Property Tax Limitations, Covariance Risk, and Mortgage Distress*

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Abstract

Property tax limitations reduce the pro-cyclicality of property taxes, creating a distinct form of risk that we define as *covariance risk*. We find that a one standard deviation increase in *covariance risk* raises mortgage distress by 30%, with stronger effects for residents of majority-black neighborhoods, owners of over-assessed properties, high loan-to-value borrowers, and long-tenured homeowners. We identify these effects using parcel-level data, a state border discontinuity design, and a property tax simulator we develop that incorporates assessment, rate, and levy limitations. These findings underscore how tax policy affects risk and supports policies, such as targeted tax deferral programs, that could mitigate these risks.

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

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1 Introduction

Property tax payments represent a significant cost of homeownership, typically amounting to 0.25–2% of housing values annually across the U.S. While these payments are a stable revenue source for local governments, their timing can create financial strain for homeowners. Recent research has shown that unexpected changes in property tax liabilities can contribute to mortgage distress, particularly when they coincide with periods of financial hardship or when changes are not salient to taxpayers (Anderson and Dokko, 2009, 2016; Bradley, 2013; Hayashi, 2020; Wong, 2020). In response to concerns over rising tax burdens, nearly all U.S. states have adopted property tax limitations designed to curb the growth of assessed values, tax rates, or overall revenue collection (Anderson, 2006). While these policies are intended to stabilize tax burdens, they also alter the *timing* of tax liabilities, potentially increasing financial risk for homeowners.

This paper develops a new framework to quantify a distinct yet underexplored dimension of risk in property taxation: *covariance risk*. It captures how the timing of tax payments interacts with economic conditions—specifically, the extent to which tax liabilities increase when homeowners are least able to afford them. Using a state-contingent Arrow-Debreu pricing framework, we decompose property tax streams into their *certainty equivalent* level and *covariance risk* component. The *certainty equivalent* component captures how the average tax payments change as a result of a policy.[1] The *covariance risk* component captures the timing of tax liabilities and whether they become more pro- or counter-cyclical. While property taxes are always an expense, they become particularly burdensome in downturns, when homeowners experience reduced income and liquidity constraints. By isolating the impact of tax payment timing, we provide new insights into how property tax limitations may inadvertently increase financial distress.

To empirically study the effect of property tax limitations on *covariance risk* and mortgage distress, we construct a property tax simulator that models the impact of various tax system characteristics—including assessment limits, effective tax rates, and reassessment frequencies—while holding the broader economic environment constant. This allows us to compare actual property tax obligations with a counterfactual "no-policy" scenario in which taxes are reassessed annually without limitations. We define this difference as Δ *covariance risk* and we use it as our focal measure of risk. The simulator also allows us to isolate different property tax limitations by turning them on and off. We validate

[1] Limiting property tax liability is one rationale for property tax limitations, but in practice, it is not always the case that the level of taxation goes down (Dye and McGuire, 1997; Eliason and Lutz, 2018).

the accuracy of the simulation by comparing the simulated and observed property tax payments. Across all states, the correlation is high, ranging from 0.73 (PA) to 0.97 (MO).

We estimate the effect of Δ *covariance risk* on mortgage distress using nationwide parcel-level data from ATTOM Data Solutions and Zillow (ZTRAX). [2] This data allows us to use a border discontinuity design, comparing properties near state borders that are subject to different property tax regimes but share similar economic conditions.

Our findings show that property tax limitations systematically increase **covariance risk**, with assessment limitations exerting the most pronounced influence. A one standard deviation increase in Δ *covariance risk* raises the probability of mortgage distress by approximately 30%, underscoring the unintended consequences of these policies. For context, the impact of such an increase is 70% greater than the effect of owning a home in disrepair and about one-quarter as large as the effect of a home becoming underwater. Our analysis further reveals that these adverse effects are disproportionately concentrated among homeowners in predominantly Black neighborhoods, as well as those with higher loan-to-value ratios or longer housing tenures. This pattern suggests that property tax limitations may intensify preexisting financial vulnerabilities.

Moreover, we observe that shifts in the timing of tax liabilities generate risk that affects mortgage distress as much as—or even more than—changes in the level of property taxes. In particular, a one standard deviation increase in Δ *covariance risk* produces a more pronounced effect on mortgage distress (0.433) than a comparable increase in Δ *certainty equivalent* (0.335). This insight allows us to derive a back-of-the-envelope estimate of the overall impact of property tax limitations, which influence tax liability levels and timing. For instance, our estimates indicate that property tax rate limits raise Δ *covariance risk* by 0.744 standard deviations while reducing Δ *certainty equivalent* by 1.055 standard deviations. Although the net effect appears relatively small (-1.055 $\times$ 0.335 + 0.744 $\times$ 0.433 = -0.03), it conceals substantial shifts in mortgage distress due to the near cancellation of the opposing level and timing effects. On the other hand, we find property tax assessment limits increase risk and the level of property payments. In practice, this suggests that while governments are constrained in increasing the taxable value of properties, they adjust the rate to bring in more revenues. Mortgage distress increases due to assessment limits due to both the risk and level of effects, and the risk effect is substantially larger; risk effect 0.347= 0.802 $\times$ 0.433 level effect 0.056= 0.167 $\times$ 0.335.

Our findings suggest that policies designed to lower property tax payments should avoid increasing risk or should be paired with measures to offset such risks. One po-

[2] We have permission from Zillow to continue to use ZTRAX for this project.

tential solution is the expansion of tax deferral programs, which could help reduce risk for vulnerable homeowners by spreading tax payments over time. While current deferral programs typically focus on low-income seniors, broadening eligibility criteria could provide targeted relief without jeopardizing the stability of local government revenues. More generally, our results highlight the importance of considering both the level of taxation and the timing of tax payments as key factors influencing household financial stability.

Our paper contributes to several strands of literature. First, we contribute to studies on the fiscal impact of property tax limitations (Lutz, 2008; Eliason and Lutz, 2018) by showing that these policies alter not only the level of taxation but also the volatility of payments relative to economic conditions. Second, we build on research linking unexpected tax increases to mortgage distress (Hayashi, 2020; Wong, 2020), extending the analysis to the timing of payments rather than just their magnitude. Third, we build on a housing distress literature that has shown regulations governing repossession risk (O'Malley, 2021), deficiency judgments (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.[3] Fourth, we introduce a novel risk measure—*covariance risk*—that provides a unified framework for assessing the intertemporal financial impact of tax policy, drawing from work on tax volatility and automatic stabilizers (Dye and Merriman, 2004; Clemens, 2012; Cashin et al., 2018).[4]

Our analysis focuses on mortgage distress as an observable metric. However, the welfare implications of shifting risk to households are likely much larger. First, mortgage distress and foreclosure can lead to a host of negative outcomes 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). Second, 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 (Domar and Musgrave, 1944).

[3]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 (Tian et al., 2016; Gerardi et al., 2017; Low, 2022).

[4]Early work focused on 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). Recent work shows 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). The role of tax policy as an automatic stabilizer or as a form of insurance has also received extensive attention (e.g., 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 the mechanics of property taxation and tax limitations. Section 3 explains our property tax simulation, introduces the Arrow-Debreu pricing of tax liabilities, and formally defines *covariance risk* and the *certainty equivalent* of taxation. Section 4 describes our data and the construction of key regression variables. Section 5 lays out the core structure of our empirical strategy. Section 6 presents our main empirical results regarding the effects of *covariance risk* and *certainty equivalent* amounts on mortgage distress, including a discussion of heterogeneous effects. Section 7 concludes.

2 Property Tax Limitations

2.1 Property Tax Basics

Property tax obligations are calculated at the parcel level as the product of parcel i's *taxable value*, TV_i, and the statutory *millage rate* in jurisdiction j, τ_{ij}.[5] In principle, this gives local governments two levers of adjustment to achieve their desired aggregate *tax levy*, $Levy_j = \sum_{i=1}^{N_j} \tau_{ij} TV_i$. In practice, taxable values are anchored to assessed (market) values, which are themselves intended to reflect the local assessor's best estimate of fair market value. Under canonical market-value-based assessments with annual reassessments and a 100 percent assessment ratio, taxable values and assessed values thus coincide, such that property tax obligations are solely determined by market values and the choice of millage rate.

Motivated by a mix of concerns over the impact of rising home prices, the growth of state and local governments' budgets, and the desire for predictable changes in property tax obligations and revenues, all but three U.S. states (Hawaii, New Hampshire, and Vermont) have implemented some form of statewide property tax limitations since 1978.[6] These limitations differ as to whether they are intended to restrict the evolution of the tax base (TV_i), tax rates (τ_{ij}), or their product ($Levy_j$) and are referred to as assessment, rate, and levy limits, respectively. Overall revenue/expenditure limits may also apply and extend beyond property taxes by encompassing other sources of state and local tax

[5]The applicable τ_{ij} may combine rates from multiple overlapping taxing jurisdictions (e.g., counties, municipalities, and school districts) and may differ by property class or according to owners' residency status.

[6]See O'Sullivan et al. (1995) for a discussion of the set of factors that precipitated the widespread adoption of property tax limitations in the U.S. Numerous studies 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)).

revenue. Each of these types of limitations represents deviations from the canonical property tax regime described above. As shown in **Table 1**, all but nine states employ multiple types of property tax limitations, including three states (Arizona, Michigan, and New Mexico) that use some version of all four.[7] Some states have limits that are not particularly binding, like Colorado's rate limit. More broadly, **Table 1** highlights the wide range of limit stringency and/or implementation rules that exist across states' assessment, rate, and levy limitation regimes.

These property tax limitations can make property tax payments less pro-cyclical and can lead to perverse settings. For example, during housing market downturns, taxable values subject to assessment limitations need not necessarily decline. Indeed, taxable values in most states 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 equivalent reductions in taxable value.[8]

Figure 1a illustrates a hypothetical version where taxable values increase while market values decrease when tax assessment limits exist. The red line depicts the evolution of tax payments subject to assessment limitations, while the solid blue line represents tax payments under market value assessments. The dashed orange line mirrors the 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 under assessment limitations during a housing market boom, yet they can continue to increase during a bust so long as taxable values remain below market values. Despite limiting tax liabilities when property values are rising, assessment limitations may thus result in smaller reductions (or even ongoing increases) in tax liabilities during market downturns—precisely when households may already be at greater risk of financial distress. This risk may exacerbate the negative consequences of housing market downturns and act as a trigger event for mortgage foreclosure.

In **Figure 1b**, we show that the hypothetical situation given in **Figure 1a** is not un-

[7] Haveman and Sexton (2008) describe the general characteristics of assessment limitation regimes and other types of property tax limits. 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.

[8] States differ in whether there is a subsequent provision for "catching up" to some alternative base year value once house prices begin rising again.

usual. 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 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.

2.2 Assessment Limits

Assessment limits generally restrict the growth rate of taxable values over time, regardless of the true evolution of housing prices. 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—which marked the first implementation of assessment limitations—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. Other states apply a range of maximum capped growth rates, 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, we hence distinguish the "traditional" acquisition-value-based assessment limitations that more closely resemble California's Proposition 13 from other forms of assessment limits. **Table 1** describes the high-level features of assessment limits by state as of 2016 which we summarize from the legislative language.

As reported in the sixth column of **Table 1**, the frequency of legally mandated reassessments varies substantially across states. Reassessment intervals range from as little as one year (e.g., Alabama, Georgia, Idaho, etc.) up to as long as eight years in North Carolina, while several states have no statutes dictating a specific reassessment frequency (e.g., Delaware, New York, Pennsylvania, etc.).[9] It is worth noting 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

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

regime, with assessment growth capped at 0% for extended periods of time. This has important implications for the calculation of *covariance risk* and we return to this point in Section 3.

Figure 1c show home prices and tax payments for homes in states with assessment limits (solid red and dashed red) and no limit states (solid blue and dashed blue) from 2006-2016. Homes in assessment-limit states experienced far more pronounced swings in average prices than homes in no-limit states. Meanwhile, tax liabilities remained relatively elevated in both groups of states 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 1d**, 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-limit states—nearly double the corresponding amounts for states without assessment limits. The large gap in assessment-limit states is clear evidence that assessment limitations make tax liabilities less pro-cyclical.

