9	11.0	8.9	6	9.2	-2.8
Age	55.5	53	33.2	59.1	58	33.6	3.6
Renovation Age	48.8	47	35.5	53.1	54	36.2	4.3
Average AGI ($000s)	61.144	48.608	51.301	49.766	43.045	35.836	-11.377
Education $\leq$ HS (%)	45.99	47.20	17.81	50.19	51.40	16.50	4.20
Education $\geq$ BA (%)	27.56	22.60	18.93	22.23	18.00	15.51	-5.33
Population	4594.7	4448.0	1723.3	4620.4	4465.0	1745.2	25.6
Population 18-24	419.2	362.0	344.0	443.9	394.0	305.3	24.7
Population $\geq$ 25	3059.9	2980.0	1141.2	2984.1	2911.0	1130.1	-75.8
Percent White	70.1	83.8	30.9	55.5	64.4	35.0	-14.5
Percent Black	20.1	5.5	29.2	33.7	17.3	35.4	13.6
Percent Latino	8.9	4.0	13.5	10.9	4.6	15.6	1.9
Percent Asian	3.7	1.5	5.9	3.3	1.2	5.4	-0.4
Observations		30,765,775			449,494		

The table represents the summary statistics of the properties in the sample. *Tax Policy Risk* is the amount of money an average property owner would be willing to pay per year to do away with the housing distress risk induced by state-specific limitation policies. *Tax Policy Level* is the amount of money an average property owner saves per year due to state-specific limitation policies. See detailed descriptions for them in Sections 5.4. Price is inferred using a combination of interpolation of transaction value and a machine learning hedonic estimation detailed in Appendix A. See definitions of other variables in Appendix D.

Table 2: Mortgage Distress and Percent Changes in Annual Tax Liability

$Y = Pr(Distressed_t = 1), Y \in \{0, 100\}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\%\Delta Tax$	0.036	0.035	0.026	0.038***	0.036***	0.027**	0.062***	0.061***
	(0.025)	(0.021)	(0.020)	(0.014)	(0.013)	(0.012)	(0.017)	(0.018)
FE and Controls:								
County pair FE	x	x	x					
10 km^2 grid FE				x	x	x		
10 km^2 grid × Year FE							x	x
Controls		x	x		x	x		x
Year FE			x			x		
R-squared	0.004	0.017	0.018	0.005	0.018	0.019	0.010	0.023
Observations		31,209,231			31,209,241		31,209,241	

Significance levels are designated as *** $p<0.01$, ** $p<0.05$, and * $p<0.1$. Standard errors (in parentheses) are clustered by county pair or 10 km^2 grid cell, depending on the fixed effects employed. $\%\Delta Tax$ is a measure of the year-over-year percent change in annual tax obligations standardized to have an in-sample mean value of 0 and standard deviation of 1. For brevity, only main effects are shown. All specifications except (1), (4), and (7) include controls for parcel-specific LTV, house price, lagged ETR, tenure, age, and renovation age; zip code-level adjusted gross income, tract-level demographics related to educational attainment, population, and race; and indicators for recourse and non-judicial review states. Complete results are reported in Table E.2.

Table 3: 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	3
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		1
KS			x				x		1
KY			x	x		x	x		1
LA			x	x			x		4
MA			x	x			x		1
MD	x					x	x		3
ME			x		x		x		-
MI	x		x	x	x		x	x	1
MN			x		x			x	5
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	5
NJ			x		x		x		-
NM	x		x	x	x		x		1
NV			x	x			x	x	5
NY		x	x				x		-
OH			x	x			x		3
OK	x			x			x	x	1
OR		x		x				x	1
PA			x	x			x		-
RI			x				x	x	3
SC	x			x			x		5
SD			x	x			x		1
TN			x				x	x	5
TX		x	x	x		x	x	x	3
UT			x	x		x	x	x	1
VA			x			x	x	x	4
VT							x		1
WA			x	x	x			x	1
WI			x		x				5
WV			x	x			x	x	1
WY				x			x	x	1

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

This table describes key tax policies across states as of 2016. We discuss them in detail in Section 5.2.

Table 4: Determinants of Tax Policy Risk and Tax Policy Level

Dependent variable:	*Tax Policy Risk*	*Tax Policy Level*
	(1)	(2)
$\mathbb{1}$(Levy Limit)	0.330***	-0.626***
	(0.024)	(0.027)
$\mathbb{1}$(Rate Limit)	0.744***	-1.055***
	(0.059)	(0.075)
$\mathbb{1}$(Assessment Limit)	0.802***	0.167***
	(0.039)	(0.049)
Constant	-1.585***	1.785***
	(0.065)	(0.075)
Year fixed effects	Yes	Yes
Controls	Yes	Yes
R-squared	0.740	0.602
Observations	441	441

Significance levels are designated as *** p<0.01, ** p<0.05, and * p<0.1. Standard errors (in parentheses) are clustered by year. *Tax Policy Risk* and *Tax Policy Level* are calculated at the state-policy year level as described in Section 5.4 and both are standardized to have an in-sample mean value of 0 and standard deviation of 1. Levy, rate, and assessment limits are defined in Section 5.2. Controls include appraisal frequency as a categorical variable and the effective tax rate. All included variables vary at the state-year level. This table excludes nondisclosure states and includes New York City; Cook County, IL; and Washington, DC as distinct property tax regimes.

Table 5: Mortgage Distress and Tax Policy Risk

$Y = Pr(Distressed_t = 1), Y \in \{0, 100\}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tax Policy Risk	0.296**	0.366**	0.315*	0.305**	0.278**	0.240*	0.445***	0.433**
	(0.126)	(0.176)	(0.174)	(0.123)	(0.140)	(0.144)	(0.157)	(0.220)
Tax Policy Level	0.168*	0.298**	0.201	0.165*	0.212**	0.099	0.297***	0.335*
	(0.090)	(0.137)	(0.137)	(0.092)	(0.107)	(0.111)	(0.115)	(0.172)
FE and Controls:								
County pair FE	x	x	x					
10 km² grid FE				x	x	x		
10 km² grid × Year FE							x	x
Controls		x	x		x	x		x
Year FE			x			x		
R-squared	0.004	0.017	0.018	0.005	0.018	0.019	0.010	0.023
Observations		31,215,255			31,215,269		31,215,269	

Significance levels are designated as *** p<0.01, ** p<0.05, and * p<0.1. Standard errors (in parentheses) are clustered by county pair or 10 km² grid cell, depending on the fixed effects employed. *Tax Policy Risk* and *Tax Policy Level* are calculated at the state-policy year level as described in Section 5.4 and both are standardized to have an in-sample mean value of 0 and standard deviation of 1. For brevity, only main effects are shown. All specifications except (1), (4), and (7) include controls for parcel-specific LTV, house price, lagged ETR, tenure, age, and renovation age; zip code-level adjusted gross income, tract-level demographics related to educational attainment, population, and race; and indicators for recourse and non-judicial review states. Complete results are reported in Table E.3.

Online Appendix to
The Impact of Property Taxation and Tax Limitations on Mortgage Distress

Sebastien Bradley Da Huang Nathan Seegert[1]

Contents

List of Tables

List of Figures

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Disclosure:
The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

Appendix A Machine Learning Hedonic Estimation

We use two different methods to calculate annual property values—an imputation method and a hedonic estimation method. Each provides different coverage—and we use whichever method produces the longer parcel-specific history for each property in our analysis.[2] 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. We use both indices individually to extrapolate housing values forward and backward based on local pricing trends. 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 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.

