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by

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Abstract

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This dissertation establishes that loss aversion fundamentally influences the tax avoidance behavior of property taxpayers. Upon receiving notice of a new assessed value, homeowners have the option to appeal, which, if successful, could lower their tax base. I conjecture that a lagged, salient value—a property's assessed value in the previous year—serves as a natural and prominent reference point to property owners. Guided by a reference-dependent model of assessment protests, I demonstrate various predictions using a sample of 8.2 million administrative property assessment records associated with 1.6 million appeals. Foremost, loss aversion introduces an extensive margin effect around the reference point that induces property owners to disproportionately appeal assessments that have increased relative to the prior tax year. In aggregate, this leads to a sharp kink in the probability of protesting as a function of percent change in assessed value exactly at zero percent change. Additionally, homeowners not only *achieve* but also *seek out* value adjustments that result in a final assessed value precisely at the property's previous assessed value. Evidence is strongest for owner-protesters, for whom the reference point is presumably most relevant. Finally, I employ a simple counterfactual estimation strategy. It suggests that loss aversion has a sizable impact on annual household property taxes, most notably for properties constituting the top quartile of value, while also highlighting the importance of one's position in the loss domain in understanding average effect sizes.

To Gabriela and Nolan.

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Introduction

Models of reference-dependent preferences dating back to prospect theory (Kahneman and Tversky, 1979) are a cornerstone of behavioral economics. In these models, loss aversion[1] generates a distinctive set of predictions. Even though many presume that reference points and loss aversion affect decision-making in a variety of contexts, clearly demonstrating their pervasive influence in natural settings has proven elusive (Barberis, 2013). Considering the essential role of the reference point, surprisingly few field applications pinpoint values that plausibly register as reference points in the minds of individuals.[2] Often, this precludes identification of a broad spectrum of behavior that could be predicted by loss aversion, which to fully distill, necessitates several conditions: (i) a precisely-identified reference point, (ii) a setting involving a choice with both an extensive and intensive margin, and (iii) data precise enough to pinpoint the exact impact of the reference point.[3]

In this dissertation,[4] I consider a setting that satisfies these criteria and present evidence which establishes that loss aversion fundamentally influences the property tax avoidance behavior of homeowners. The first chapter outlines a reference-dependent model of property assessment protests, laying the groundwork for the empirical investigation in Chapter 2. In Chapter 2, I establish evidence of reference-dependence and loss aversion in a sample of 8.2 million annual property assessments.

Upon receiving notice of a new assessed value, a homeowner typically has the option to appeal[5] her property's assessed value, the tax base for the *ad valorem* tax. I conjecture that a property's assessed value in the previous year serves as a salient reference point to property owners, causing them to frame increases in their property's assessed value as a *loss*, and decreases as a *gain*, insofar as taxes are concerned. Property assessment notices, sent to property owners at the beginning of the tax year, prominently display not only the new, proposed assessed value, but also the property's assessed value in the previous year—often quite literally side-by-side. This calls attention to a natural reference point that is likely to make *changes* in assessed value especially salient. Detailed administrative property records, which include information on the initial assessed value, protest choice, and final assessed value, allow me to demonstrate effects associated with both the extensive and intensive margin, using discontinuity and bunching methods. At the same time, the heterogeneity of

[1]Loss aversion refers to the psychological tendency to be more sensitive to losses relative to a reference point than to gains of equivalent size—an unexpected loss of $100 is felt more acutely than an unexpected gain of $100.

[2]For example, Camerer et al. (1997) estimate a negative daily income elasticity positing a daily income target, but it would be dubious to suggest that one could pick out the target used by any individual driver.

[3]Certain tests, such as bunching, are also unavailable if the outcome involves substitution to a consumption dimension that differs from that of the reference point, such as in (Mas, 2006) and (Card and Dahl, 2011).

[4]This dissertation is the basis for the working paper, Jones (2020).

[5]Throughout this paper I use the terms *protest*, *appeal*, and *challenge* interchangeably.

property values allows for precise identification of an individual-specific reference point and granular examination of behavior.