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 absolute 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. 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 millage rate *growth*.[10] **Table 1** describes the high-level features of state-level millage rate limits (expressed as percentages of fair market value for comparability across states) as of 2016 which we summarize from the legislative language.

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

[10]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.

be more or less effective at constraining overall property tax rates.[11] 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. 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 which may well vary as a function of interactions with other tax system characteristics.[12]

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

[11] 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%.)

[12] 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.

both the growth rate and total tax levy in relation to aggregate market values.[13] **Table 1** describes the high-level features of state-level levy limits (expressed as percentages of fair market value for comparability across states) as of 2016 which we summarize from the legislative language. We also report revenue limits, which are similar to levy limits – the former restricts the growth of total tax revenue of the local government whereas the latter restricts only the property tax revenue. Under the assumption that revenue limits affect property taxes and other taxes equally, we treat revenue limits the same as levy limits in all subsequent analyses.

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. When combined with restrictive rate limits that are also defined in terms of percentage growth (e.g., Colorado), this can result in a "ratcheting down" phenomenon, whereby rate reductions that occur during boom times can never be relaxed thereafter and thereby limit states' flexibility in raising rates during housing market downturns. More generally, levy limits should dampen pro-cyclical fluctuations in property tax obligations, especially in states that do not otherwise limit taxable value growth.[14] Much like assessment limits, however, this dampening effect ought to predominantly affect tax obligations during periods of rising housing prices. During periods of declining values, levy limits of the percentage growth variety do not preclude rising tax obligations.

3 Modeling Covariance Risk

3.1 Arrow-Debreu Pricing

Taxpayers care not only about *how much* they must pay in ongoing property taxes but also about *the timing of those payments* in relation to their marginal utility of consumption. In the absence of property tax limitations, property taxes are inherently pro-cyclical due to the co-movement of housing values with macroeconomic conditions. This pro-

[13] 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).

[14] 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).

cyclicality provides natural consumption-smoothing insurance. Insofar as tax limitations are intended to smooth government revenues and mitigate unpredictable swings in tax payments, this inevitably renders property taxes less pro-cyclical and introduces a distinct form of risk for taxpayers. In this section, we formalize this insight and introduce an Arrow-Debreu framework to enable the decomposition of the streams of tax liabilities into separate *covariance risk* and *Certainty Equivalent* components.

Consider the canonical problem in which a consumer wants to maximize their expected utility of consumption:

$$E_0 \sum_{t=0}^{\infty} \beta^t u(c_t) \ , \tag{1}$$

where $\beta \in (0,1)$ is the discount factor, $u(\cdot)$ is a twice continuously differentiable, increasing, strictly concave utility function, and E_0 denotes expectations conditional on time 0 information. Let q_t be a state vector governed by a Markov process with transition probability $\pi(q'|q)$, where q and q' are elements of a common state space $\mathbb{Q}$. Let $p(q'|q)$ be the price of one unit of consumption next period in state q' when the state in this period is q. With no subjective time preference (i.e., $\beta = 1/(1+r)$, where r is the risk-free return) and in a complete market where households can trade state-contingent Arrow-Debreu (AD) securities, the Euler equation that solves the problem is

$$E_t \frac{u'(c_{t+1})}{u'(c_t)} = 1 \ , \tag{2}$$

and the price of the AD security is

$$p(q_{t+1}|q) = \frac{1}{1+r} \frac{u'\big(c_{t+1}(q_{t+1})\big)}{u'\big(c_t(q_t)\big)} \pi(q_{t+1}|q) \ . \tag{3}$$

The state price p_t is smaller in good times and larger in bad times because the same unit of consumption is less valuable in good times and more valuable in bad times for a risk-averse person with decreasing marginal utility.

3.2 Covariance Risk

Consider an arbitrary series of property tax liabilities x_t. We define *Covariance Risk* as

$$\mathbb{R} = \sum_{t=1}^{T} x_t p_t - \sum_{t=1}^{T} \bar{x} p_t \ . \tag{4}$$

The first term $\sum_{t=1}^{T} x_t p_t$ is the property tax at time t scaled by the state price p_t. This term can be thought of as the "subjective price" of the series of tax obligations given the homeowner's utility and consumption stream. $\sum_{t=1}^{T} \bar{x} p_t$ represents the certainty equivalent of total property tax obligations. Similarly, the certainty equivalent is the "subjective price" of total tax obligations if the homeowner pays a constant property $\bar{x}$ at all times. Thurs, *Covariance risk* can be interpreted as the insurance premium a homeowner would be willing to pay to face constant tax liabilities given a consumption path defined by p_t.

Importantly, *covariance risk* is smaller for more pro-cyclical streams of tax obligations. To see this dynamic, rewrite Equation (4) as

$$\mathbb{R} = \sum_{t=1}^{T} (x_t - \bar{x}) p_t \equiv \sum_{t=1}^{T} \Delta x_t \cdot p_t \ , \tag{5}$$

where Δx_t is the deviation from the mean level of taxation at time t. Pro-cyclical taxation produces $\Delta x_t > 0$ during good times with small p_t. During bad times, pro-cyclical taxes correspond to $\Delta x_t < 0$ and large p_t. As a result, pro-cyclical taxes lead to negative *covariance risk*, the magnitude of which represents the extent of consumption-smoothing insurance provided. In contrast, counter-cyclical taxes yield $\mathbb{R} > 0$. Intuitively, this risk measure can be interpreted as a weighted average of tax payments over time. The weighting scheme p_t reflects homeowners' intertemporal marginal rate of substitution, wherein (demeaned) tax payments are down-weighted during good times (with high consumption) and up-weighted during bad times (with low consumption).

For a numeric illustration of the effect of tax limitations on *covariance risk*, consider the following stylized example featuring a property initially valued at $300,000. The housing market experiences a boom-bust cycle with the property value increasing by 10% to $330,000 in year 1 before falling by 5% to $313,500 in year 2. In the absence of all tax limitations and annual reassessments, taxable values and market values coincide. Assuming a constant 1% tax rate, tax obligations in the no-limit regime therefore evolve in lock-step with property values: $3,300 in year 1 and $3,135 in year 2, for a total liability of $6,435 (ignoring discounting for ease of exposition). Property taxes in the no-limit regime are thus perfectly pro-cyclical. If the property is instead subject to assessment limitations with a relatively loose 5% cap on annual taxable value growth, taxable values will instead be $315,000 in year 1 and $313,500 in year 2. Assuming a revenue-neutral tax rate of 1.024%, the homeowner will then face tax bills of $3,225 and $3,209 in years 1 and 2, respectively. Despite netting the same $6,435 overall, loose assessment limitations

result in taxes falling by less in year 2 (0.48%) than housing values, thereby making the property taxes less pro-cyclical.

		Year 0	$\xrightarrow{+10\%}$	Year 1	$\xrightarrow{\text{-5\%}}$	Year 2
	Market Value:	\$300,000		\$330,000		\$313,500
No Limit	Taxable Value:	\$300,000	$\xrightarrow{+10\%}$	\$330,000	$\xrightarrow{\text{-5\%}}$	\$313,500
	Tax ($\tau = 1.000\%$):			\$3,300		\$3,135
Loose Limit (5%)	Taxable Value:	\$300,000	$\xrightarrow{+5\%}$	\$315,000	$\xrightarrow{\text{-0.48\%}}$	\$313,500
	Tax ($\tau = 1.024\%$):			\$3,225		\$3,210
Strict Limit (1%)	Taxable Value:	\$300,000	$\xrightarrow{+1\%}$	\$303,000	$\xrightarrow{\text{+1\%}}$	\$306,030
	Tax ($\tau = 1.057\%$):			\$3,201		\$3,234

Tax rates, τ, are chosen to yield the same total tax payments over periods 1 and 2 (i.e., \$6,435) to highlight the change in tax timing. Taxable values are the lesser of market value and the last period's taxable value times one plus the capped growth rate (5% and 1% in the loose and strict regimes, respectively).

With even more strict assessment limitations (i.e., a 1% cap on annual taxable value growth), tax liabilities become outright counter-cyclical. Due to the mechanics of assessment limitations, taxable values are limited to \$303,000 in year 1, but continue to increase to \$306,030 in year 2 (despite declining market value). Assuming a tax rate of 1.057% to raise the same \$6,435 in total revenues, tax obligations under strict limitations are now \$3,201 and \$3,234. In this case, property taxes increase by 1% during the recession, even as property values are falling and homeowners face lower incomes and consumption.

Now suppose that the prices of the AD securities corresponding to the state of the world in years 1 and 2 are 0.8 and 1.2, respectively (i.e., consistent with risk-averse individuals valuing consumption more highly during periods of low consumption and vice versa). Applied to the sequence of liabilities detailed above, we obtain the following measures of *covariance risk*:

	Year 1 $p_1 = 0.8$	Year 2 $p_2 = 1.2$	Average	*Covariance Risk* ($\mathbb{R}$) $\sum(x_t - \bar{x})p_t$	*Δ Covariance Risk* $\mathbb{R}^{\text{Limit}} - \mathbb{R}^{\text{NoLimit}}$
No Limit	\$3,300	\$3,135	\$3,217.50	(\$3,300 - \$3,217.50) × 0.8 + (\$3,300 - \$3,217.50) × 1.2 = -\$33.00	N.A.
Loose Limit	\$3,225	\$3,210	\$3,217.50	(\$3,225 - \$3,217.50) × 0.8 + (\$3,210 - \$3,217.50) × 1.2 = -\$3.07	-\$3.07 - (-\$33.00) = \$29.93
Strict Limit	\$3,201	\$3,234	\$3,217.50	(\$3,201 - \$3,217.50) × 0.8 + (\$3,234 - \$3,217.50) × 1.2 = \$6.40	\$6.40 - (-\$33.00) = \$39.40

Pro-cyclical property taxes subject to no tax limitations provide a degree of consumption-smoothing insurance value to homeowners as given by *covariance risk* of -$33. Even loose assessment limitations in this scenario provide a modest degree of insurance, yet the difference between *covariance risk* of -$3.07 and -$33 represents a relative increase in risk. Under strict assessment limitations, *covariance risk* rises to $6.40, reflecting the fact that owing higher taxes during periods of low consumption is especially burdensome.

The measure of *Covariance Risk* and the decomposition of streams of tax liabilities into distinct risk and level components has two key advantages. First, our measure of risk properly emphasizes the temporal covariance between tax liabilities and households' state-dependent marginal utility of consumption, whereas traditional risk measures reflect variability alone. In the preceding numerical example, the no-limit tax regime results in the highest standard deviation of tax liabilities and would hence be regarded as the least favorable regime according to variability-based measures. Our framework correctly identifies it as the most favorable due to the insurance value that it provides.

Second, our procedure for distinguishing *covariance risk* from the *certainty equivalent* of taxation allows us to evaluate separately two noteworthy aspects of property tax limitations that carry distinct policy implications: (1) the potential for tax limitations to dampen the overall level of property taxation and thereby reduce the probability of mortgage distress, and (2) the potential for tax limitations to shift the burden of property taxation for households from more to less prosperous times and thereby increase the probability of mortgage distress. Popular rhetoric has implicitly latched onto (1) (despite conflating level and risk effects) and neglected (2) as the way to support homeowners financially, yet a proper understanding of (2) opens avenues for property tax reforms that mitigate *Covariance Risk* without necessarily undermining revenue needs.

We use our measure of *Covariance Risk* on simulated property tax streams and consumption paths to simultaneously capture the interaction effects of property tax limits and control for other macroeconomic effects. We discuss these simulations in the next section.

3.3 Simulated Tax Liabilities

As noted above, property tax obligations reflect the effects of the foregoing tax policies as well as endogenous and exogenous factors affecting market values. In this section, we outline how we simulate property tax payments as a function of state-level property tax system characteristics to isolate policy effects and obtain counterfactual tax liabilities

(subject to annual reassessments and zero tax limitations).[15] A more detailed description of our simulation procedure can be found in Appendix A.