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 about the observable characteristics of the property. We predict 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

[2] 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.

price (prediction target) and property characteristics (prediction input, including number of rooms, lot size, zip code, existence of fireplace, etc.), we use an ensemble method with a gradient boosting regression tree. The method is able to select information for the best fit taking into account 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.[3]

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 prediction 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 housing prices in the focal tract, the more information we are using, which improves prediction quality. However, at the same time, the more Census tracts we include in the sample, the more distant are the properties that we are using to predict prices in the focal tract (i.e., the relevance of location-specific information goes down and prediction quality could decrease). For each focal Census tract, we repeat the process of expanding the sample to incorporate additional adjacent tracts until the sample includes at least 20,000 transactions. We then pick the iteration that yields the lowest mean squared error, which usually bottoms between 5,000 and 10,000 transactions.

The predictions we obtain using this process are therefore parameter-optimized and

[3] 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.

sample-optimized. We apply this process to all Census tracts in our sample to obtain a machine-learning prediction of market value (hedonic price) for the largest possible sample of properties subject to minimal available property characteristic information.

Appendix B 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.[4]

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.[5]

We apply a parallel set of procedures to format the universe of parcel-level data from ZTRAX (Zillow, 2018) 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

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

[5]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.

not include sufficient information for geocoding (i.e., due to missing latitude/longitude coordinates or–where unavailable–missing or incomplete 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 5^{th} through 95^{th} 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 1^{st} through 99^{th} 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.[6]

We further 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.

Figure E.1a 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.

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

Appendix C 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 shocks, individual consumption shocks, and property values. We then calculate property tax obligations using all applicable tax limitations, and we compare these to the level of tax obligations that would be owed under a counterfactual regime without any tax limitations and annual property reassessments. Finally, we price tax payments as Arrow-Debreu securities and isolate the risk price of different states' applicable tax limits and key property tax system characteristics.

• Simulating 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 aggregate consumption data from the Bureau of Labor Statistics for the period 1997-2020. 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 a Poisson distribution. We assume that recessions happen once every 15 years on average and that aggregate consumption growth declines 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 shocks are on average 10 times as volatile as aggregate consumption shocks. 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 (all-item CPI) 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 the Case-Shiller National Home Price Index to calculate the year-over-year change in property value, h_t, and estimate the following equation:

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

We use the Case-Shiller National Home Price Index instead of more granular housing price indices on state or even local level (e.g., Zillow and FHFA indices) such that we hold the housing value (and more broadly the entire economy) fixed and all variation in our *Tax Policy Risk* solely comes from tax policy.

In addition, we assume that on average property value declines by 30% during recessions given that the Case-Shiller Index lost about 30% of its value from the peak to the bottom around the 2008 financial crisis. 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.

• **Calculating Property Tax Payments**

We next calculate two different property tax payments for each property i in (simulation) year z in the simulated economy – one based on all applicable property tax policies in state s in (policy) year t and one without any tax limitations imposed. Before applying any tax limits, we make three adjustments with respect to heterogeneous property values across states, downward stickiness, and infrequent reassessment. First, we re-scale property values 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 assessed values in the following way: if the change in property value, $h_{i,z}$, is positive, the assessed value in the next year changes (grows) by $h_{i,z}$; but if the change is negative, there is a 30% chance that the assessed value in the next year stays the same and a 70% chance that the assessed value changes (declines) by $h_{i,z}$. Lastly, for states that do not have assessment limits and do not reassess properties annually, we process assessed values in one of the two following ways: (1) if the state mandates reassessment at specific intervals, we only update assessed values at the corresponding frequency and leave assessed values unchanged in non-reassessment years, or (2) if the state does not mandate a specific reassessment frequency, we assume that properties are reassessed to current market value with a 10% idiosyncratic reassessment probability (i.e., akin to a 10-year interval between reassessments), consistent with the average practice in DE, ME, NJ, NY, and PA.

In the absence of assessment limits, we set taxable values equal to assessed (market) values in every period. Otherwise, if assessed value growth for a given property exceeds the allowed taxable value growth rate, the taxable value is set such that it grows at exactly the assessment limit. In most assessment limit states, the maximum permissible growth rate for taxable values is anchored to inflation, usually the lesser of statewide CPI inflation and some fixed number. We model these limitations accordingly, based on our model simulated CPI, f_z. For *acquisition value* based assessment limitation regimes (e.g., CA, FL, MI), we reset taxable values to market value every time the property is transacted and resume application of assessment limitations to the property throughout the tenure of the new owner.

In order to apply levy limits, we start by using the simulated distribution of taxable values and the median effective tax rate (ETR) observed in our data in state s year t to calculate property tax liability for each property i in simulation year z. We then assume that states target 80% of the revenue growth of g_z (i.e., the state imperfectly tracks the aggregate consumption growth), and we compare the implied growth in aggregate tax revenues to the revenue target and any applicable levy limits. If the state has a levy limit and simulated aggregate consumption growth exceeds the limit, the revenue target is set at the maximum amount permissible under the levy limit. The mill rate is then adjusted such that next year's aggregate tax revenue meets the revenue target. This implies that when the housing market is too hot, the state must reduce the mill rate such that the total tax revenue grows in line with the lesser of aggregate consumption growth or the levy limit. When the housing market is in decline, in contrast, the state may increase the mill rate to compensate for the smaller tax base (subject to any applicable rate limitations) in order to maintain its revenue target.

Finally, we apply any relevant rate limits. These have the practical effect of restricting states' ability to achieve their revenue targets during periods of declining taxable values. Rate limits and levy limits together yield a dynamically determined millage rate which feeds into our final property tax payment calculation. Formally, we calculate the final property tax, $q_{s,t,i,z}$, for property i in simulation year z with the tax policy regime of state s in year t to be the product of the taxable value and the dynamic millage rate. We also calculate a counterfactual property tax amount assuming no tax limitations and annual reassessments, $q'_{s,t,i,z}$, which is simply equal to market value times the median state ETR observed empirically.

- **Pricing Property Taxes and Isolating Policy Risk**

For each property i in year z, we calculate the Arrow-Debreu price of the stream of property tax payments owed over the entire tenure of the property. We assume CRRA utility with a risk aversion parameterization 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).

We denote the tenure of property i in year z as $T_{i,z}$. Throughout homeowners' tenure, the AD property tax price for property i in simulation year z under the policy in state s and year t is:

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

We further decompose the AD property tax price into a certainty-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 homeowners' tenure, and a risk component:

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

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 tax limitations, $q_{s,t,i,z}$, 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 states' property tax system characteristics, 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 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 simulation year 20, most properties have at least "naturally" been transacted once before, which mitigates the potential unintended interactions. Second, we also drop observations for 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.

Lastly, 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 at the state $\times$ policy year level is the main independent variable of interest for our empirical analysis.

• **Validation**

We provide a quick validation of our measure of tax policy risk by examining correlations with related factors in Figure E.6. Panel (a) shows that *Tax Policy Risk* positively correlates with the assessment gap between market values and taxable values in the simulation. Intuitively, the assessment gap represents a bubble that builds up in good times and bursts in bad times. The bursting of the bubble results in increases in property tax liabilities when property values fall. In other words, as the assessment gap builds up, homeowners are subject to increasing risk from market downturns. Expressed in percentage growth terms, this assessment gap in turn gives rise to the tax-price adjustment gap discussed in Section 5.2.2, whose reduced form effects on mortgage distress are evaluated in Appendix E. The positive correlation between the assessment gap and *Tax Policy Risk* again points to the importance of assessment limitations and infrequent reassessments as key drivers of risk for households.

In panel (b), we plot the average parcel specific risk price ($\mathbb{R}$) observed in the data against *Tax Policy Risk*.[7] As shown, our simulated measure of *Tax Policy Risk* is positively associated with empirically observed risk prices. There is nevertheless a considerable portion of the variation in average risk prices that is unexplained by *Tax Policy Risk*. This is by design and illustrates an advantage of the measure. In particular, the unexplained variation in risk prices is likely due to differences in economic conditions and other idiosyncratic characteristics at the state level that are unrelated to tax policies. Our measure of *Tax Policy Risk* captures risk arising solely from tax policies while holding all else fixed.