Other features of the setting make it worthy of investigation. Assessing the value of residential property is challenging for several reasons: goods are heterogenous, comparable market transactions can be infrequent, and consumers and taxing authorities may have asymmetric information pertinent to a property's value. Given that valuations are necessarily noisy, the option to protest serves an important function, providing property owners a mechanism to appeal (and thereby potentially change) what they may feel is an inappropriate assessment. In 2017, on average U.S. homeowners paid approximately $3,200 in real estate property taxes, roughly 3% of annual household income;[6] appealing an assessment can reduce a homeowner's tax liability by several hundred dollars or more. Even though appeals are the primary tax avoidance measure available in the setting, and significant economic stakes are involved, little is known about the decision process underlying the choice to protest assessments.[7] This void is somewhat surprising considering that the property tax is commonly cited as the most disliked and unfair tax (Cabral and Hoxby (2018), Sheffrin et al. (2010)).

This study is the first to suggest, examine, and establish the importance of reference-dependence and loss aversion in the context of property taxation. Identifying reference points has proven to be a challenge in applying prospect theory in economics (Barberis, 2013). By suggesting a setting where loss aversion may be not only important, but also detectable, and by identifying *the* relevant reference point, I add to a small, but growing number of studies that provide large-scale field evidence of loss aversion.[8] One of the most closely related studies, Genesove and Mayer (2001), argues that homeowners, when later selling a house, exhibit loss aversion with respect to the price at which they purchased it. Juxtaposed against that result, the findings in this paper might, at first glance, seem paradoxical, and highlight how seemingly related reference points and frames can result in ostensibly contradictory behavior, depending upon the incentives involved.

My findings complement related work that examines reference-dependent behavioral responses to income taxes discussed further in Chapter 2. More broadly, this dissertation adds to an emerging literature in public finance which underscores important ways psychological biases and tax morale mediate behavioral responses to taxes (Luttmer and Singhal (2014), Alm (2019)).[9] Salience and inattention have proven especially important (Chetty et al. (2009), Finkelstein (2009), Goldin and Homonoff (2013), Taubinsky and Rees-Jones (2017)), and recently, have been brought specifically to the context of property taxes (Cabral and Hoxby

[6] In total $>$ 1.2% of GDP (estimated from owners' reported property tax liabilities in the 2018 ACS).

[7] Existing property tax appeals research focuses on assessment accuracy and uniformity (Weber and McMillen (2010), Plummer (2014), McMillen (2013), Avenancio-León and Howard (2020)) and racial disparities in protesting (Doerner and Ihlanfeldt (2014), Grotto (2017), Avenancio-León and Howard (2020)).

[8] In addition to those discussed, there is large-scale field evidence of loss aversion in home-selling behavior (Andersen et al., 2019), the labor supply of taxi-drivers (Camerer et al. (1997), Crawford and Meng (2011), Thakral and Tô (2019)), labor negotiations (Mas, 2006), insurance choice (Sydnor (2010), Barseghyan et al. (2013)), domestic violence resulting from upset football losses (Card and Dahl, 2011), professional golfers' putting accuracy (Pope and Schweitzer, 2011), mergers and acquisitions activity (Baker et al., 2012), marathon runners' finishing times (Markle et al. (2015), Allen et al. (2016)), unemployment exit (DellaVigna et al., 2017), and plastic bag taxes (Homonoff, 2018).

[9] This paper also relates to work examining heuristics used in (i) evaluations of taxes (Ito (2014), Rees-Jones and Taubinsky (2019)) and (ii) property valuation and transactions (Northcraft and Neale (1987), Pope et al. (2015)).

(2018), Bradley (2017), Wong (2020)). Though related to these studies by context, this paper directly informs a larger discussion of the determinants of tax compliance and avoidance, as well as the political acceptability of the property tax.[10] I return to these points in the conclusion of Chapter 2.

0.1 Background on Property Assessment and Assessment Protests

Before introducing a model, a few institutional details are useful to understand. In Section 2.2, I discuss assessment practices and features idiosyncratic to the two Texas counties I study in the empirical analysis. This discussion provides a broader overview.

0.1.1 The Property Assessment Cycle

A typical real estate tax assessment cycle follows a timeline like that in Appendix Figure A.1. First is an *Assessment Period*, during which the county assessor determines each property's market value. Property assessment is a data-driven process based on property characteristics and recent sale prices of nearby properties.[11] Once determined, owners are notified of the proposed *Initial Assessed Value*[12] for the current tax year, and there is a *Protest Period* during which they can declare intent to contest the assessor-determined *Initial Assessed Value*. If contesting, an owner must file a protest by a specified deadline—usually 30-60 days after notification. After the *Protest Period* is a *Resolution Period*, wherein protests are settled, and *Final Assessed Values* are determined. A *Payment Period* concludes the cycle.