We begin by simulating the economic conditions that dictate the evolution of property values, household consumption, and any inflation-anchored tax limitations. These processes apply to all state-years. The simulation jointly determines homeowners' tax obligation and the Arrow-Debreu price by incorporating features such as tax rates, turnover rates, and household consumptions. Aggregate consumption growth and inflation are modeled as AR(1) processes with a stochastic residual term and Poisson recession arrival rate. Both series are calibrated to the mean, standard deviation, and correlation between the two using personal consumption expenditures from the Consumer Expenditure Survey and the Consumer Price Index from the Bureau of Labor Statistics. We obtain property prices using the Case-Shiller U.S. National Home Price Index and calibrate the correlations with consumption growth and inflation. We simulate the economy for 50 years, long enough to capture the effects of tax limitations but not so long as to reach a point where the AR(1) process could generate outliers. We repeat this process 1,000 times and average over simulated economies so that individual economic processes do not drive results.

Next, we apply the set of tax policies in effect in state-year s (e.g., California in 2016) in conjunction with simulated economic conditions to obtain taxable values $TV_{i,t}^{s}$ and millage rates τ_t^s for our panel of simulated properties, the product of which yields property tax payments, $x_{i,t}^{s}$. Levy limits require the sequential determination of (aggregate) taxable values and millage rates. Accordingly, we proceed in several steps. First, we set the statutory millage rate in the initial year of the simulation to equal the median effective tax rate for newly purchased homes that we observe in the data. We allow tax rates thereafter to evolve according to any applicable rate or levy limitations and revenue needs, where revenue needs are assumed to grow in proportion to aggregate consumption. Similarly, we assume in the first year of the simulation that taxable values and market values coincide at $300,000. In subsequent years, market values evolve following a random path with moments matching the observed empirical housing data. Taxable values vary with market values subject to any assessment limits, with taxable value un-

[15] We do not model local option tax limitations, as the details of these regimes are poorly tracked, especially on a historical basis. Thus, for example, we treat Georgia as having no assessment limitations outside of the years 2009-2010, despite the state allowing local assessment freezes in other years. Similarly, 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.

capping occurring upon sale.[16] In states without assessment limits, taxable values are reset to equal market values according to each state's reassessment frequency.[17] Next, we model the effects of levy limits by calculating the percentage growth in property tax revenues that would result from applying the previous year's tax rates to current taxable values in the state and comparing these to the state's revenue growth target and capped levy growth amount. Tax rates are then adjusted to yield revenues that match the lesser of the state's permissible levy limit or growth target, subject to any further rate limits. In cases where the state would want to raise the millage rate to a level that would exceed their rate limit to meet their revenue target, the tax rate will be set *at* the limit and the revenue target will not be met without further increases in taxable values.

This procedure produces property tax obligations, $x_{i,t}^{\text{Limit}_s}$, as the product of simulated taxable values and millage rates, subject to all applicable assessment, rate, and levy limits; reassessment frequency; and starting revenue requirements. We repeat the procedure to obtain counterfactual property tax obligations, $x_{i,t}^{\text{NoLimit}_s}$, based on the product of current market value (i.e., assuming annual reassessment) and the unrestricted millage rate anchored to the same initial revenue requirements and revenue growth targets as $x_{i,t}^{\text{Limit}_s}$. The difference between $x_{i,t}^{\text{Limit}_s}$ and $x_{i,t}^{\text{NoLimit}_s}$ measures the collective impact of property tax limitations—including all interactions thereof—on property tax liabilities.

We evaluate the validity of the simulation by comparing our simulation to observed property tax liabilities in the data. We produce a series of simulated property taxes using our simulation and observed property values. This process results in a series of property taxes that would match the observed property taxes in the data if our simulation process accurately captures the property tax policy features. We find a high correlation between the simulated and actual property tax liabilities. Specifically, the correlation ranges from 0.73 in Pennsylvania to 0.97 Missouri.

We calculate the main variable of interest Δ *Covariance Risk* on the state-year level s:

$$\Delta \textit{ Covariance Risk}_s = \Delta \mathbb{R}^s = \mathbb{R}^{\text{Limit}_s} - \mathbb{R}^{\text{NoLimit}_s}, \tag{6}$$

[16] In Arizona and Oregon, changes of ownership do not trigger taxable value uncapping. As such, we model taxable values in these states as being subject to perpetual limits on taxable value growth.

[17] For those states where reassessment frequency is not statutorily mandated, we assume a 10 percent idiosyncratic reassessment probability (i.e., akin to a 10-year interval between reassessments). In practice, states like Delaware and Pennsylvania tend to go much longer between county reassessments, whereas states like Maine and New York reassess somewhat more frequently. The results of our empirical analysis are qualitatively unchanged by instead assuming reassessment frequencies that are more closely aligned to actual practices in these states (i.e., 5 percent annual reassessment probability for Delaware and Pennsylvania and 33.33 percent for Maine, New York, and New Jersey).

where $\mathbb{R}^{\text{Limit}_s}$ and $\mathbb{R}^{\text{NoLimit}_s}$ are *Covariance Risk* from the property tax series $x_{i,t}^{\text{Limit}_s}$ and $x_{i,t}^{\text{NoLimit}_s}$ using **Equation (4)**. Δ *Covariance Risk* is the difference between the *Covariance Risk* of a state-year and the counterfactual *Covariance Risk* of the same state-year if there were no tax limitations. In other words, Δ *Covariance Risk* isolates the increase in *Covariance Risk* due to the enactment of property tax limitations.

3.4 Characteristics of Covariance Risk

Figures 2a and **2b** depict our simulated measures of Δ *Covariance Risk* and Δ *Certainty Equivalent* for the continental U.S., averaged over the period 2006-2016. For purposes of interpretation, these are standardized to have a mean value of 0 and standard deviation of 1.[18] States appearing in darker colors in both maps are ones whose tax limits policies induce a high level of *covariance risk* while simultaneously offering larger reductions in the *certainty equivalent* of taxation. New York states' unique combination of restrictive rate and levy limits and infrequent reassessments (i.e., equivalent to assessment limitations with a 0% cap on taxable value growth between reassessments) yields the highest level of Δ *Covariance Risk* and the lowest Δ *Certainty Equivalent*. The degree of negative correlation between Δ *Covariance Risk* and Δ *Certainty Equivalent* varies across states, however. For instance, Maine has a relatively large increase in Δ *Covariance Risk* relative to its decrease in *certainty equivalent*, while Michigan has a relatively low increase in Δ *Covariance Risk* for its large reduction in *certainty equivalent*.

Figure 3 highlights the importance of interactions between property tax limits in determining Δ *Covariance Risk*. In each subfigure, we graph two lines: a red solid line subject to all applicable limitations, and a blue dashed line with only the focal limit in place (i.e., assessment, rate, and levy limits in panels a-c, respectively). As shown, Δ *Covariance Risk* (vertical axis) is decreasing as limits become less restrictive, as measured by relaxing the relevant percentage caps (horizontal axis). The distance between lines in each panel provides evidence on the extensive margin and confirms that implementing tax limitations of all types increases *covariance risk*, while the slopes of these lines provide evidence regarding the intensive margin of limit stringency. Differences in slopes between lines in each panel show how interactions between the focal limit and other limitations tend to amplify risk.

Figure 3a shows how Δ *Covariance Risk* responds to changes in the capped TV growth rate under assessment limitations. The red solid line represents Δ *Covariance Risk* with

[18] See **Table 2** for the corresponding average dollar amounts in our estimation sample.

rate and levy limitations at their in-sample median levels, while the dashed blue line represents the hypothetical level of Δ *Covariance Risk* without any levy or rate limitations. The former is above the latter, suggesting that rate and levy limitations increase Δ *Covariance Risk* on the extensive margin. Both lines decline as the allowable TV growth rate increases (i.e., becoming less stringent), suggesting that assessment limitations increase Δ *Covariance Risk* on the intensive margin. The lines flatten out to the right as the assessment limitation becomes effectively non-existent with the growth cap being so high that it never binds. Holding rate and levy limitations at their median values, implementing assessment limits with a 0.5% capped TV growth rate increases Δ *Covariance Risk* by about \$240 (the difference between the left-most and right-most points along the red line), or approximately 0.75 standard deviations. **Figures 3b** and **3c** show similar patterns, such that all three types of tax limitations increase Δ *Covariance Risk* along both the extensive and intensive margins.

In addition to tracing our the Δ *Covariance Risk* in the simulation sandbox where we can turn the dial on each type of limitation policy, we also examine the relationship between Δ *Covariance Risk* and the actual tax limitation policies observed empirically. Given the high-dimensional nature of the policy space in practice, we only investigate the extensive margin of each type of tax policy. We regress Δ *Covariance Risk* on whether the state has levy, rate, and assessment limitations each year from 2006 to 2016. **Table 3** shows the results. Column 1 shows that implementing any type of limitation policy increases Δ *Covariance Risk*, consistent with the simulation sandbox results in **Figure 3**. We see that assessment limits have the largest effect. Column 2 shows that there is a tradeoff in levy and rate limits – implementing these policies increases Δ *Covariance Risk* but reduces Δ *Certainty Equivalent*. However, we see an increase in Δ *Certainty Equivalent* associated with implementing assessment limits. This pattern suggests that assessment limits are often implemented alongside increases in tax rates to raise tax revenue.

4 Data

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.[19] These data encompass the universe of property tax assessment information and purchase, loan, and foreclosure transaction records span-

[19]We have written approval to continue to use Zillow Ztrax.

ning the continental U.S. These enable us to observe historical sale prices, assessed values, tax liabilities, 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. To the best of our knowledge, we are the first to combine data from ATTOM and Zillow 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.[20]

We also collect information on property tax system characteristics and other state-specific policies that influence default probabilities. Data on time-varying state-level property tax limitations (from which we construct our tax simulator) 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 designating 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) are from Ghent and Kudlyak (2011) and Mian et al. (2015).

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.[21] 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,

[20] 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.

[21] 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 B.

assuming full monthly payments.[22] Taking the ratio of imputed loan balances to property values yields our desired time-varying parcel-specific estimates of LTV, which we subsequently classify into discrete intervals.

We geocode all parcels with valid street address and zip code information using ArcGIS, and we use the resulting latitude and longitude coordinates to calculate the shortest distance as the crow flies from each parcel to all neighboring counties located in other states. 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 C. 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.[23] 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.[24] **Figure 4** describes the geographic distribution of parcels in our final estimation sample that contributes to identification (i.e., where we have complete infor-

[22]Initial interest rate information is infrequently populated in either ATTOM or ZTRAX and typically only for adjustable rate mortgages. Term information is more consistently recorded, but it is 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.

[23]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.

[24]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.

mation for parcels on opposite sides of a state border within border-straddling regions).

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.[25]

Table 2 summarizes the set of means, medians, and standard deviations for our key regression variables as used in our estimation sample. 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. $\Delta CovarianceRisk$ and ΔCE amounts are calculated as described in Section 3 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 discrete logical intervals.[26]

We report values separately for distressed and non-distressed properties, with differences in means reported in the final column of **Table 2**. All differences in means between groups are statistically significant, with p-values uniformly well below 0.001. Distressed properties are thus significantly less valuable and face higher effective tax rates (despite lower overall tax bills), and they experience larger year-over-year changes

[25]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.1** shows the evolution of foreclosure activity in our complete national sample 2006-2016.

[26]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.

in tax liability. At the same time, distressed properties face modestly lower simulated $\Delta CovarianceRisk$ and larger (less negative) ΔCE. Distressed properties also exhibit significantly higher average LTVs,[27] 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.

5 Empirical Strategy

Our 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:

$$\begin{aligned}\mathbb{1}(\text{Distressed})_{i,t} =& \alpha + \beta \Delta \textit{Covariance Risk}_{s,t} + \delta \Delta \textit{Certainty Equivalent}_{s,t} \\ &+ X_{i,t}\gamma_i + X_{k,t}\gamma_k + Z_{s,t}\gamma_s + \lambda_{j,t} + \varepsilon_{i,t}. \end{aligned} \tag{7}$$

The dependent variable in all specifications is pre-multiplied by 100 such that point estimates can be interpreted directly as percentage point effects. The independent variable of interest is $\Delta CovarianceRisk$, which we standardize with a mean of 0 and standard deviation of 1 and control for Δ *Certainty Equivalent*$_{s,t}$, similarly standardized.