[7]In order to obtain the risk price, we first calculate the total AD price ($\mathbb{P}$) of property tax payments at the parcel level by up-weighting tax obligations in bad times and down-weighting tax payments in good times using a pricing kernel anchored to national-level consumption growth. We then calculate the certainty equivalent component of the tax price ($\mathbb{C}$) by up-weighting and down-weighting the average statewide property tax amount in a similar way. The remaining portion of $\mathbb{P}$ represents the risk price ($\mathbb{R}$) for each property in the sample.

Appendix D 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 of the property tax policy.
$p_{i,z}$	The pricing kernel for property owner i in year z.
π_z	The state probability of the world in year z.
$C_{i,z}$	The consumption of property owner i in year z.
$q_{s,t,i,z}$	The tax payment of property owner i in simulation year z under the policy in state s in year t.
$\mathbb{P}_{s,t,i,z}$	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 t.
$\mathbb{C}_{s,t,i,z}$	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 t.
$\mathbb{C}'_{s,t,i,z}$	The counterfactual of $\mathbb{C}_{s,t,i,z}$, i.e., the certainty equivalent without any tax limit policy.
$\Delta\mathbb{C}_{s,t,i,z}$	The difference between $\mathbb{C}_{s,t,i,z}$ and $\mathbb{C}'_{s,t,i,z}$, 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 t.
$\mathbb{R}_{s,t,i,z}$	The property tax risk during the entire tenure of property owner i in simulation year z under the policy in state s in year t.
$\mathbb{R}'_{s,t,i,z}$	The counterfactual of $\mathbb{R}_{s,t,i,z}$, i.e., the property tax risk without any tax limit policy.

Continued on next page

Table D.1 – continued from previous page

Variable Definitions	Description
$\Delta\mathbb{R}_{s,t,i,z}$	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 t.
Tax Policy Risk$_{s,t}$	The simple average of $\Delta\mathbb{R}_{s,t,i,z}$ over i and z for state s in year t.
Tax Policy Level$_{s,t}$	The simple average of $\Delta\mathbb{C}_{s,t,i,z}$ over i and z for state s in year t.
$\mathbb{1}$(Distressed)$_{i,t}$	An indicator that equals one if property i experiences any form of mortgage distress in year t and zero otherwise.
$\mathbb{1}$(Levy Limit)$_{s,t}$	An indicator that equals one if state s has a levy limit in year t and zero otherwise.
$\mathbb{1}$(Rate Limit)$_{s,t}$	An indicator that equals one if state s has a millage rate limit in year t and zero otherwise.
$\mathbb{1}$(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 E Assessment Limits and the Tax-Price Gap

As we show in Section 5.4.1, assessment limitations contribute more to tax risk than any other type of tax limit. This is not entirely surprising given the discussion in Section 5.2.2 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 3d.

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 E.5. 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.[8] 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 in-

[8]As noted in the last column of Table 3, a large number of states only reappraise property every four years or more, and some, like Pennsylvania, have no fixed schedule for doing so.

creases that are approximately 5 percentage points greater, on average, consistent with a relatively modest "pop-up tax" due to taxable value 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 5.2.2 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 1 in Section 3.

As shown in the first column of Table E.6, 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 5.2.2. 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.

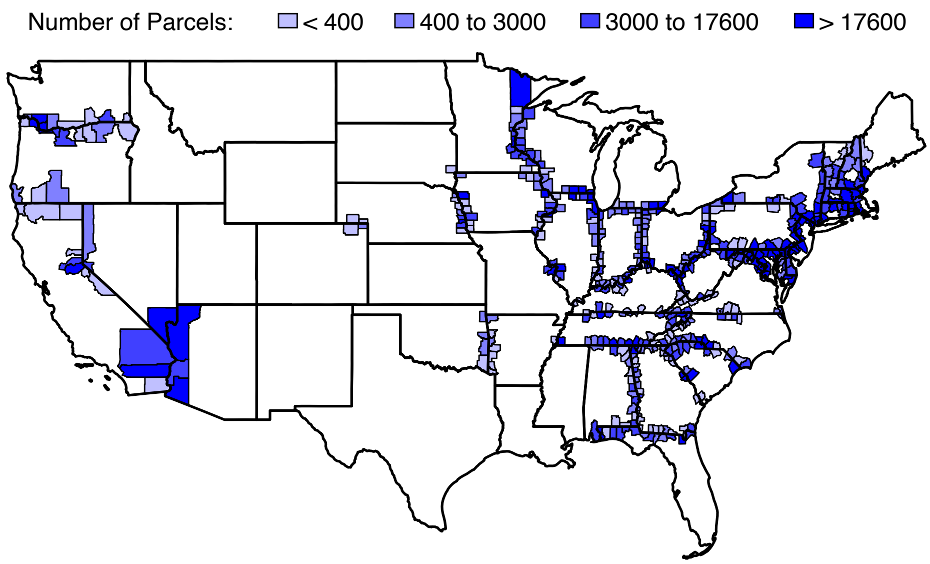
As shown in column 1 of Table E.7, larger tax-price gaps are responsible for a higher probability of mortgage distress everywhere, but this effect is significantly more pronounced in assessment limitation states and virtually twice as large. Furthermore, this effect is again largest for the 25 percent 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 5.2.2 and documented in Figure 3d, the average Δ Tax-Price Gap in assessment limitation states peaked at nearly 15 percentage points in 2008 and 2009.

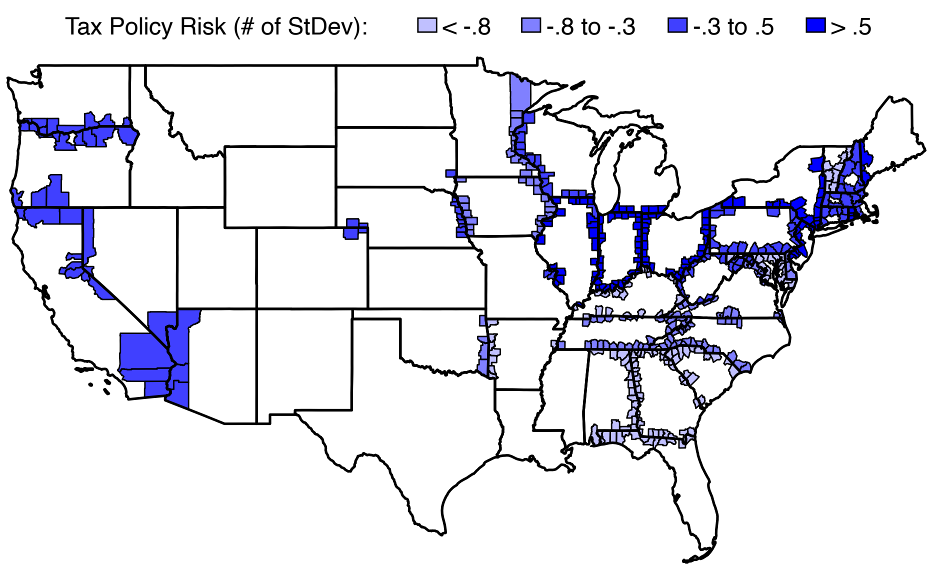
Rescaling the overall partial effect of the tax price gap for homeowners in assessment limitation states who have resided in their homes 2-5 years by this average 15 percentage point amount translates to an implied increase in the probability of distress of approximately 0.29 percentage points.[9] For comparison, homes with an LTV of 91 to 160 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.