In most states, tax payments are due in one or two installments near the end of the tax year. If a homeowner pays for their mortgage through an escrow account, they effectively make monthly tax payments, bundled together with their regular mortgage payments and held by the mortgage servicer until payment is due. Most escrow accounts are updated once annually, adjusting the borrower's monthly payments to appropriately offset any changes in estimated property taxes and property insurance premiums, *in the month after a tax bill for the current year is due* (Wong, 2020).[13] As such, neither lump-sum taxpayers nor escrow-paying taxpayers are likely to face an unexpected shock requiring increased payment immediately after receiving notice of a new assessed value.

The *Protest Period*, *Resolution Period*, and *Payment Period* usually occur annually, but the *Assessment Period* may or may not. Jurisdictions differ, but in most, reassessment occurs at least once every three years, and may occur as often as every year. Significant events like ownership transfer, new construction, or remodeling may trigger a supplementary assessment, but under normal circumstances, the assessed value of a property may not change in consecutive years. Tax *rates* can change from year to year, causing a homeowner's tax liability to change, even if the assessed value does not; however, rates are usually determined after the *Protest Period*.

[10] Chirico et al. (2019) test the effectiveness of alternative nudge strategies in an effort to increase the collection of property taxes in Philadelphia; however, they find reminders which threaten (conventional) economic sanctions to be more effective than reminders which instead coax sentiments intended to increase tax morale.

[11] In-person walk-throughs and drive-bys are less common and less frequent than they used to be.

[12] Sometimes termed the *Notified Value* or *Noticed Value*.

[13] Escrow accounts require payments that leave a buffer to draw upon in case *current year* expenses increase.

0.1.2 Assessment Protests

Protests are resolved in one of two ways. If the grounds for objection are easily verified and undisputed, most assessors will settle the protest informally, not requiring a formal hearing. If an informal appeal is not entertained, is unsuccessful, or is otherwise unsatisfactory, a homeowner may proceed to a formal stage adjudicated by independent reviewers.[14]

In either case, property owners face a cost-benefit analysis. The cost of protesting is primarily effort-based. Minimally, protesting requires a homeowner to complete a form indicating intent to appeal and to provide written explanation detailing the reasons they believe the initial assessment to be incorrect. Broadly, grounds substantiating a reduction include (i) factual inaccuracies in the assessor's records, (ii) idiosyncratic value-based cases, such as documenting unusual depreciation or damage to a property, with descriptions and accompanying photos, or (iii) market-based or uniformity-based appeals, which either argue that the assessor incorrectly valued a neighborhood, or point to discrepancies between an assessed value of a property and the assessed values of comparable properties. Regardless of the basis, gathering tangible evidence that justifies a reduction is imperative for success.[15][16]

An appeal could involve monetary costs as well. Many owners hire a lawyer or tax professional to aid in the process.[17] Others might hire an independent appraiser to walk through the property, including an appraisal as evidence in support of an appeal.

Once a protest is filed, it could take several months before a final determination is made. Benefits vary, but many protests are successful, reducing taxes by several hundred dollars or more. Unsuccessful protest rarely results in a *higher* assessed value, and some jurisdictions explicitly protect homeowners against this possibility.

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[14] Other protest options may also be available—such as bringing a case to civil court—but are rarely exercised.

[15] See, for example, Travis County Standards of Documentation Evidence for Informal and Formal Hearings (Link).

[16] Assessors and review arbiters both emphasize that evidence is necessary for a reduction. Property owners corroborate this view in first-hand accounts online. In a 2015 survey of formal hearing attendees in the counties I study, 95% said that they brought 'documentation' to the formal hearing [$N = 3,754$].

[17] Payment structures for hired third-party representatives vary. Common structures include (i) fixed fee, (ii) fixed fee if an appeal is successful, and (iii) a percentage of the tax reduction achieved if an appeal is successful.

Chapter 1

Reference-Dependent Property Tax Avoidance: A Theoretical Framework

In this chapter, I model the decision to protest a property tax assessment of a property owner whose preferences exhibit reference-dependence and loss aversion. Drawing on theoretical examinations of reference-dependence (e.g. Tversky and Kahneman (1991) and Kőszegi and Rabin (2006)), I introduce a framework that grounds the empirical analysis in Chapter 2.