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 "neighborhood" k zip code-level or tract-level demographic controls, including measures of average income, age-specific population, racial composition, and educational attainment.

[27] 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.

$Z_{s,t}$ 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 isolate the influence of state property tax regimes on mortgage distress while holding local economic conditions fixed. 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 covariance risk.

Concretely, we consider two different types of border pairings: county pairs and 10 km^2 grid cells. County pairs have the virtue of being convenient to visualize and implement. These are widely used in the literature as a result. However, counties may differ substantially in area and population density, thereby potentially undermining our identifying assumption. To standardize land area, we use the U.S. National Grid coordinate system to construct 10 km^2 grid cells.[28] 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 focus on border pairings that use the 10 km^2 grid cells. Using the broader county pairs, 5 km^2 grid cells, or 15 km^2 grid cells produces qualitatively similar results.

In **Figure 5**, 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 just north and south of the state border exhibit relatively similar median characteristics, especially in terms of housing prices (**5a**) and LTV (**5c**). Outside of the more densely populated areas, foreclosure rates are more heterogeneous (**5d**), and effective tax rates

[28]The U.S. National Grid coordinate system divides the world into equal-sized "square" grid cells (100 km^2) 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.

(5b) 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 6**, 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 km^2 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 5**) is also quite sparsely populated, as shown in **Figure 6**, and thereby contributes little to identification.

6 Covariance Risk and Mortgage Distress

6.1 Main Estimates

In **Table 4**, we report that Δ *Covariance Risk* has a positive, statistically significant effect on mortgage distress.[29] We isolate the effect of Δ *Covariance Risk* by controlling for the change in tax payment, Δ *Certainty Equivalent*, in all specifications. Our preferred and 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 Δ *Covariance Risk* raises the probability of mortgage distress by 0.44 percentage points, or approximately 30 percent. This is a sizable effect. For comparison, the effect of Δ *Covariance Risk* is roughly one-quarter as large as the effect of a home becoming underwater and seventy percent more than owning a home in disrepair. We report the effect of the loan-to-value and home in disrepair in **Table E.2**, which replicates **Table 4** and reports the coefficients on all of the control variables.

We report estimates using county pairs in the first three columns of **Table 4**. These specifications identify the effect of Δ *Covariance Risk* by comparing counties across state lines. Column 2 adds control variables and column 3 adds year fixed effects. Across all of these specifications, Δ *Covariance Risk* has a positive effect on mortgage distress.

We report estimates using 10 km^2 grid pairs in columns 4 through 6 of **Table 4**. These specifications identify the effect using standardized grid across the country. Column 5

[29] For brevity, we only report the set of coefficient estimates that relate to Δ *Covariance Risk* and Δ *Certainty Equivalent* in **Table 4**. Complete estimates can be found in **Table E.2**.

adds controls and column 6 adds year fixed effects. The effects are similar to those with county pairs. For example, the estimate in column 1 with county pairs is 0.296 and the estimate with grid pairs in column 4 is 0.305.

We report estimates using grid by year fixed effects in columns 7 and 8 of **Table 4**. The previous columns considered county and grid pairs and controlled for changes across years with control variables and year-fixed effects. The specifications in 7 and 8 consider within year and grid, which flexibly controls for many other potential confounding factors. The estimates in these specifications continue to find a positive effect of Δ *Covariance Risk* on mortgage distress.

Our specification allows us to compare the effect of Δ *Covariance Risk* and Δ *Certainty Equivalent*. We find that a one standard deviation increase in Δ *Covariance Risk* affects mortgage distress more than a one standard deviation increase in Δ *Certainty Equivalent*. Said differently, we find that Δ *Covariance Risk* is as important, if not more so, than changes in the level of property tax.

We can also consider the policy question of whether property tax limits increase or decrease mortgage distress using these estimates and back-of-the-envelope calculations. Property tax limitations have two effects: they can change the timing and thus risk of tax payments (captured by Δ *Covariance Risk* and the focus of this paper) and they can change the level of tax payments (captured by Δ *Certainty Equivalent*). We find a tradeoff with levy and rate limits: they increase risk and decrease the level. For example, in **Table 3** we report that property tax rate limits increase Δ *Covariance Risk* by 0.744 standard deviations and decrease Δ *Certainty Equivalent* by 1.055 standard deviations. Combining these estimates, we find that the effect of rate limits is to slightly decrease mortgage distress by 0.03, as the effect of dampening property tax payments -1.055 $\times$ 0.335 = -0.35, is almost entirely offset by the increase in risk 0.744*0.433 = 0.32. On the other hand, we find assessment limits increase the risk, and the level of property tax payments, increasing mortgage distress. This suggests that while taxable values are damped by the assessment limit, governments, in practice, adjust the rate to increase property taxes. Doing a similar calculation, we find mortgage distress increases by 0.347= 0.802 $\times$ 0.433 due to risk and 0.056= 0.167 $\times$ 0.335 due to the level of implementing assessment limits.

6.2 Heterogeneous Effects

In **Figure 7**, we report heterogeneity in the effect of *covariance risk* by neighborhood- and parcel-level characteristics. All of the estimates use our preferred specification from

column 8 in **Table 4**, with grid-by-year fixed effects. We add to that specification interactions of Δ *Covariance Risk* and census tract-level race indicators, parcel-specific assessment ratios, and owner-specific loan to value and tenure and similar interactions for Δ *Certainty Equivalent*. We report the estimates of these interactions in Panels (a)-(d), respectively. Complete results, including uninteracted covariates and the full set of relevant interactions, are provided in **Table E.3**.

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 *covariance 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 7a** reports the implied overall partial effects of Δ *Covariance Risk* and Δ *Certainty Equivalent* by racial group. Consistent with the prior literature, residents of predominantly Black neighborhoods face significantly higher baseline rates of mortgage distress (**Table E.3**, Column 1). Households in predominantly Black neighborhoods also face significantly larger effects of Δ *Covariance Risk* and Δ *Certainty Equivalent*. The 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 be differentially affected.[30]

There is also a growing literature that documents the prevalence of errors in property assessment, with negative ramifications for the relative progressivity of the property tax (McMillen and Singh, 2020; Berry, 2021; Avenancio-León and Howard, 2022). Despite scant evidence of direct effects of under- or overassessment, Atuahene and Berry (2019) suggest that overassessments are responsible for "an epidemic of tax foreclosures" in cities like Detroit. We investigate more generally whether households that face higher assessment ratios (i.e., the ratio of assessed value to market value), and thus bear relatively heavier property tax burdens, are more susceptible to the effects of *covariance risk* on mortgage distress. As shown in **Figure 7b**, the partial effects of Δ *Covariance Risk* and Δ *Certainty Equivalent* are indeed increasing in households' assessment ratios.

[30]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 risk effects in the latter group suffer from weaker statistical precision.

Households whose properties are assessed at two or more times their market value are estimated to face an effect of tax risk that is 80 percent greater than households whose properties are assessed at less than half of their market value.

We also consider homeowner-level characteristics. First, we document that households in the third and fourth quintiles of the loan-to-value distribution—around the threshold for being underwater—incur the largest effects of Δ *Covariance Risk* on mortgage distress (**Figure 7c**). The effects are larger and monotonically increasing across the bottom four loan-to-value quantiles when we limit the analysis to the subset of observations with known loan-to-value, which presumably excludes a substantial proportion of homeowners without mortgages (**Figure E.2**). Strategic motives for mortgage delinquency and default are thus amplified in states whose combined property tax system characteristics result in more *covariance risk*. Equivalently, *covariance risk* constitutes a stronger trigger for mortgage distress when homeowners are already confronted with being underwater.

Second, we show that the foregoing loan-to-value heterogeneity is not an artifact of newer homeowners being more susceptible to *Covariance Risk*. In fact, as depicted in **Figure 7d**, longer-tenured homeowners (i.e., households who have owned their homes for more than 5 years) exhibit the largest partial effects of both Δ *Covariance Risk* and Δ *Certainty Equivalent*. 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 unsurprising that we find no statistically significant differential effect of Δ *Covariance Risk* or Δ *Certainty Equivalent* 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 Δ *Covariance Risk* and Δ *Certainty Equivalent*, where low-income homeowners have the option to smooth their tax payments over time, but these negative differential effects remain imprecisely estimated. Similar issues preclude estimation of differential effects of *covariance risk* in states with property tax circuit breakers for low-income households.

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 *covariance 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 Δ *Covariance Risk* and Δ *Certainty Equivalent* across both groups. Taken together, areas with high itemization rates or high AGI do not exhibit significantly weaker effects of tax risk or tax levels on mortgage distress.[31] Given our border discontinuity design and lack of data on parcel-specific variation in itemization behavior, incomes, and eligibility for tax deferral 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 *covariance risk* until such data can be assembled.

7 Conclusion

Our findings highlight an important yet often overlooked consequence of tax policy: shifting the timing of tax payments can increase financial risk for households and lead to higher rates of mortgage distress. We introduce a novel measure-*covariance risk*-which quantifies how much a household would be willing to pay to smooth its tax liabilities over time rather than face countercyclical tax liabilities. Using this measure, we show that property tax limitations, such as California's Proposition 13, significantly increase *covariance risk* as an unintended consequence of their design.

To isolate the policy-driven effects of property tax limitations, we develop a simula-

[31] Results available from the authors upon request.

tion that accounts for different types of tax caps and their interactions. Our empirical analysis, based on parcel-level panel data covering nearly all U.S. residential properties and a border discontinuity design, shows that a one standard deviation increase in *covariance risk* raises the probability of mortgage distress by 30%. These results underscore the real financial consequences of tax policy decisions.

The concept of *covariance risk* offers several advantages both for this analysis and future research. First, it allows us to separate the timing effects of tax payments from their overall level—an essential distinction in evaluating tax policy impacts. In the case of property tax limits, this decomposition reveals countervailing forces: while tax limits lower overall tax burdens (their intended effect), they also create counter-cyclical payments that raises household financial risk (an unintended effect). Second, our approach demonstrates how *covariance risk* can be used to isolate policy-driven changes in risk exposure, making it a valuable tool for assessing the broader effects of tax policy in the presence of economic fluctuations. Third, despite the conceptual importance of tax risk for both firms and households, empirical research has been constrained by the absence of a widely accepted measure. Our framework provides a flexible and implementable solution to this gap.

At a broad level, this paper demonstrates that tax policy must consider not only the magnitude of tax liabilities but also their timing. More specifically, our results suggest that policymakers have an opportunity to mitigate risk by offering mechanisms that allow taxpayers to smooth their tax payments over time. In the context of property taxes, targeted tax deferral programs—expanding beyond low-income seniors to a broader set of homeowners—could help reduce the financial strain caused by tax payment risk while preserving the revenue stability that property tax limitations aim to achieve.