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

Figure E.1: In-Sample Distribution of Unique Parcels



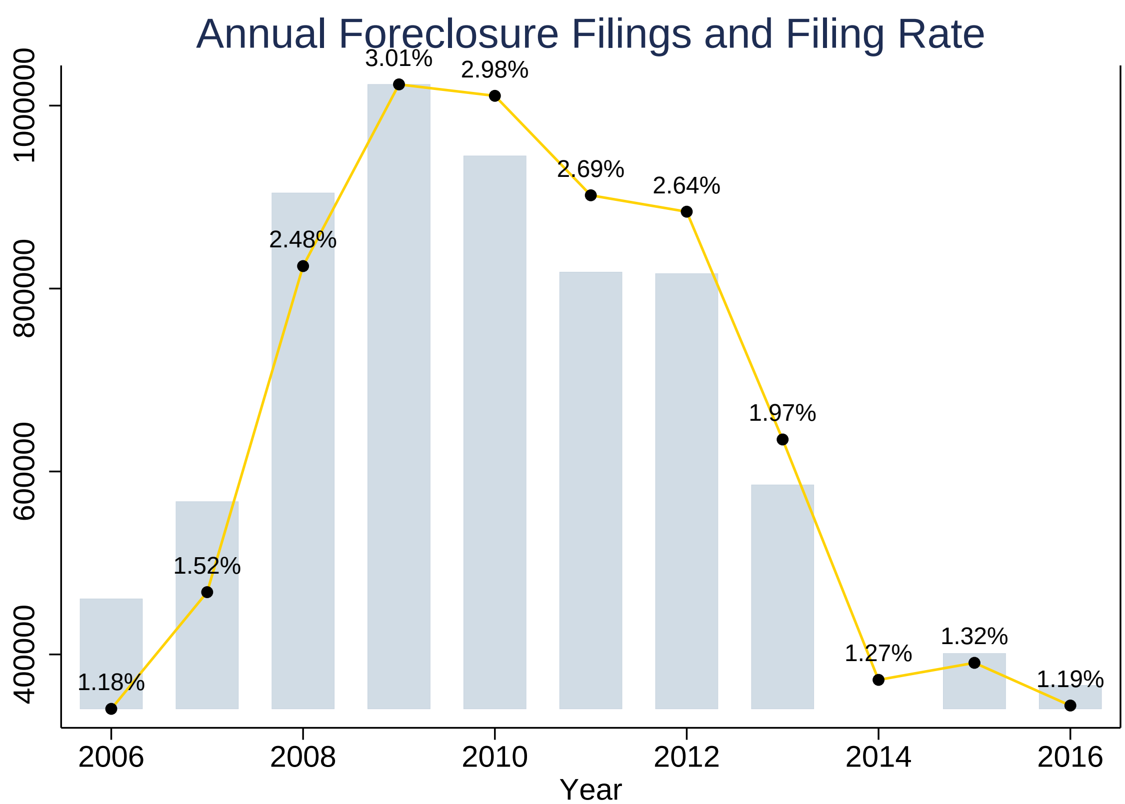
(a)



(b)

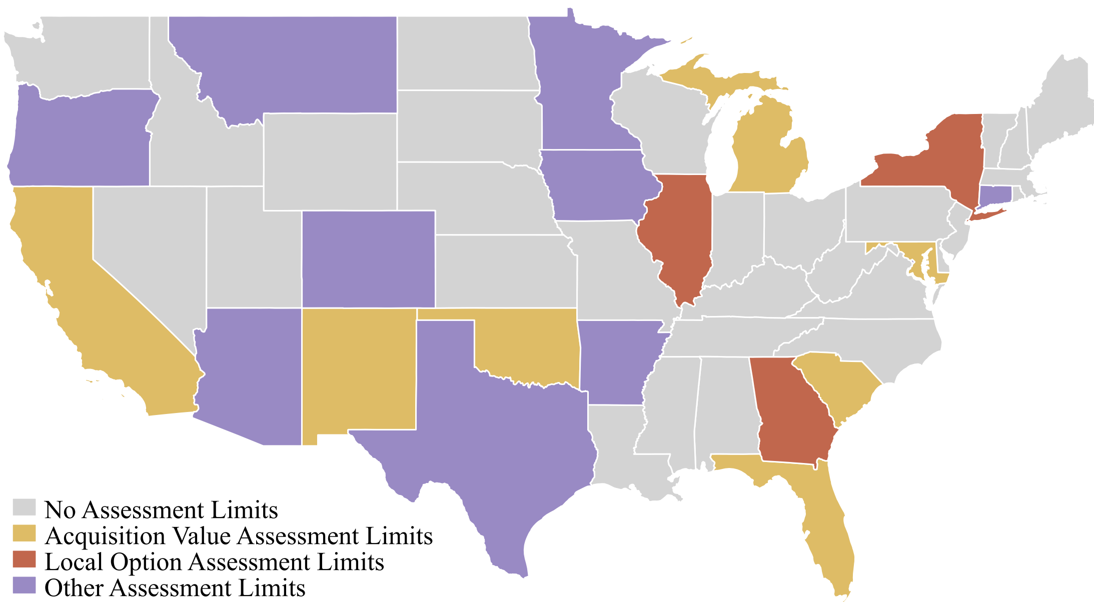
Observation counts refer to the number of unique parcels in the main estimation sample, aggregated by border county.

Figure E.2: Trends in National Foreclosure Activity



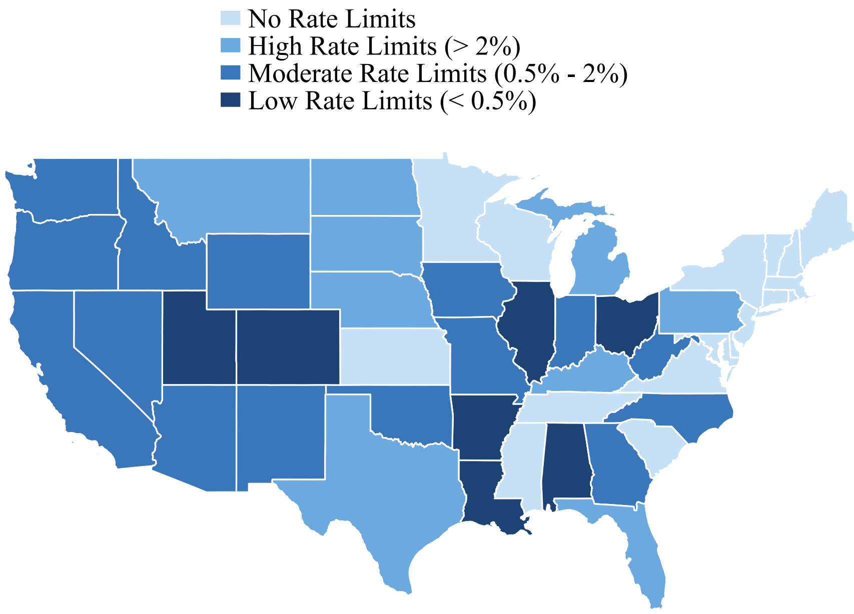
Foreclosure activity reflects only the first foreclosure event in a sequence of distressed transactions for our initial (national) sample of linked property tax assessment, realty transaction, loan, and foreclosure data.