Incorporating loss aversion with respect to previous assessed value into a property owner's preferences results in a sharp, discontinuous increase in the marginal disutility of paying taxes on an assessed value that exceeds that of the prior year. I focus on two primary behavioral predictions related to the *extensive* margin and *intensive* margin, respectively. First, homeowners who receive an initial assessment that increased relative to the prior year will disproportionately appeal, resulting in a sharp kink in the probability of appealing above zero percent change in initial assessed value. Second, protesting homeowners will disproportionately seek out value adjustments that result in a final assessed value precisely at the reference point. In aggregate, this results in a distribution of changes in final assessed value (relative to previous assessed value) that exhibits excess mass bunched at zero (i.e. no change).

Auxiliary model predictions bolster evidence of the mechanism. The model distinguishes between and predicts both bunching in the distribution of final assessed value and bunching in the distribution of homeowner *opinion of value*. Two other predictions, discussed further in Chapter 2, solidify evidence of the *extensive* margin effect induced by loss aversion.

1.1 A Reference-Dependent Model of Property Assessment Protests

1.1.1 Model Preliminaries

A homeowner has reference-dependent utility over the property taxes she pays T_t in year t, and derives disutility from asserting effort, e_t, if she protests her property's assessed value in an effort to lower her tax liability. Altogether, her utility is given by,

$$u(T_t, e_t | r_t) = v(T_t | r_t) - k(e_t) \tag{1.1}$$

where,

$$v(T_t|r_t) = \begin{cases} -(T_t - r_t) & \text{if } T_t < r_t \quad \text{(Gain Domain)} \\ -\lambda(T_t - r_t) & \text{if } T_t \geq r_t \quad \text{(Loss Domain)} \end{cases} \tag{1.2}$$

represents the *gain-loss utility* from taxes owed *relative to a time-varying reference point*, r_t. Appealing to Rabin's (2000) calibration, utility is piecewise linear on either side of the reference point,[1] with coefficient of loss aversion $\lambda \geq 1$ capturing the extra marginal disutility associated with losses. If the homeowner protests ($e_t > 0$), she incurs an effort cost,

$$k(e_t) = \begin{cases} \kappa + c(e_t) \geq 0 & \text{if } 0 < e_t \leq 1 \quad \text{(Protest)} \\ 0 & \text{if } e_t = 0 \quad \text{(No Protest)} \end{cases} \tag{1.3}$$

which may include a fixed component, $\kappa \geq 0$, and a weakly convex marginal cost, $c(e_t) \geq 0$, with $c'(e_t) \geq 0$, $c''(e_t) \geq 0$, and $c(0) = 0$. Additionally, the homeowner is atomistic to the overall supply of local amenities, which her property taxes presumably finance.

Tax liabilities in year t are described by, $T_t = \tau_t \cdot (V_t + \varepsilon_t)$, where tax rate $\tau_t \in [0, 1]$ is applied to a time-varying *Assessed Value*, $A_t = V_t + \varepsilon_t$ comprised of the *True Value*, V_t, and a noise term, $\varepsilon_t \sim F(\varepsilon_t)$, both known to the homeowner.[2]

The backward-looking reference point is given by, $r_t \equiv \tau_{t-1} \cdot A_{t-1} = T_{t-1}$. Tax rates are typically determined *after* a protest decision must be made; hence, expectations about the current year's tax rate are formed in year t, but before τ_t is realized. To simplify, I assume $\mathbb{E}[\tau_t] = \tau_{t-1}$, allowing me to drop the time subscript on tax rates (suppressed after the next expression), and to define the reference point solely in terms of A_{t-1}. and *gain-loss utility* as,

$$v(A_t|A_{t-1}) = \begin{cases} \tau_{t-1}(A_{t-1} - A_t) & \text{if } A_t < A_{t-1} \\ \lambda\tau_{t-1}(A_{t-1} - A_t) & \text{if } A_t \geq A_{t-1}. \end{cases} \tag{1.4}$$

This is mathematically convenient, but also motivated by two institutional features. First, property tax rates often *do not* change from year to year, which makes the lagged tax rate a reasonable, if heuristic, expectation of the yet-to-be-determined current year's rate. Second, in addition to prominently displaying both the proposed *Initial Assessed Value* and the *Previous Assessed Value*, assessment notices commonly include *estimated tax liabilities* for the current year calculated assuming the *previous year's tax rates*.[3] [4]

[1] Piecewise-linearity is a common assumption in the literature (e.g. Benartzi and Thaler (1995), Card and Dahl (2011), Engström et al. (2015), DellaVigna et al. (2017), Homonoff (2018), Rees-Jones (2018)).