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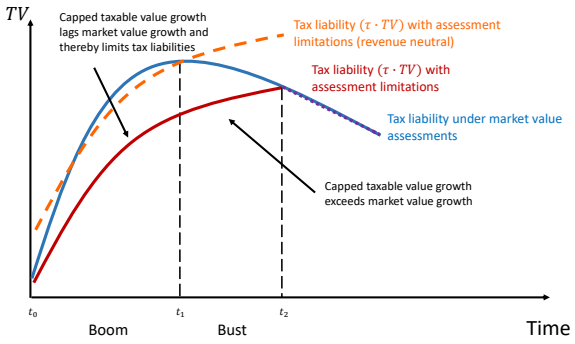
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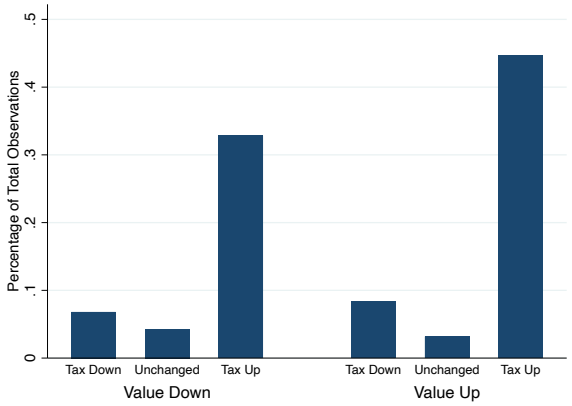
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Figure 1: **Housing Prices and Tax Payments**

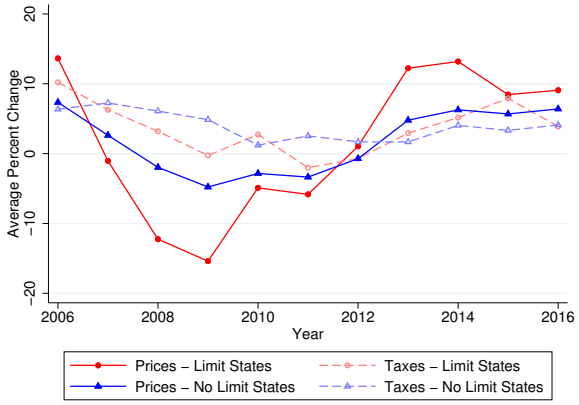
(a) Framework for shifting tax payments



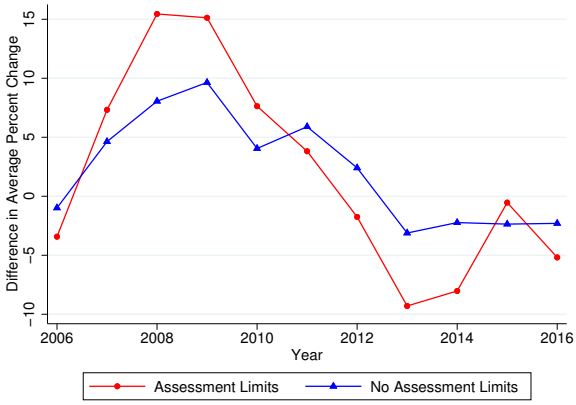
(b) Histogram of tax payments



(c) Prices and Taxes



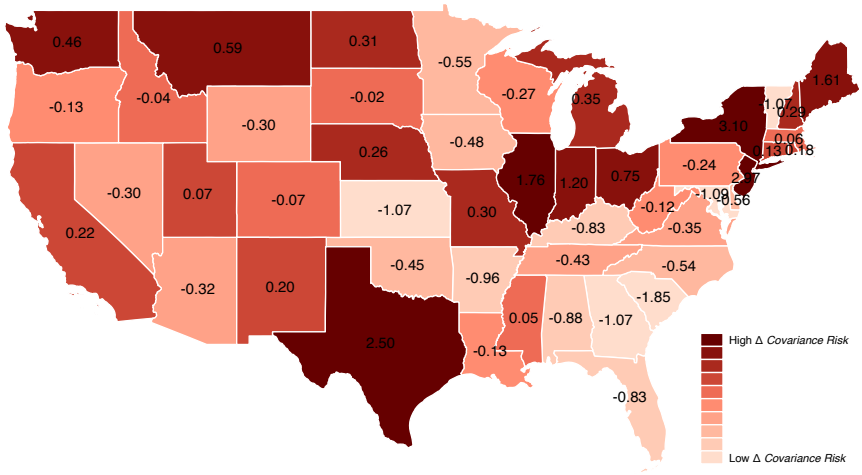
(d) Tax-Price Adjustment Gap



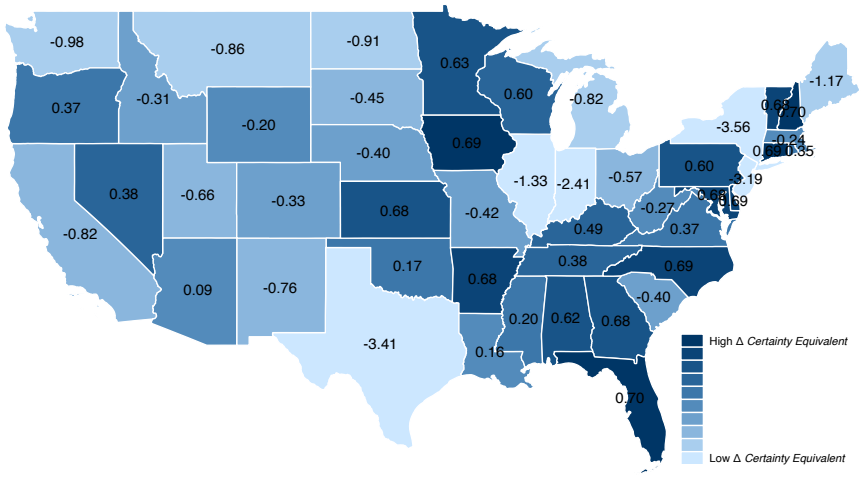
The figure describes the relation between housing prices and property tax payments. Panel 1a illustrates a hypothetical dynamic wherein tax payments may continue to increase even while market values are declining. Panel 1b shows the proportion of instances in which property tax payments fall, remain unchanged, or rise while market values are rising or falling in our estimation sample. Panel 1c plots year-over-year changes in housing prices and property tax payments for states with and without assessment limitations. Panel 1d plots the "tax-price adjustment gap", defined as the percentage change in taxes (dashed lines in panel 1c) minus the percentage change in housing price (solid lines in panel 1c).

Figure 2: *Δ Covariance Risk* **and***Δ Certainty Equivalent* **from Property Tax Limitations by State**

(a) *Δ Covariance Risk*

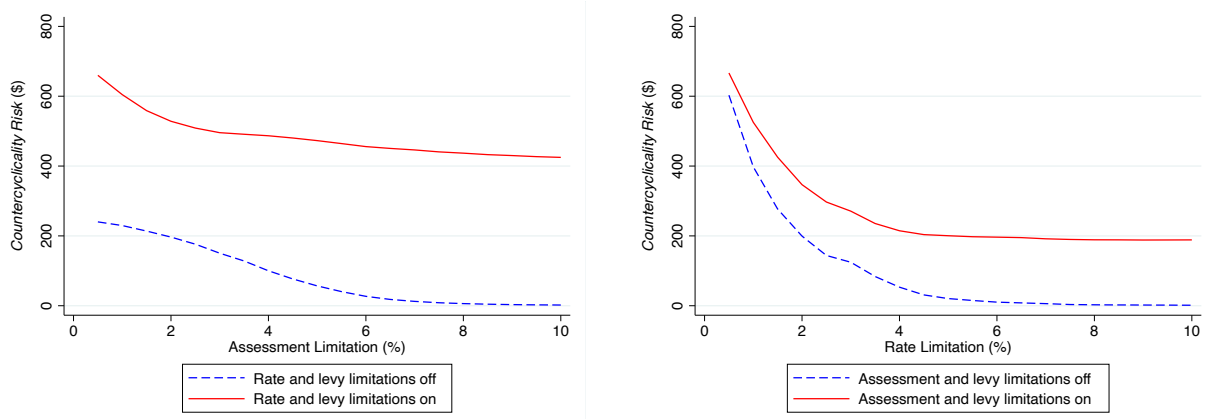


(b) *Δ Certainty Equivalent*



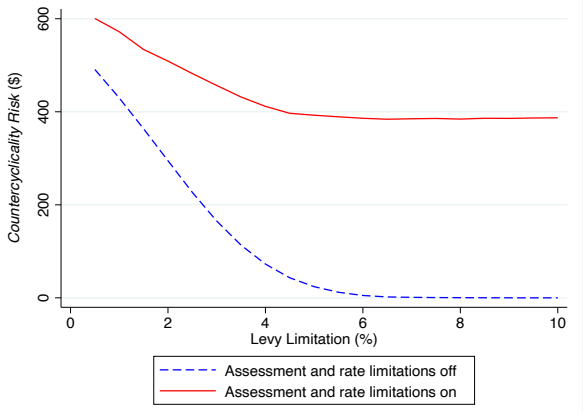
Panel 2a depicts *Δ Covariance Risk* by state (standardized to have a mean of 0 and standard deviation of 1) for the period 2006-2016. Panel 2b shows the comparable standardized measures of *Δ Certainty Equivalent* by state for the same period. Note that the color gradients in both panels are inverted, such that similar colors in both are indicative of a negative association between the risk and level of taxation induced by property tax limitations.

Figure 3: *Δ Covariance Risk* **and Individual Tax Limitations**



(a) Assessment Limitations

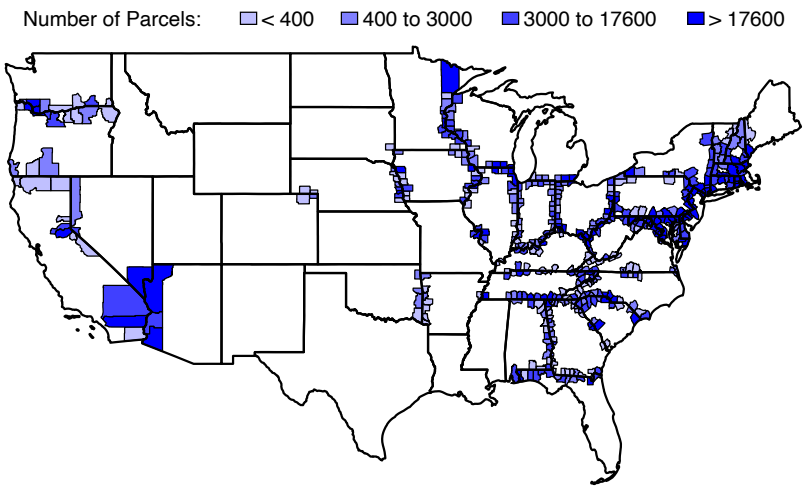
(b) Rate Limitations



(c) Levy Limitations

This figure plots the relation between different types of tax limitations and *Δ Covariance Risk*. Panel (a) plots *Δ Covariance Risk* against different levels of capped TV growth rates, lower rates being more strict. The dashed blue line represents *Δ Covariance Risk* without other limitations imposed. The solid red line represents *Δ Covariance Risk* with both other types of limitations imposed at their in-sample median stringency rates. Panels (b) and (c) depict the corresponding relation for rate and levy limitations, respectively.

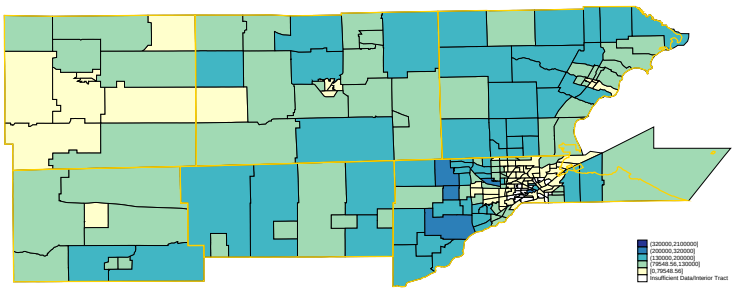
Figure 4: **In-Sample Distribution of Unique Parcels**



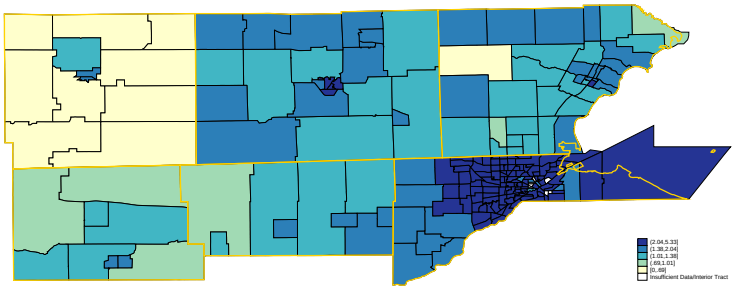
This figure visually illustrates the geographic distribution of sample parcels. Each grid in the map is a border county that contains parcels used in the border discontinuity estimates. Darker blue indicates that the county contains more parcels.