Figure E.3: State Assessment Limitation Regimes (2016)

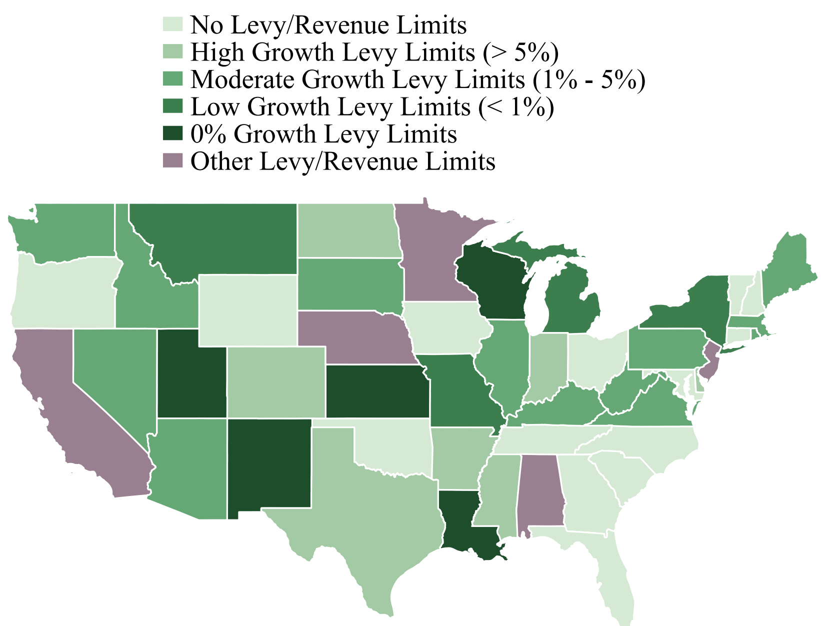


The figure shows the different assessment limitation regimes across states in 2016. Yellow indicates state-wide acquisition-value-based assessment limitations. Red indicates assessment limitations with local options (e.g., New York City in NY and Cook County in IL). Purple indicates assessment limits with other features. See detailed descriptions of these assessment limitations in Section 5.2.2.

Figure E.4: State Rate and Levy/Revenue Limitation Regimes (2016)



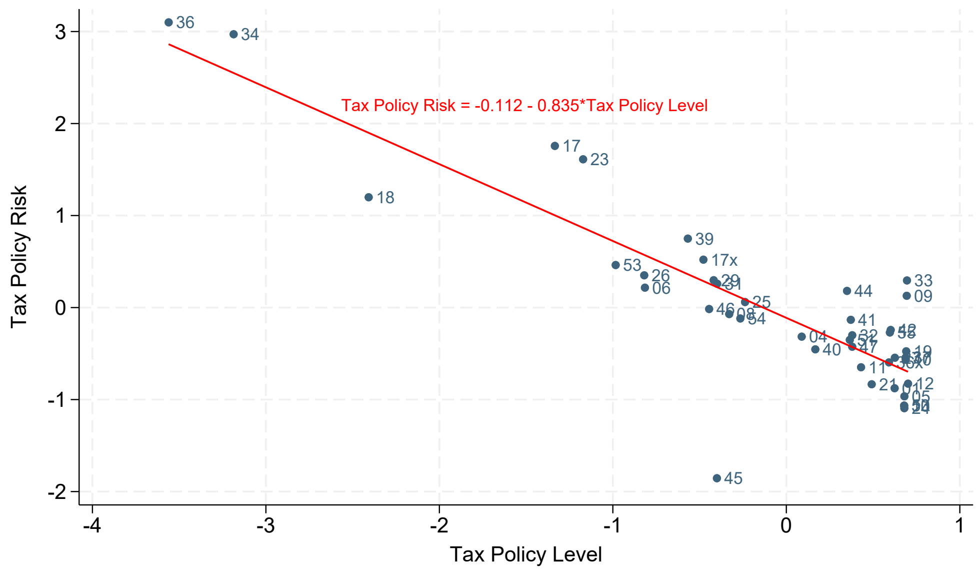
(a)



(b)

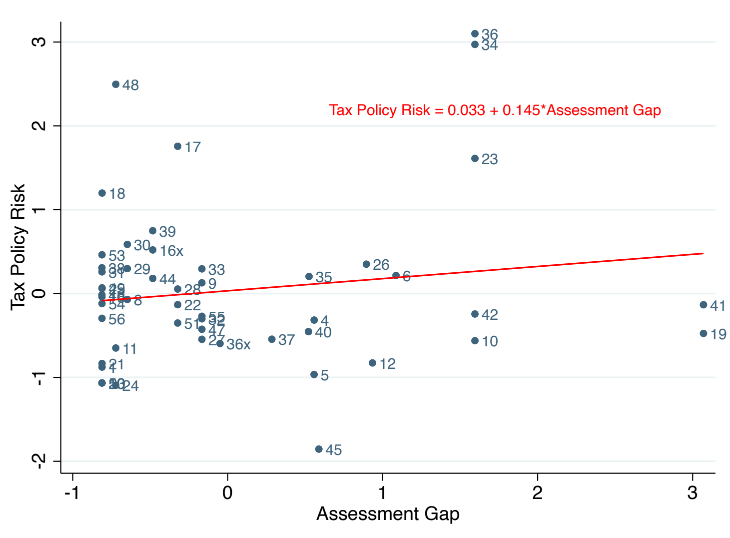
Panel E.4a shows the different rate limitation regimes and panel E.4b shows the different levy limitation regimes across states in 2016. We translate the statutory millage rate caps into percentages of fair market value using applicable assessment ratios to ensure comparability across states. Darker shades of color indicate stricter limitations. See detailed descriptions of these assessment limitations in Sections 5.2.3 and 5.2.4.

Figure E.5: Negative Correlation Between Tax Policy Risk and Tax Policy Level



This figure shows the strong negative association between standardized values of *Tax Policy Risk* and *Tax Policy Level* for policy year 2016. Labels denote state FIPS codes. Cook County, IL and New York City are denoted "17x" and "36x" respectively.

Figure E.6: Positive Correlation Between Tax Policy Risk and Assessment Gap

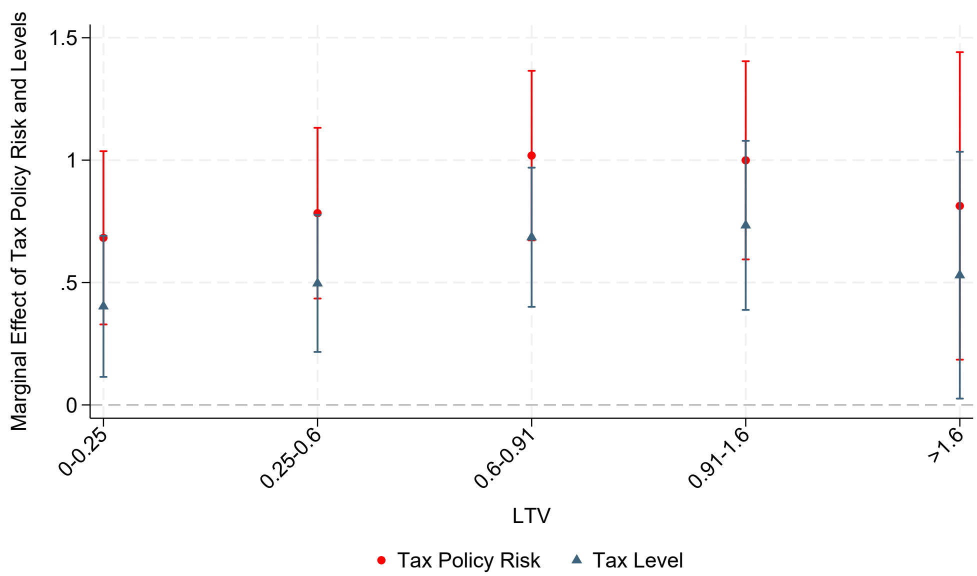


(a)

(b)

This figure shows the positive association between standardized values of *Tax Policy Risk* and key variables. Assessment Gap is calculated as the market value minus the taxable value of the property from the simulation. Empirically observed risk price is calculated following equation (4) with property taxes observed in the data. Labels denote state FIPS codes. Cook County, IL and New York City are denoted "17x" and "36x" respectively.