[2] *True Value* connotes a meaning that some may quibble with; consequently, some readers may prefer to think of V_t more agnostically as the component of the assessed value that a protester cannot influence.

[3] Alternatively, property owners might react directly to the *Initial Assessed Value* and *Previous Assessed Value*, deriving utility from changes in assessed value itself (rather than taxes *per se*). Ultimately, this distinction does not affect the model's predictions; moreover, a property owner would presumably only respond this way if they viewed the assessed value as if it sufficiently reflected their tax liability (the outcome we expect ultimately matters to her).

[4] Two additional assumptions are not discussed above. (1) For simplicity, households do not consider the relationship between income taxes and property taxes. For most standard-deduction taking households, this consideration is moot. Even if households consider the relationship, the model's essential predictions would not change, only the effective tax rate. (2) The homeowner is naïve in the sense that she does not anticipate how her current actions will affect her gain-loss utility in future years.

1.1.2 The Homeowner's Protest Choice & Predictions of Minimal Models

I introduce the theoretical predictions progressively, increasing the complexity of protesting in successive model variants. Simulations in Figure 1.2 shows the qualitative predictions of the full *Stochastic Reduction Model*, introduced last. As illustrated, predictions from the simpler models (introduced before the full version) remain intact.

To decide whether or not to protest her *Initial Assessed Value*, the homeowner compares,

(i) Protest *Initial Assessed Value*:

$$u^P(T_t, e_t > 0|r_t) = \begin{cases} \tau\left[(V_{t-1} + \varepsilon_{t-1}) - (V_t + \tilde{\varepsilon}_t)\right] - k(e_t) & \text{if } \tilde{A}_t < A_{t-1} \\ \lambda\tau\left[(V_{t-1} + \varepsilon_{t-1}) - (V_t + \tilde{\varepsilon}_t)\right] - k(e_t) & \text{if } \tilde{A}_t \geq A_{t-1} \end{cases}$$

where $\tilde{\varepsilon}_t$ represents a new noise term associated with a (revised) *Final Assessed Value* $\tilde{A}_t$.

(ii) Accept *Initial Assessed Value* as *Final Assessed Value* (Don't Protest):

$$u^{DP}(T_t, e_t = 0|r_t) = \begin{cases} \tau\left[(V_{t-1} + \varepsilon_{t-1}) - (V_t + \varepsilon_t)\right] & \text{if } A_t < A_{t-1} \\ \lambda\tau\left[(V_{t-1} + \varepsilon_{t-1}) - (V_t + \varepsilon_t)\right] & \text{if } A_t \geq A_{t-1} \end{cases}$$

Fixed Cost Noise Removal Model

The model's first prediction relates to the probability of protesting. To begin, consider a *Fixed Cost Noise Removal Model*, wherein protesting removes the entire noise term from an *Initial Assessed Value*, at the expense of a fixed cost of effort (and hence no intensive effort margin). Table 1.1 summarizes conditions under which the homeowner protests in this minimal model. Figure 1.1 is also instructive, illustrating six cases that enumerate the possible ways A_t, A_{t-1}, and V_t, can be positioned relative to each other.[5]

Proposition 1. *Given a fixed cost of protesting $\kappa > 0$, and holding constant the noise ε_t in her Initial Assessed Value, a homeowner with $\lambda > 1$ is more likely to protest her property's Initial Assessed Value if it has increased relative to the property's Previous Assessed Value, $A_t > A_{t-1}$.*

The intuition is straightforward. Loss aversion causes the marginal benefit of assessment reductions to be greater (by a factor of λ) for each dollar reduced above the property's *Previous Assessed Value*. If the *Final Assessed Value* after reductions is greater than the *Previous Assessed Value*, then the marginal benefit of all reductions are λ-inflated; if, alternatively, the *Final Assessed Value* after reductions is less than the *Previous Assessed Value*, then only part of the reduction benefit is λ-inflated.