Figure 5: **Local Housing Market Characteristics Across State Borders: MI-OH**

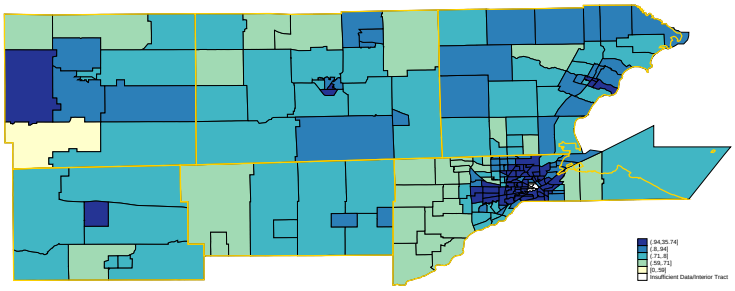
(a) Estimated House Price ($)



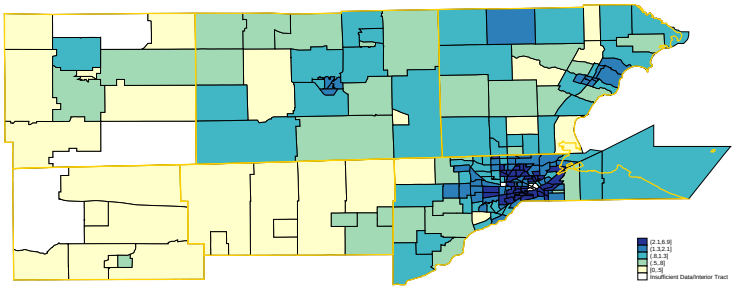
(b) Market ETR (%) - Estimated Prices



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

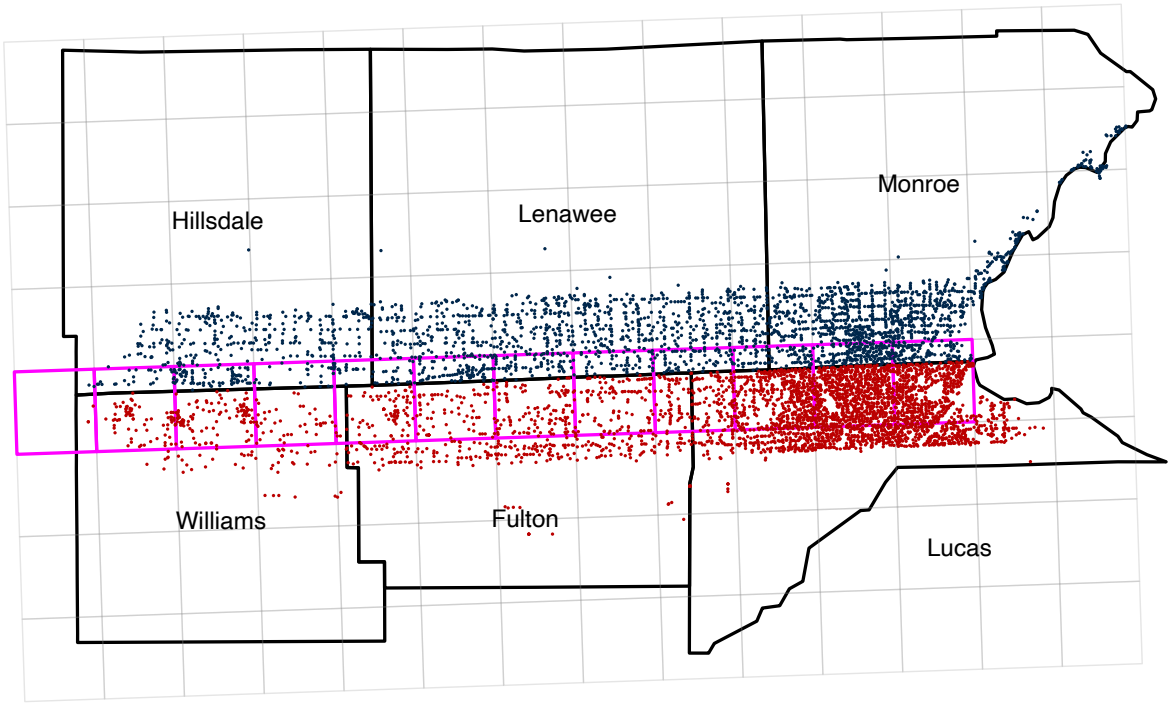


(d) Annual Foreclosure Rate (Parcels)



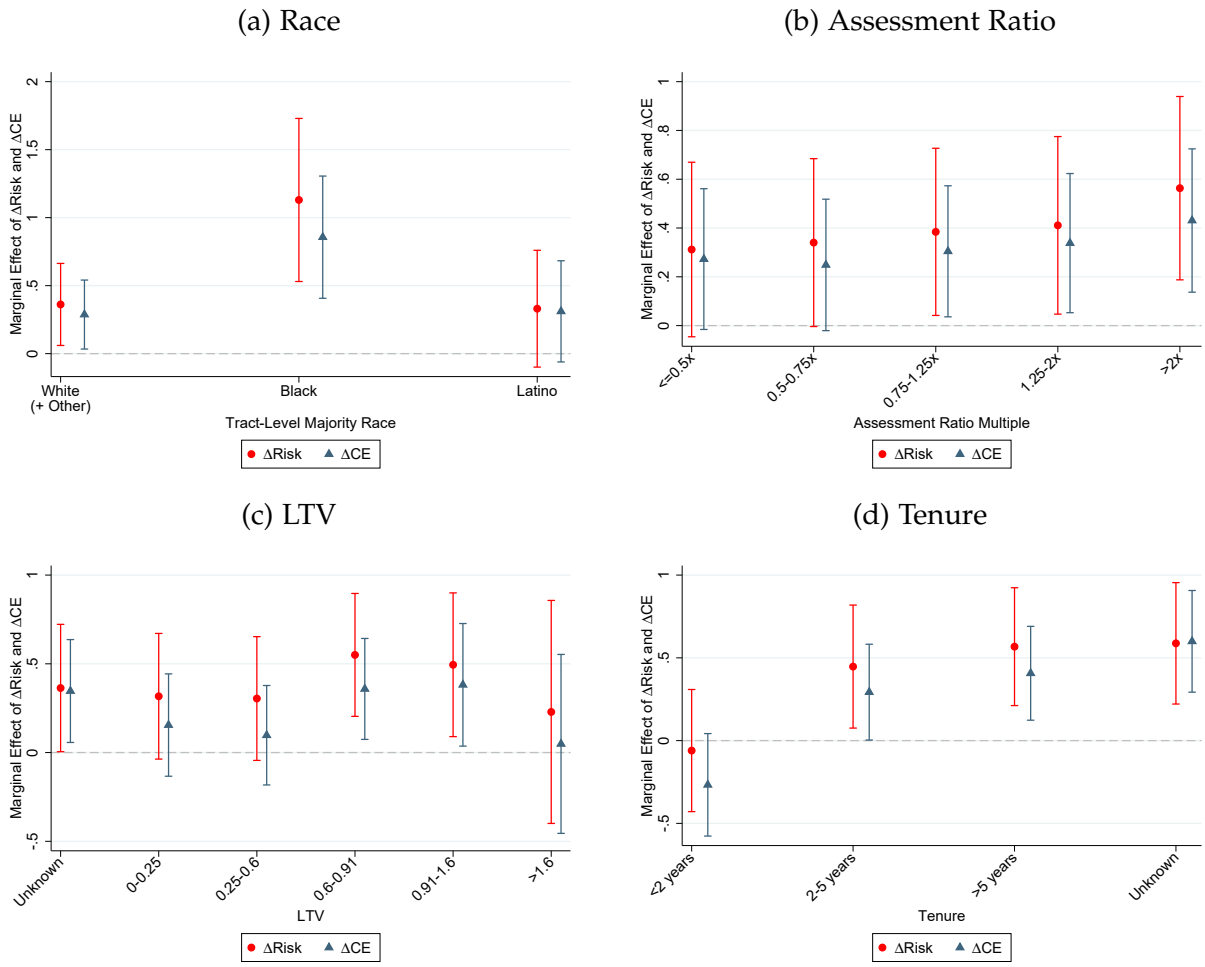
The figure shows median property characteristics in 2015 for all Census tracts located in the six counties at the Michigan-Ohio border. Solid yellow lines are county borders. The state border follows the near-horizontal midsection line. The tight cluster of tracts in the southeast corner of the map is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

Figure 6: **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 7: **Heterogeneous Effects of Δ *Covariance Risk* andΔ *Certainty Equivalent* on Mortgage Distress**



Marginal effects are estimated from extensions of Equation 7 featuring interactions of Δ *Covariance Risk* andΔ *Certainty Equivalent* with (a) binary indicators denoting majority race by Census tract, (b) categorical values of assessment ratio multiples, (c) categorical values of approximate LTV quintiles (plus a sixth category for parcels with unknown LTV), and (d) categorical indicators of homeowner tenure duration. Complete results with the full set of controls and interactions are reported in **Table E.3**. Error bands denote 90% confidence intervals.

Table 1: **State Policy Characteristics - 2016**

State	Assessment Limits	Rate Limits	Levy Limits	Revenue Limits	Reassessment Interval	Lender Recourse	Non-judicial Review
AL		.39%			1	✓	✓
AZ	5%	1%	2%	f(COLA, Population)	1		✓
AR	5%	.2%	10% on reassessment		3	✓	✓
CA	min(2%, CPI), uncapping	1%		f(COLA, Population)	1[a]		✓
CO		*	min(5.5%, Denver urban CPI)	CPI	2	✓	✓
CT				2.6% (Hartford)	5	✓	
DE			15% on reassessment		Not defined	✓	
DC	10%, uncapping	.85%	7%		1	✓	✓
FL	min(3%, CPI), uncapping	3%			1	✓	
GA		.8%			1	✓	✓
ID		1%	3%		1	✓	✓
IL		.33%	min(5%, CPI)		4	✓	
IN		.67%	min(6%, Non-farm income)		1	✓	
IA	3%	1.2%			2		
KS			CPI		1	✓	
KY		3.5%	4%		1	✓	
LA		.16%	0% on reassessment		4	✓	
ME				f(CPI, income, AV)	Not defined	✓	
MD	10%, uncapping				3	✓	
MA		2.5%	2.5%		1	✓	
MI	min(5%, CPI), uncapping	2.5%[b]	CPI	f(Income)	1	✓	✓
MN				f(Tax Capacity)	5		✓
MS			3.2%		4	✓	✓
MO		.52%	min(5%, CPI)		2	✓	✓
MT		10%	half of CPI		2		✓
NE		3.1%		2.5%	1	✓	✓
NV		1.3%	3%		5	✓	✓
NH					5	✓	✓
NJ		2%		min(COLA, 2.5%)	Not defined	✓	
NM	3%, uncapping	1.1%		max(min(5%, urban CPI), 0)	1	✓	
NY		2%	min(2%, CPI)		Not defined	✓	
NC		1.5%			8		✓
ND		1.1%	12%		1		
OH		.35%	0% on reassessment		3	✓	
OK	3%, uncapping	1.5%			1	✓	✓
OR	3%	1.5%			1		✓
PA		13%	wage		Not defined	✓	
RI			4%		3	✓	✓
SC	**, uncapping	***	0% on reassessment[c]		5	✓	
SD		4.6%	min(3%, CPI)		1	✓	
TN			0% on reassessment		5	✓	✓
TX	10%, uncapping	2.6%	8%		3	✓	✓
UT		.39%	0%		1	✓	✓
VT					1	✓	
VA			1% on reassessment		4	✓	✓
WA		1%	min(1%, CPI)		1		✓
WV		.9%	1%		1	✓	✓
WI			0%	f(State aids, # of pupils)	5		
WY		.65%			1	✓	✓

[*] For local governments, the tax rate is capped at the prior year's rate, effectively a 0% growth limit. For school districts, the tax rate is capped at the lesser of the prior year's rate and 27 mills. [**] 15% over 5 years. [***] Tax rates cannot grow faster than CPI.
[a] California only reassesses properties upon sale. Conditional on sale, however, appraisal frequency is implicitly annual.
[b] Michigan has a 15-mill limit subject to voter override up to 50 mills. With an assessment ratio of 50%, the effective binding limit is 2.5%.
[c] Technically implemented as a "rollback millage" – rates must be rolled back after county reassessment so that tax revenues remain at the level of prior years (adjusted for new construction/improvements).