Figure E.7: Marginal Effects of *Tax Policy Risk* and *Tax Policy Level* as a Function of Parcel-Level LTV



Marginal effects are estimated from a model featuring interactions of *Tax Policy Risk* and *Tax Policy Level* with categorical LTV indicators by approximate LTV quintile. Parcels with unknown LTV are excluded from the analysis. Complete results are reported in Table E.4. Error bands denote 90% confidence intervals.

Table E.2: Mortgage Distress and Percent Changes in Annual Tax Liability

$Y = Pr(Distressed_t = 1), Y \in \{0, 100\}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
%Δ Tax (Standardized)	0.036	0.035	0.026	0.038***	0.036***	0.027**	0.062***	0.061***
	(0.025)	(0.021)	(0.020)	(0.014)	(0.013)	(0.012)	(0.017)	(0.018)
LTV								
0.25 - 0.6		-0.067**	-0.075**		-0.076***	-0.083***		-0.083***
		(0.029)	(0.029)		(0.023)	(0.024)		(0.016)
0.6 - 0.91		0.652***	0.669***		0.644***	0.660***		0.650***
		(0.060)	(0.060)		(0.042)	(0.042)		(0.028)
0.91 - 1.6		2.321***	2.313***		2.311***	2.303***		2.252***
		(0.142)	(0.137)		(0.089)	(0.087)		(0.053)
$>$ 1.6		2.895***	2.876***		2.880***	2.861***		2.838***
		(0.267)	(0.258)		(0.156)	(0.151)		(0.096)
Unknown		-1.505***	-1.545***		-1.541***	-1.580***		-1.618***
		(0.099)	(0.102)		(0.075)	(0.078)		(0.051)
Price		-0.000***	-0.000***		-0.000***	-0.000***		-0.000***
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)
Lagged ETR		0.027*	0.048***		0.019*	0.041***		0.032***
		(0.015)	(0.015)		(0.010)	(0.009)		(0.008)
Tenure								
$<$ 2 years		-0.947***	-0.980***		-0.965***	-0.996***		-1.023***
		(0.110)	(0.115)		(0.061)	(0.064)		(0.042)
2-5 years		-0.031	-0.087		-0.047	-0.101**		-0.114***
		(0.078)	(0.077)		(0.043)	(0.043)		(0.029)
Unknown		1.425***	1.415***		1.458***	1.447***		1.484***
		(0.108)	(0.106)		(0.065)	(0.063)		(0.067)
Age								
10-19 years		-0.380***	-0.343***		-0.360***	-0.325***		-0.317***
		(0.058)	(0.060)		(0.034)	(0.036)		(0.021)
20-59 years		-0.362***	-0.306***		-0.328***	-0.276***		-0.284***
		(0.066)	(0.069)		(0.038)	(0.041)		(0.023)
60-99 years		-0.296***	-0.192**		-0.242***	-0.143***		-0.108***
		(0.071)	(0.076)		(0.046)	(0.051)		(0.029)
>99 years		-0.129	0.004		-0.101	0.026		0.043
		(0.092)	(0.094)		(0.078)	(0.077)		(0.038)

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Unknown		-0.193	-0.015		-0.153	0.010		-0.065
		(0.147)	(0.148)		(0.143)	(0.145)		(0.121)
Renovation Age								
11-32 years		0.021	-0.008		-0.009	-0.031		-0.004
		(0.028)	(0.028)		(0.020)	(0.020)		(0.011)
33-59 years		0.118***	0.076***		0.104***	0.071***		0.079***
		(0.034)	(0.028)		(0.022)	(0.020)		(0.016)
> 59 years		0.303***	0.235***		0.306***	0.248***		0.249***
		(0.044)	(0.037)		(0.032)	(0.031)		(0.028)
Unknown		-0.517***	-0.583***		-0.531***	-0.582***		-0.458***
		(0.158)	(0.150)		(0.144)	(0.142)		(0.126)
Average AGI		0.000	0.001***		0.000	0.001***		0.001***
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)
Educ $\leq$ HS Pct		0.004	0.004		0.004**	0.004**		0.005***
		(0.003)	(0.003)		(0.002)	(0.002)		(0.002)
Educ $\geq$ Bachelor's Pct		-0.007***	-0.009***		-0.008***	-0.009***		-0.009***
		(0.003)	(0.002)		(0.002)	(0.002)		(0.001)
Population		0.000***	0.000***		0.000***	0.000***		0.000***
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)
Population 18-24 Pct		-0.000***	-0.000***		-0.000***	-0.000***		-0.000***
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)
Population $\geq$ 25 Pct		-0.000***	-0.000***		-0.000***	-0.000***		-0.000***
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)
White Pct		-0.005*	-0.005*		-0.006**	-0.006**		-0.006***
		(0.003)	(0.003)		(0.003)	(0.003)		(0.002)
Black Pct		0.009**	0.009**		0.007**	0.008**		0.007***
		(0.004)	(0.004)		(0.003)	(0.003)		(0.002)
Latino Pct		0.002	0.002		0.001	0.001		0.001
		(0.003)	(0.003)		(0.002)	(0.002)		(0.001)
Asian Pct		-0.005	-0.005		-0.007**	-0.007*		-0.007***
		(0.005)	(0.005)		(0.004)	(0.004)		(0.002)
I[Recourse=1]		0.207	0.250		-0.006	0.060		0.022
		(0.284)	(0.284)		(0.216)	(0.224)		(0.142)
I[NonJudicialReview=1]		-0.190	-0.153		-0.284	-0.258		-0.210
		(0.246)	(0.240)		(0.230)	(0.228)		(0.283)

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fixed Effects:								
County pair FE	x	x	x					
10 km^2 grid FE				x	x	x		
10 km^2 grid $\times$ Year FE							x	x
Year FE			x			x		
R-squared	0.004	0.017	0.018	0.005	0.018	0.019	0.010	0.023
Observations		31,209,231			31,209,241		31,209,241	

Significance levels are designated as *** p<0.01, ** p<0.05, and * p<0.1. Standard errors (in parentheses) are clustered by county pair or 10 km^2 grid cell, depending on the fixed effects employed. $\%\Delta\ Tax\ (Standardized)$ is a measure of the year-over-year percent change in annual tax obligations standardized to have an in-sample mean value of 0 and standard deviation of 1.

Table E.3: Mortgage Distress and Tax Policy Risk

$Y = Pr(Distressed_t = 1), Y \in \{0, 100\}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Tax Policy Risk	0.296**	0.366**	0.315*	0.305**	0.278**	0.240*	0.445***	0.433**
	(0.126)	(0.176)	(0.174)	(0.123)	(0.140)	(0.144)	(0.157)	(0.220)
Tax Policy Level	0.168*	0.298**	0.201	0.165*	0.212**	0.099	0.297***	0.335*
	(0.090)	(0.137)	(0.137)	(0.092)	(0.107)	(0.111)	(0.115)	(0.172)
LTV								
0.25 - 0.6		-0.069**	-0.078***		-0.077***	-0.085***		-0.085***
		(0.029)	(0.030)		(0.023)	(0.024)		(0.016)
0.6 - 0.91		0.650***	0.666***		0.643***	0.659***		0.649***
		(0.061)	(0.061)		(0.042)	(0.042)		(0.028)
0.91 - 1.6		2.319***	2.312***		2.310***	2.302***		2.251***
		(0.143)	(0.138)		(0.089)	(0.087)		(0.053)
$>$ 1.6		2.901***	2.887***		2.884***	2.870***		2.843***
		(0.270)	(0.261)		(0.157)	(0.153)		(0.096)
Unknown		-1.509***	-1.549***		-1.541***	-1.583***		-1.619***
		(0.099)	(0.103)		(0.074)	(0.077)		(0.051)
Price		-0.000***	-0.000***		-0.000***	-0.000***		-0.000***
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)
Lagged ETR		0.016	0.034***		0.012	0.031***		0.026***
		(0.013)	(0.012)		(0.009)	(0.008)		(0.007)
Tenure								
$<$ 2 years		-0.943***	-0.979***		-0.958***	-0.993***		-1.016***
		(0.113)	(0.117)		(0.063)	(0.065)		(0.042)
2-5 years		-0.032	-0.089		-0.045	-0.102**		-0.115***
		(0.078)	(0.077)		(0.043)	(0.043)		(0.029)
Unknown		1.425***	1.410***		1.459***	1.447***		1.483***
		(0.107)	(0.105)		(0.065)	(0.063)		(0.066)
Age								
10-19 years		-0.377***	-0.336***		-0.361***	-0.322***		-0.315***
		(0.058)	(0.061)		(0.034)	(0.036)		(0.021)
20-59 years		-0.354***	-0.292***		-0.330***	-0.269***		-0.280***
		(0.065)	(0.069)		(0.038)	(0.041)		(0.023)
60-99 years		-0.286***	-0.177**		-0.245***	-0.136***		-0.103***
		(0.069)	(0.074)		(0.045)	(0.052)		(0.029)