Proposition 1 proves difficult to test directly since it necessitates conditioning on ε_t, which may be unobservable. A naïve modification of this proposition might be to assume that the noise term is equal in expectation for those that receive an increase, and those that receive a decrease; however, if, in year t, a homeowner happens to receive a bad (high) noise draw, then not only is it more likely that the protest condition is met, it's also more likely that her *Initial Assessed Value* increased relative to the previous year.[6] As a result, mechanically,

[5] If protesting can only move the homeowner closer to the V_t (as is the case in this *Fixed Cost Noise Removal Model*), only over-assessments are protested (Cases 1, 3, and 4 in Figure 1.1 and Table 1.1).

[6] To illustrate this second point under relatively benign assumptions, let $Cov(\varepsilon_t, \varepsilon_{t-1}) = 0$ and $Cov(\varepsilon_t, \Delta V_t) = 0$. $Cov(\varepsilon_t, \Delta A_t) = Cov(\varepsilon_t, \varepsilon_t) + Cov(\varepsilon_t, \Delta V_t) + Cov(\varepsilon_t, \varepsilon_{t-1}) = Var(\varepsilon_t) > 0$.

the probability of protesting should be positively related to a change in *Initial Assessed Value*, even in a model without loss aversion (where $\lambda = 1$). By contrast, a model with loss aversion predicts that a homeowner will be *disproportionately* more likely to protest if her assessment has increased relative to the previous year, as a *marginal increase* in ε_t will cause a greater change in the probability of protesting if in the loss domain.

Kink Prediction. *Holding constant the fixed cost of protesting κ, if $\lambda > 1$ the slope of the expectation of protesting conditional on a homeowner's percent change in Initial Assessed Value will increase exactly at the reference point, resulting in a probability of protesting that is kinked at zero percent change in Initial Assessed Value. Equivalently, the elasticity of protesting with respect to change in Initial Assessed Value will be discreetly larger above the reference point than below the reference point.*

The kink at the reference point results from an extensive margin effect related to the portion of a potential reduction benefit expected to be λ-inflated. Imagine an owner received an *Initial Assessed Value* one dollar above her *Previous Assessed Value*. Though in the loss domain, her protest behavior will not drastically differ from a similar owner that received an *Initial Assessed Value* just below his *Previous Assessed Value*; even if she protested and received a reduction, only the first dollar reduced has a λ-inflated marginal benefit. In other words, close to the reference point but moving further into the loss domain, there's an extensive margin effect coming from the fact that, on average, the λ-inflated *fraction* of the benefit associated with *potential* reductions increases, inducing more owners to protest on the margin.

Eventually this effect subsides, when increases in assessed value are sufficiently large such that any potential reductions will still leave the homeowner in the loss domain. At that point the slope of the conditional expectation of protesting will flatten, but remain steeper than below the reference point, as the same increase in ε_t is still associated with greater disutility.[7]

Figure 1.2(A) illustrates the kink prediction presenting both the pattern predicted with loss averse owners ($\lambda > 1$) and a counterfactual without loss averse owners ($\lambda = 1$). In the simulation, individual marginal cost parameters, changes in underlying value, and noise terms are all normally distributed; the fixed cost parameter is log-normally distributed. Individual λ's are normally distributed with $\mu_\lambda = 2$ and $\sigma_\lambda = 0.3$. As shown, the probability of protesting increases sharply at zero percent change in assessed value if owners are loss averse, but is smoothly distributed through the reference point if they are not.

Effort-Based Noise Reduction Model

Allowing for an effort margin introduces a second prediction of loss aversion. Minimally extending the fixed cost model above, consider an *Effort-Based Noise Reduction Model*, which incorporates effort, $e_t \in [0, 1]$, by having the reduction a protester receives be a fraction of the initial noise term, exactly proportional to the effort asserted such that protesting removes $e\epsilon_t$ from an initial assessment. If the amount of effort asserted is related to the reduction

[7] Engström et al. (2015) present a model with a similar prediction about the probability of claiming an income tax deduction of fixed size δ (and tax rate τ). This leads to a sharp second kink in the loss domain $\tau\delta$ dollars above the reference point. Here, a homeowner's reduction is varying in size based on the random draw ε_t; as a result, there is an analogous "second kink" in the conditional probability of protesting, but its position harder to pin down.

achieved, then we should expect *some* loss averse homeowners to pursue reductions only up to the point where the marginal benefit drops.