This table describes the high-level summary of key features of states' policy regimes as of 2016. Implementation rules appear as percentages and/or formulas (e.g., f(·)). For assessment limits, percentages refer to the maximum annual growth rate of taxable values, with "uncapping" indicating that taxable values reset to market value upon sale. Rate limits typically restrict the maximum millage rate on taxable values. These are converted to effective tax rates (as a percent of fair market value) for comparability across states. Levy limits restrict the annual growth rate of aggregate local tax revenues, where "on reassessment" indicates that the limit only applies following a community-wide reassessment. Revenue limits are treated analogously to levy limits (despite applying to a broader range of tax instruments). See Section 2 for more detailed descriptions.

Table 2: **Summary Statistics**

	I[Distress]=0			I[Distress]=1			
Variable	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.	Diff.
$\Delta CovarianceRisk$ ($000s)	0.355	0.275	0.333	0.351	0.275	0.309	-0.004
Δ *Certainty Equivalent* ($000s)	-9.539	-3.751	14.058	-9.197	-4.086	12.761	0.342
Δ *Covariance Risk* (Standardized)	0.000	-0.238	1.001	-0.011	-0.238	0.930	-0.012
Δ *Certainty Equivalent* (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			

This table provides summary statistics for key variables using our main estimation sample. Statistics are presented separately for non-distressed and distressed properties. Δ *Covariance Risk* is the amount of money an average property owner would be willing to pay per year to do away with the risk induced by state-specific limitation policies. Δ *Certainty Equivalent* is the amount of money an average property owner saves per year due to state-specific limitation policies. See Section 3 for detailed descriptions of the construction of these two variables. Price is inferred using a combination of methods involving interpolation of transaction values and a machine learning hedonic estimation procedure detailed in Appendix B.

Table 3: **Determinants of Δ *Covariance Risk* and Δ *Certainty Equivalent***

Dependent variable:	Δ *Covariance Risk* (1)	Δ *Certainty Equivalent* (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. Δ *Covariance Risk* and Δ *Certainty Equivalent* are calculated at the state-policy year level as described in Section 3 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 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 4: **Mortgage Distress and Δ *Covariance Risk***

$Y = Pr(Distressed_t = 1), Y \in \{0, 100\}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ *Covariance 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)
Δ *Certainty Equivalent*	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. Δ *Covariance Risk* and Δ *Certainty Equivalent* are calculated at the state-policy year level as described in Section 3 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 with the full set of controls and interactions are reported in **Table E.2**.

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

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Appendix A Simulation Procedure

This section describes the detailed procedure for our tax simulation. The simulation captures two aspects of property tax Δ *Covariance 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 *covariance risk* associated with different states' applicable tax limits and other 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 t). 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:

$$g_t = \beta_1 + \beta_2 g_{t-1} + \epsilon_t,$$

where g_t is the growth of the personal consumption expenditure (linecode = 1) 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% (the average of past recessions) during recessions. Put together, we simulate the aggregate consumption shock as the following:

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

$$\tilde{g}_t = \hat{g}_t + \hat{\sigma}_\epsilon \tilde{\chi}_1 - 0.06 \cdot \tilde{\chi}_2,$$

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

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:

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

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 occasionally producing extreme values and yields 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:

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

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 Δ *Covariance 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:

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

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 the 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 t in the simulated economy – one based on all applicable property tax policies in state-year s (e.g., the tax limitation policy in California in 2016) 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-year s. 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, $h_{i,t}$, is positive, the assessed value in the next year changes (grows) by $h_{i,t}$; 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 $h_{i,t}$. 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_t. 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 the application of assessment limitations to the property throughout the tenure of the new owner.

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-year s to calculate property tax liability for each property i in simulation year t. We then assume that states target 80% of the revenue growth of g_t (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) 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, $x_{i,t}^{\text{Limit}_s}$, for property i in simulation year t subject to the tax limitation policy regime in state-year s to be the product of the taxable value and the dynamic millage rate. We also calculate a counterfactual property tax amount $x_{i,t}^{\text{NoLimit}_s}$ assuming no tax limitations and annual reassessments following the same consumption-tracking logic.

• Pricing Property Taxes and Isolating Policy Risk

For each property i in year t, 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 (different values produce qualitatively

similar results in the empirical analysis since the main independent variable of interest is standardized). The pricing kernel for property i in year t 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 t as $T_{i,t}$. Throughout homeowners' tenure, the total state price of taxes for property i in simulation year z under the policy in state s and year t is:

$$\mathbb{P}_{i,t}^{\text{Limit}_s} = \sum_{j=t-T_{i,t}}^{t} p_{i,j} x_{i,t}^{\text{Limit}_s}$$

We further decompose the total state price of taxes into a *certainty equivalent* component:

$$\mathbb{C}_{i,t}^{\text{Limit}_s} = \sum_{j=t-T_{i,t}}^{t} p_{i,j} \bar{x}_{i,j}^{\text{Limit}_s},$$

where $\bar{q}_{i,j}$ is the average property tax payment throughout homeowners' tenure, and a *covariance risk* component:

$$\mathbb{R}_{i,t}^{\text{Limit}_s} = \sum_{j=t-T_{i,t}}^{t} p_{i,j} (x_{i,j}^{\text{Limit}_s} - \bar{x}_{i,j}^{\text{Limit}_s}).$$

By construction, $\mathbb{P}_{i,t}^{\text{Limit}_s} = \mathbb{C}_{i,t}^{\text{Limit}_s} + \mathbb{R}_{i,t}^{\text{Limit}_s}$. We also apply the same pricing kernel to the counterfactual property tax without tax limitations, $x_{i,t}^{\text{NoLimit}_s}$, and obtain the counterfactual version of $\mathbb{P}_{i,t}^{\text{Limit}_s}$, $\mathbb{C}_{i,t}^{\text{Limit}_s}$, and $\mathbb{R}_{i,t}^{\text{Limit}_s}$. The risk induced by states' property tax system characteristics, or *covariance risk*, is then:

$$\textit{Δ Covariance Risk}_s = \Delta\mathbb{R}^s = \mathbb{R}^{\text{Limit}_s} - \mathbb{R}^{\text{NoLimit}_s},$$

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., $t < 20$) 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., $T_{i,t} > 15$) to avoid potential outliers driving the simulation results.

Lastly, we average across the remaining observations in the simulated property panel to obtain one value, $\Delta\mathbb{R}^s$, that captures the Δ *Covariance 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 conduct a validation exercise to confirm how accurately our simulation captures the property tax policy dynamic in the real world. State by state, we apply the tax policy process described above to the property values, obtain a series of simulated property taxes (using the real property value data), and compare the series of simulated and empirically observed property taxes. We restrict this validation exercise to states with over 70% observations having non-missing property values and property taxes. The correlation between the two series ranges from 0.73 (PA) to 0.97 (MO).

Appendix B 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

[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.

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 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:

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

[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.

where Y is the prediction from the gradient boosting regression tree. We calculate $\hat{Y} = \hat{\beta}_0 + \hat{\beta}_1 \text{Year}$ 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 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 C 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

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

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 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

[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.

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 1^{st} percentile or above the 99^{th} 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

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

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 4 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.

Appendix D Estimates on Changes in Property Tax Payment

In this appendix, we perform a naive approach to estimate the relation between property taxes and mortgage distress. We examine how year-over-year changes in property tax liabilities affect the distress probability. This analysis allows us to benchmark our empirical strategy against previous studies such as Hayashi (2020) and Wong (2020). It also highlights the advantages of our novel measure *Δ Covariance Risk*.

We calculate parcel-level percentage changes in property tax liability compared to the previous year $\%\Delta Tax$. We repeat the empirical specifications in **Table 4** but use $\%\Delta Tax$ as the main independent variable. **Table E.1** presents the results. Under the most narrowly identified specification in Column 8, a one standard deviation increase in $\%\Delta Tax$ (i.e., a 17.3 percent increase in tax liability, or $590) implies a 0.06 percentage point increase in the probability of distress (4.2 percent). Equivalently, this implies that a $1,000 increase in annual tax liabilities raises the probability of distress by 7.2 percent.

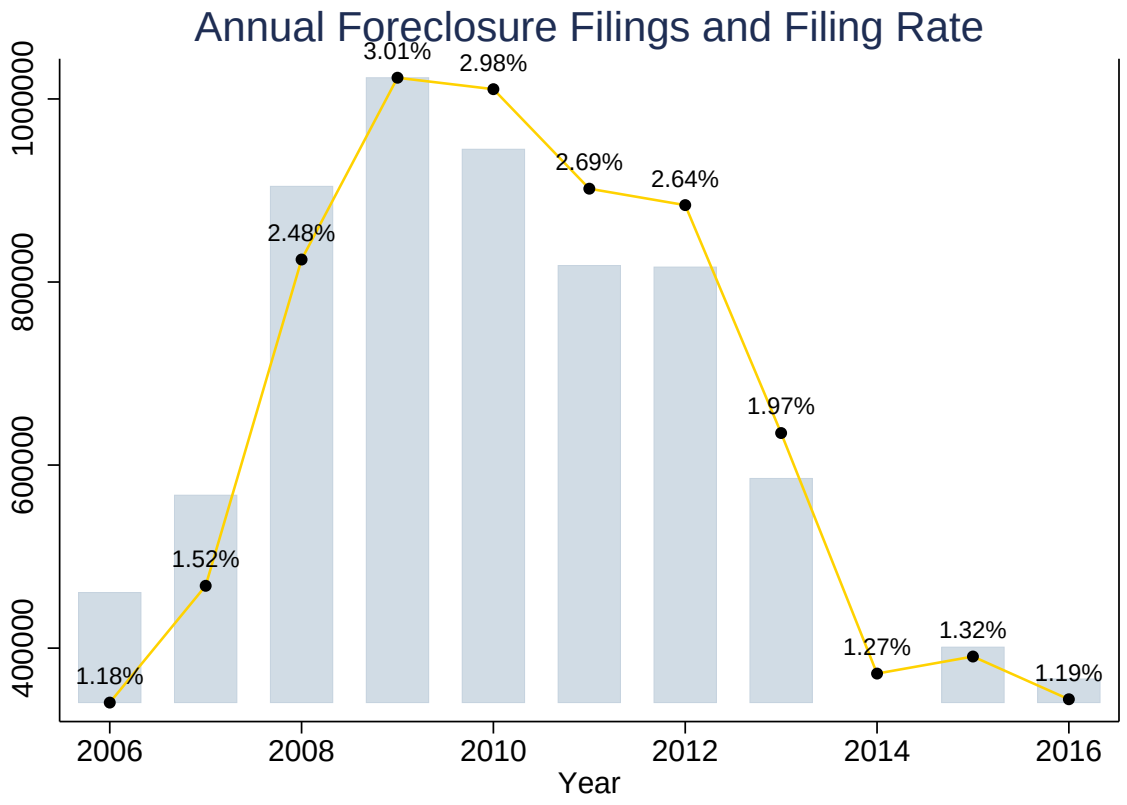
This magnitude is comparable to related work. For comparison, Hayashi (2020) finds that a $1,000 increase in annual tax payments results in a 0.1 percentage point (5.6 percent) increase in the probability of mortgage default due to property reassessments in Maryland. Wong (2020) extends a similar analysis 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. We note that a direct comparison of effect sizes is complicated because 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.

Examining the effect of changes in tax payments on mortgage distress nevertheless neglects two important considerations. First, 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.). Second, 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 timing effect represents a source of risk different from pure changes in the level of payment. It is therefore difficult to pinpoint the effects of specific policies by focusing on changes in tax payments. We address the first of these deficiencies with a property tax simulation in Section 3.3 in which we fix economic conditions and abstract from endogenous variation in observed liabilities. We address the second deficiency with an Arrow-Debreu decomposition of simulated liabilities in Section 3.1.