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
>99 years		-0.119	0.014		-0.106	0.029		0.046
		(0.091)	(0.090)		(0.079)	(0.075)		(0.037)
Unknown		-0.188	-0.016		-0.158	0.009		-0.065
		(0.148)	(0.149)		(0.143)	(0.145)		(0.121)
Renovation Age								
11-32 years		0.017	-0.017		-0.006	-0.033*		-0.004
		(0.029)	(0.027)		(0.019)	(0.019)		(0.011)
33-59 years		0.110***	0.066**		0.107***	0.070***		0.080***
		(0.035)	(0.029)		(0.021)	(0.020)		(0.016)
> 59 years		0.306***	0.237***		0.314***	0.254***		0.255***
		(0.045)	(0.037)		(0.032)	(0.031)		(0.027)
Unknown		-0.513***	-0.579***		-0.532***	-0.589***		-0.457***
		(0.159)	(0.151)		(0.143)	(0.142)		(0.126)
Average AGI		0.000	0.001**		0.000	0.001***		0.001***
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)
Educ $\leq$ HS Pct		0.004	0.004		0.004**	0.004**		0.005***
		(0.003)	(0.003)		(0.002)	(0.002)		(0.002)
Educ $\geq$ Bachelor's Pct		-0.008***	-0.009***		-0.008***	-0.009***		-0.009***
		(0.003)	(0.002)		(0.002)	(0.002)		(0.001)
Population		0.000***	0.000***		0.000***	0.000***		0.000***
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)
Population 18-24 Pct		-0.000***	-0.000***		-0.000***	-0.000***		-0.000***
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)
Population $\geq$ 25 Pct		-0.000***	-0.000***		-0.000***	-0.000***		-0.000***
		(0.000)	(0.000)		(0.000)	(0.000)		(0.000)
White Pct		-0.006**	-0.006*		-0.007**	-0.007**		-0.007***
		(0.003)	(0.003)		(0.003)	(0.003)		(0.002)
Black Pct		0.008**	0.009**		0.007**	0.007**		0.006***
		(0.004)	(0.004)		(0.003)	(0.003)		(0.002)
Latino Pct		0.001	0.001		0.000	0.000		0.000
		(0.003)	(0.003)		(0.002)	(0.002)		(0.001)
Asian Pct		-0.007	-0.006		-0.008**	-0.007**		-0.007***
		(0.004)	(0.004)		(0.004)	(0.004)		(0.002)
I[Recourse=1]		0.363	0.333		0.105	0.059		0.208**
		(0.253)	(0.268)		(0.159)	(0.171)		(0.100)
I[NonJudicialReview=1]		-0.314	-0.263		-0.345	-0.316		-0.303
		(0.284)	(0.277)		(0.245)	(0.241)		(0.320)

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Fixed Effects:								
County pair FE	x	x	x					
10 km^2 grid FE				x	x	x		
10 km^2 grid $\times$ Year FE							x	x
Year FE			x			x		
R-squared	0.004	0.017	0.018	0.005	0.018	0.019	0.010	0.023
Observations		31,215,255			31,215,269		31,215,269	

Significance levels are designated as *** $p<0.01$, ** $p<0.05$, and * $p<0.1$. Standard errors (in parentheses) are clustered by county pair or 10 km^2 grid cell, depending on the fixed effects employed. *Tax Policy Risk* and *Tax Policy Level* are calculated at the state-policy year level as described in Section 5.4 and both are standardized to have an in-sample mean value of 0 and standard deviation of 1.

Table E.4: Mortgage Distress and Tax Policy Risk - Heterogenous Effects

$Y = Pr(Distressed_t = 1), Y \in \{0, 100\}$	(1)	(2)	(3)	(4)
Tax Policy Risk	-3.901	0.064	-0.032	0.327***
	(2.389)	(0.099)	(0.237)	(0.092)
Tax Policy Level	-1.275	-0.006	-0.209	-0.504***
	(2.527)	(0.092)	(0.200)	(0.113)
$UnempRate$	2.749			
	(2.269)			
$UnempRate^2$	-0.465			
	(0.351)			
$UnempRate^3$	0.025			
	(0.017)			
$UnempRate$	1.711*			
× Tax Policy Risk	(1.023)			
$UnempRate^2$	-0.223			
× Tax Policy Risk	(0.144)			
$UnempRate^3$	0.009			
× Tax Policy Risk	(0.007)			
$UnempRate$	0.664			
× Tax Policy Level	(1.010)			
$UnempRate^2$	-0.097			
× Tax Policy Level	(0.132)			
$UnempRate^3$	0.004			
× Tax Policy Level	(0.006)			
I[HighAGI=1]		0.038		
		(0.088)		
I[HighAGI=1]		0.110		
× Tax Policy Risk		(0.073)		
I[HighAGI=1]		0.101		
× Tax Policy Level		(0.078)		
I[MajorityBlack=1]		0.362		
		(0.548)		
I[MajorityBlack=1]		0.683***		
× Tax Policy Risk		(0.137)		
I[MajorityBlack=1]		0.549***		
× Tax Policy Level		(0.126)		
I[MajorityLatino=1]		-0.333*		
		(0.200)		
I[MajorityLatino=1]		-0.121		
× Tax Policy Risk		(0.158)		
I[MajorityLatino=1]		-0.114		
× Tax Policy Level		(0.135)		
LTV × Tax Policy Risk				
0 - 0.25			0.117	
			(0.229)	
0.25 - 0.6			0.106	
			(0.229)	
0.6 - 0.91			0.353	
			(0.219)	
0.91 - 1.6			0.281*	
			(0.166)	
> 1.6				
Unknown			0.154	
			(0.232)	
LTV × Tax Policy Level				
0 - 0.25			0.126	
			(0.200)	
0.25 - 0.6			0.071	
			(0.195)	
0.6 - 0.91			0.332*	
			(0.187)	
0.91 - 1.6			0.339**	

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	(1)	(2)	(3)	(4)
			(0.146)	
$>$ 1.6				
Unknown			0.318	
			(0.199)	
Tenure × Tax Policy Risk				
$<$ 2 years				-0.622***
				(0.079)
2-5 years				-0.126*
				(0.072)
Unknown				0.018
				(0.070)
Tenure × Tax Policy Level				
2-5 years				0.551***
				(0.069)
$>$ 5 years				0.671***
				(0.088)
Unknown				0.870***
				(0.132)
I[Recourse=1] $\times UnempRate$	-2.541			
	(2.128)			
I[NonJudicialReview=1] $\times UnempRate$	-0.672			
	(1.192)			
I[Recourse=1] $\times UnempRate^2$	0.396			
	(0.324)			
I[NonJudicialReview=1] $\times UnempRate^2$	0.101			
	(0.181)			
I[Recourse=1] $\times UnempRate^3$	-0.021			
	(0.016)			
I[NonJudicialReview=1] $\times UnempRate^3$	-0.005			
	(0.009)			
I[Recourse=1] × I[HighItemizationRate=1]				
I[NonJudicialReview=1] × I[HighItemizationRate=1]				
I[Recourse=1] × I[HighAGI=1]		-0.169**		
		(0.086)		
I[NonJudicialReview=1] × I[HighAGI=1]		-0.085		
		(0.092)		
I[Recourse=1] × I[MajorityWhite=1]				
I[NonJudicialReview=1] × I[MajorityWhite=1]				
I[Recourse=1] × I[MajorityBlack=1]		-0.316		
		(0.547)		
I[NonJudicialReview=1] × I[MajorityBlack=1]		0.115		
		(0.085)		
I[Recourse=1] × I[MajorityLatino=1]		0.243		
		(0.194)		
I[NonJudicialReview=1] × I[MajorityLatino=1]		0.458***		
		(0.152)		
I[Recourse=1] × LTV				
0.25 - 0.6			0.004	
			(0.055)	
0.6 - 0.91			0.027	
			(0.079)	
0.91 - 1.6			-0.086	
			(0.134)	
$>$ 1.6			-0.005	
			(0.218)	
Unknown			-0.263**	
			(0.133)	
I[NonJudicialReview=1] × LTV				
0.25 - 0.6			0.103**	

Continued on next page

	(1)	(2)	(3)	(4)
			(0.045)	
0.6 - 0.91			0.130*	
			(0.071)	
0.91 - 1.6			0.421***	
			(0.118)	
> 1.6			0.287	
			(0.175)	
Unknown			-0.573***	
			(0.131)	
I[Recourse=1] × Tenure				
< 2 years				-0.250**
				(0.115)
2-5 years				-0.056
				(0.056)
Unknown				-0.351***
				(0.134)
I[NonJudicialReview=1] × Tenure				
< 2 years				-0.027
				(0.086)
2-5 years				0.039
				(0.062)
Unknown				0.694***
				(0.099)
LTV				
0.25 - 0.6	-0.083***	-0.083***	-0.113*	-0.079***
	(0.022)	(0.022)	(0.060)	(0.022)
0.6 - 0.91	0.649***	0.649***	0.577***	0.657***
	(0.034)	(0.034)	(0.085)	(0.034)
0.91 - 1.6	2.243***	2.241***	2.155***	2.256***
	(0.062)	(0.062)	(0.144)	(0.063)
> 1.6	2.844***	2.840***	2.724***	2.863***
	(0.103)	(0.103)	(0.231)	(0.104)
Unknown	-1.632***	-1.633***	-1.219***	-1.621***
	(0.056)	(0.056)	(0.132)	(0.056)
Price	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Lagged ETR	0.021***	0.020***	0.023***	0.019***
	(0.006)	(0.006)	(0.006)	(0.006)
Tenure				
< 2 years	-1.025***	-1.026***	-1.018***	-0.788***
	(0.047)	(0.047)	(0.045)	(0.131)
2-5 years	-0.119***	-0.119***	-0.107***	-0.078
	(0.028)	(0.028)	(0.026)	(0.065)
Unknown	1.512***	1.512***	1.543***	1.639***
	(0.048)	(0.048)	(0.053)	(0.133)
Age				
10-19 years	-0.312***	-0.312***	-0.301***	-0.310***
	(0.027)	(0.027)	(0.027)	(0.027)
20-59 years	-0.280***	-0.284***	-0.271***	-0.292***
	(0.028)	(0.028)	(0.028)	(0.029)
60-99 years	-0.099***	-0.105***	-0.092***	-0.114***
	(0.031)	(0.031)	(0.032)	(0.032)
>99 years	0.084*	0.074*	0.091**	0.067
	(0.044)	(0.043)	(0.044)	(0.045)
Unknown	-0.122	-0.128	-0.096	-0.129
	(0.129)	(0.129)	(0.129)	(0.131)
Renovation Age				
11-32 years	0.001	0.003	0.005	0.003
	(0.013)	(0.013)	(0.013)	(0.013)
33-59 years	0.073***	0.074***	0.078***	0.075***
	(0.016)	(0.015)	(0.016)	(0.016)
> 59 years	0.239***	0.239***	0.245***	0.241***
	(0.022)	(0.022)	(0.022)	(0.022)
Unknown	-0.429***	-0.431***	-0.435***	-0.431***

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	(1)	(2)	(3)	(4)
	(0.129)	(0.129)	(0.128)	(0.131)
Average AGI	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Educ $\leq$ HS Pct	0.003**	0.002	0.003*	0.003**
	(0.002)	(0.002)	(0.002)	(0.002)
Educ $\geq$ Bachelor's Pct	-0.009***	-0.009***	-0.010***	-0.009***
	(0.002)	(0.002)	(0.002)	(0.002)
Population	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Population 18-24 Pct	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Population $\geq$ 25 Pct	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
White Pct	-0.008***	-0.007***	-0.008***	-0.007***
	(0.003)	(0.003)	(0.003)	(0.003)
Black Pct	0.006**	0.005	0.006*	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)
Latino Pct	0.000	0.002	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Asian Pct	-0.009***	-0.008**	-0.009***	-0.009***
	(0.003)	(0.003)	(0.003)	(0.003)
I[Recourse=1]	5.936	0.289	0.463**	0.276
	(4.405)	(0.223)	(0.226)	(0.255)
I[NonJudicialReview=1]	1.517	-0.015	0.286**	-0.213**
	(2.496)	(0.107)	(0.129)	(0.093)
Observations	31,209,241	31,209,061	31,209,241	31,209,241
R-squared	0.025	0.025	0.025	0.025

Significance levels are designated as *** $p<0.01$, ** $p<0.05$, and * $p<0.1$. All specifications include 10 km² grid cell × year fixed effects. Standard errors (in parentheses) are clustered by 10 km² grid cell.

Table E.5: 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] $\times$ % Δ Price		0.000	0.001
		(0.000)	(0.001)
Tenure $\times$ 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 $\times$ % Δ Price			
$>$ 5 years			0.000
			(0.000)
$<$ 2 years			
2-5 years			0.000
			(0.000)
Unknown			0.000
			(0.000)
Tenure $\times$ I[AssessmentLimit=1] $\times$ % 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 $\times$ year fixed effects.

Table E.6: 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] × 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 × 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 × I[Δ Price < 0]		
< 2 years		-0.160**
		(0.077)
2-5 years		0.200**
		(0.086)
Unknown		-0.148**
		(0.074)
Tenure × I[AssessmentLimit=1] × 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***
	(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)

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> 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] × I[Δ Price < 0]	-0.015	
	(0.025)	
I[NonJudicialReview=1] × I[Δ Price < 0]	0.047**	
	(0.018)	
Tenure × 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 × 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 × I[Recourse=1] × I[Δ Price < 0]		
< 2 years		0.107
		(0.071)
2-5 years		0.282***
		(0.085)
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 E.7: Distress Probabilities and Tax-Price Trends (≈ 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)
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		

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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 × I[Recourse=1]		
< 2 years		-0.094
		(0.083)
2-5 years		0.127*
		(0.071)
Unknown		-0.563***
		(0.175)
Tenure × I[NonJudicialReview=1]		
< 2 years		0.007
		(0.077)
2-5 years		0.200***
		(0.061)
Unknown		1.129***
		(0.130)
I[Recourse=1] × % Δ Price	0.000	0.000
	(0.000)	(0.000)
I[NonJudicialReview=1] × % Δ Price	0.000	-0.000
	(0.000)	(0.000)
Observations	22,663,442	
R-squared	0.027	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.