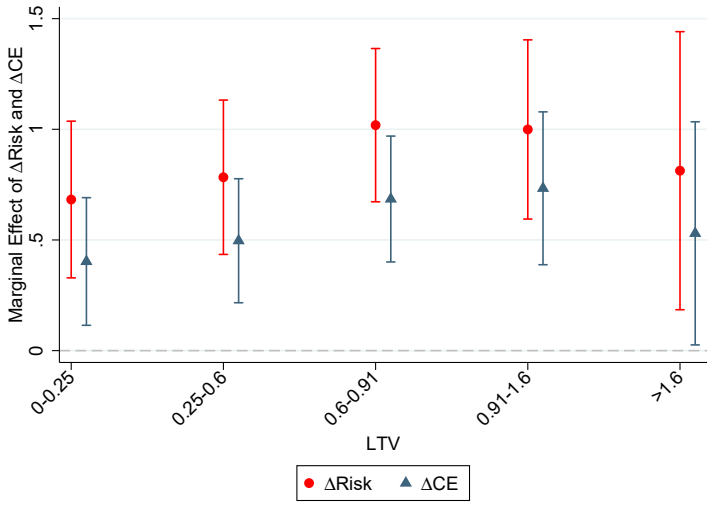
Appendix E Appendix Figures and Tables

Figure E.1: **Trends in National Foreclosure Activity**



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

Figure E.2: **Marginal Effects of Δ *Covariance Risk* and Δ *Certainty Equivalent* as a Function of Parcel-Level LTV**



Marginal effects are estimated from a model featuring interactions of Δ *Covariance Risk* and Δ *Certainty Equivalent* with categorical LTV indicators by approximate LTV quintile. Parcels with unknown LTV are excluded from the analysis. Complete results are reported in **Table E.3**. Error bands denote 90% confidence intervals.

Table E.1: **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 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	31,209,231			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 km² 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 including the full set of controls and interactions (comparable to **Table E.2**) are not reported and available upon request.

Table E.2: **Mortgage Distress and Δ *Covariance Risk*, Full Estimates**

$Y = Pr(Distressed_t = 1), Y \in \{0, 100\}$	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Δ *Covariance 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)
Δ *Certainty Equivalent*	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 km² grid FE				x	x	x		
10 km² grid × 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 km² grid cell, depending on the fixed effects employed. *Δ Covariance Risk* and *Δ Certainty Equivalent* are calculated at the state-policy year level as described in Section 3 and both are standardized to have an in-sample mean value of 0 and standard deviation of 1.

Table E.3: **Mortgage Distress and Δ *Covariance Risk* – Heterogeneous Effect, Full Estimates**

$Y = Pr(Distressed_t = 1), Y \in \{0, 100\}$	(1)	(2)	(3)	(4)
Δ *Covariance Risk*	0.342	0.312	0.229	-0.060
	(0.209)	(0.217)	(0.382)	(0.224)
Δ *Certainty Equivalent*	0.265	0.273	0.049	-0.267
	(0.172)	(0.175)	(0.306)	(0.188)
I[HighAGI=1]	-0.013			
	(0.075)			
I[HighAGI=1] $\times$ Δ *Covariance Risk*	0.030			
	(0.069)			
I[HighAGI=1] $\times$ Δ *Certainty Equivalent*	0.033			
	(0.068)			
I[MajorityBlack=1]	0.808*			
	(0.469)			
I[MajorityBlack=1] $\times$ Δ *Covariance Risk*	0.782***			
	(0.207)			
I[MajorityBlack=1] $\times$ Δ *Certainty Equivalent*	0.584***			
	(0.163)			
I[MajorityLatino=1]	-0.372			
	(0.261)			
I[MajorityLatino=1] $\times$ Δ *Covariance Risk*	-0.016			
	(0.181)			
I[MajorityLatino=1] $\times$ Δ *Certainty Equivalent*	0.041			
	(0.152)			
AR $\times$ Δ *Covariance Risk*				
$\leq 0.5\times$				
$0.5 - 0.75\times$		0.028		
		(0.039)		
$0.75 - 1.25\times$		0.072		
		(0.060)		
$1.25 - 2\times$		0.099		
		(0.076)		
$> 2\times$		0.251***		
		(0.080)		
AR $\times$ Δ *Certainty Equivalent*				
$\leq 0.5\times$				
$0.5 - 0.75\times$		-0.024		
		(0.050)		
$0.75 - 1.25\times$		0.032		
		(0.064)		
$1.25 - 2\times$		0.065		
		(0.076)		
$> 2\times$		0.158**		
		(0.068)		
LTV $\times$ Δ *Covariance Risk*				
0 - 0.25			0.088	
			(0.348)	
0.25 - 0.6			0.076	
			(0.353)	
0.6 - 0.91			0.321	
			(0.333)	
0.91 - 1.6			0.266	
			(0.244)	
> 1.6				
Unknown			0.135	
			(0.355)	
LTV $\times$ Δ *Certainty Equivalent*				
0 - 0.25			0.106	

Continued on next page

	(1)	(2)	(3)	(4)
			(0.288)	
0.25 - 0.6			0.049	
			(0.289)	
0.6 - 0.91			0.310	
			(0.272)	
0.91 - 1.6			0.333	
			(0.204)	
> 1.6				
Unknown			0.298	
			(0.297)	
Tenure $\times$ Δ *Covariance Risk*				
$<$ 2 years				
2-5 years				0.507***
				(0.097)
$>$ 5 years				0.628***
				(0.111)
Unknown				0.648***
				(0.156)
Tenure $\times$ Δ *Certainty Equivalent*				
$<$ 2 years				
2-5 years				0.560***
				(0.086)
$>$ 5 years				0.674***
				(0.123)
Unknown				0.867***
				(0.172)
I[Recourse=1] $\times$ I[HighAGI=1]	-0.169**			
	(0.069)			
I[NonJudicialReview=1] $\times$ I[HighAGI=1]	0.011			
	(0.070)			
I[Recourse=1] $\times$ I[MajorityBlack=1]	-0.638			
	(0.464)			
I[NonJudicialReview=1] $\times$ I[MajorityBlack=1]	-0.132			
	(0.120)			
I[Recourse=1] $\times$ I[MajorityLatino=1]	0.297			
	(0.250)			
I[NonJudicialReview=1] $\times$ I[MajorityLatino=1]	0.497**			
	(0.211)			
I[Recourse=1] $\times$ AR				
$\leq 0.5\times$				
$0.5 - 0.75\times$		0.151***		
		(0.058)		
$0.75 - 1.25\times$		0.059		
		(0.062)		
$1.25 - 2\times$		0.112		
		(0.076)		
$> 2\times$		0.366***		
		(0.090)		
I[NonJudicialReview=1] $\times$ AR				
$\leq 0.5\times$				
$0.5 - 0.75\times$		0.209***		
		(0.061)		
$0.75 - 1.25\times$		0.134**		
		(0.064)		
$1.25 - 2\times$		0.166**		
		(0.067)		
$> 2\times$		-0.112		
		(0.070)		

Continued on next page

	(1)	(2)	(3)	(4)
I[Recourse=1] × LTV				
0.25 - 0.6			0.015	
			(0.060)	
0.6 - 0.91			0.040	
			(0.102)	
0.91 - 1.6			-0.075	
			(0.188)	
> 1.6			-0.033	
			(0.261)	
Unknown			-0.254	
			(0.182)	
I[NonJudicialReview=1] × LTV				
0.25 - 0.6			0.117**	
			(0.050)	
0.6 - 0.91			0.141	
			(0.090)	
0.91 - 1.6			0.431**	
			(0.168)	
> 1.6			0.231	
			(0.237)	
Unknown			-0.571***	
			(0.189)	
I[Recourse=1] × Tenure				
< 2 years				-0.245*
				(0.131)
2-5 years				-0.072
				(0.078)
Unknown				-0.363**
				(0.183)
I[NonJudicialReview=1] × Tenure				
< 2 years				-0.024
				(0.117)
2-5 years				0.027
				(0.089)
Unknown				0.649***
				(0.134)
AR				
$\leq 0.5\times$				
$0.5 - 0.75\times$		-0.192***		
		(0.065)		
$0.75 - 1.25\times$		-0.138**		
		(0.070)		
$1.25 - 2\times$		-0.230***		
		(0.082)		
$> 2\times$		-0.647***		
		(0.099)		
LTV				
0.25 - 0.6	-0.084***	-0.100***	-0.129*	-0.081***
	(0.025)	(0.025)	(0.066)	(0.025)
0.6 - 0.91	0.649***	0.657***	0.562***	0.657***
	(0.042)	(0.042)	(0.108)	(0.042)
0.91 - 1.6	2.249***	2.287***	2.151***	2.264***
	(0.084)	(0.082)	(0.199)	(0.084)
> 1.6	2.838***	2.927***	2.770***	2.862***
	(0.147)	(0.149)	(0.282)	(0.148)
Unknown	-1.622***	-1.716***	-1.214***	-1.608***
	(0.081)	(0.079)	(0.174)	(0.081)
Price	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Lagged ETR	0.024***	0.070***	0.028***	0.024***
	(0.007)	(0.008)	(0.007)	(0.007)
Tenure				

Continued on next page

	(1)	(2)	(3)	(4)
$<$ 2 years	-1.017***	-1.044***	-1.010***	-0.784***
	(0.066)	(0.071)	(0.064)	(0.150)
2-5 years	-0.115***	-0.133***	-0.104***	-0.055
	(0.042)	(0.043)	(0.040)	(0.090)
Unknown	1.487***	1.631***	1.511***	1.634***
	(0.065)	(0.071)	(0.070)	(0.182)
Age				
10-19 years	-0.315***	-0.318***	-0.303***	-0.314***
	(0.032)	(0.032)	(0.032)	(0.032)
20-59 years	-0.284***	-0.290***	-0.269***	-0.293***
	(0.036)	(0.037)	(0.036)	(0.037)
60-99 years	-0.114***	-0.129***	-0.094**	-0.119***
	(0.042)	(0.045)	(0.042)	(0.044)
>99 years	0.036	0.048	0.056	0.028
	(0.059)	(0.058)	(0.062)	(0.061)
Unknown	-0.072	-0.048	-0.039	-0.070
	(0.137)	(0.136)	(0.137)	(0.144)
Renovation Age				
11-32 years	-0.004	-0.004	-0.001	-0.001
	(0.015)	(0.015)	(0.015)	(0.015)
33-59 years	0.079***	0.069***	0.085***	0.082***
	(0.019)	(0.021)	(0.020)	(0.021)
> 59 years	0.247***	0.221***	0.260***	0.258***
	(0.027)	(0.026)	(0.028)	(0.028)
Unknown	-0.466***	-0.255*	-0.460***	-0.459***
	(0.142)	(0.131)	(0.140)	(0.148)
Average AGI	0.001***	0.001***	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Educ $\leq$ HS Pct	0.004**	0.005***	0.005***	0.005***
	(0.002)	(0.002)	(0.002)	(0.002)
Educ $\geq$ Bachelor's Pct	-0.010***	-0.009***	-0.009***	-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	-0.006**	-0.007***	-0.007***	-0.007**
	(0.003)	(0.003)	(0.003)	(0.003)
Black Pct	0.005	0.006**	0.006**	0.006**
	(0.003)	(0.003)	(0.003)	(0.003)
Latino Pct	0.002	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)
Asian Pct	-0.005	-0.007**	-0.007**	-0.007**
	(0.004)	(0.004)	(0.004)	(0.004)
I[Recourse=1]	0.327*	0.005	0.434**	0.307
	(0.182)	(0.204)	(0.204)	(0.198)
I[NonJudicialReview=1]	-0.274	-0.385	-0.031	-0.472
	(0.265)	(0.318)	(0.295)	(0.302)
Observations	31,209,061	30,721,170	31,209,241	31,209,241
R-squared	0.023	0.023	0.023	0.023

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.