Bunching Prediction. *If $\lambda > 1$, homeowners will seek value reductions that result in a Final Assessed Value exactly at their Previous Assessed Value, resulting in final distribution that exhibits bunching at no change in Final Assessed Value (the reference point).*

This allows for an interior optimal effort associated with pursuing a revised assessed value exactly equal to the *Previous Assessed Value*, resulting in excess bunching at the *Previous Assessed Value* in the distribution of *Final Assessed Value*. Figure 1.2(B) illustrates the bunching prediction, showing an initial distribution of assessed values (in grey), and a final distribution of assessed values (in blue). The pink line shows the counterfactual final distribution predicted if owners were not loss averse, which, in addition to having a shifted pattern of mass relative to the loss averse case, is clearly void of bunching.

1.1.3 The Extensive Margin & Conditional Average Reductions

Another prediction of the reference-dependence model relates to the average reduction received by homeowners that protested. Without loss aversion, we would expect the average reduction received by protesters to be increasing but smooth around the reference point.

Loss aversion induces both an *intensive* and *extensive* margin effect. Assuming some margin for effort, holding constant the amount of noise in an assessment, the *intensive* margin effect induces homeowners that would have protested in the absence of loss aversion to seek a weakly larger reduction. Meanwhile, the *extensive* margin effect induces homeowners that *would not* have protested in the absence of loss aversion to seek a reduction—at the margin, for a reduction amount that they would not find worthwhile in the gain domain. If the extensive margin effect is sufficiently large, it can lead to a distinct pattern wherein the conditional (on protesting) average reduction received by protesters (or successful protesters) just barely in the loss domain is less than the average reduction received by those just barely in the gain domain. Figure 1.2(C) illustrates this point, leading to another testable prediction for the empirical analysis.

1.1.4 Stochastic Reduction Model

The predictions so far ground the empirical analysis, but the minimal models above ignore the uncertainty a homeowner faces when deciding to protest. Other somewhat unattractive features are that (i) owners only protest if over-assessed, and (ii) they never achieve a *Final Assessed Value* below V_t.

Adding uncertainty inherent to the protest reduction process, I extend the model by specifying the role of effort and introducing stochastic reductions as follows. As before, a homeowner is provided an *Initial Assessed Value* in the beginning of the year which they may optionally protest. By protesting, the homeowner can receive a new noise draw $\tilde{\varepsilon}_t$, which would replace the initial noise draw ε_t, resulting in a *Revised Final Assessed Value*, $\tilde{A}_t = V_t + \tilde{\varepsilon}_t$. The new noise draw is assumed to have a *latent* value, $\tilde{\varepsilon}_t^{\ell}$, drawn from the same distribution as the original noise draw, with CDF $F(\varepsilon_t) = F(\tilde{\varepsilon}_t^{\ell})$;[8] however, the *realized* value of the new noise

[8] And associated PDF $f(\tilde{\varepsilon}_t^{\ell}) = f(\varepsilon_t)$.

draw is censored above by ε_t—the initial noise draw that can be protested—and censored below by the quantile of $(1-e_t)$. Formally, letting $Q(p) \equiv F^{-1}(p)$ represent the quantile function, and, $q(p) \equiv Q'(p)$, the realized value of $\tilde{\varepsilon}_t$ is given by,

$$\tilde{\varepsilon}_t = \begin{cases} Q(1-e_t) & \text{if } \tilde{\varepsilon}_t^{\ell} \leq Q(1-e_t) \\ \tilde{\varepsilon}_t^{\ell} & \text{if } Q(1-e_t) < \tilde{\varepsilon}_t^{\ell} < \varepsilon_t \\ \varepsilon_t & \text{if } \tilde{\varepsilon}_t^{\ell} \geq \varepsilon_t. \end{cases}$$

As such, protesting and exerting effort e_t will, at worst, result in no change in value, and at best, result in a new $\tilde{\varepsilon}_t$ equal to $Q(1-e_t)$.

Specified this way, the model captures several elements of the environment. We can think of $\Delta A_t^O \equiv Q(1-e_t) - \varepsilon_t$ as the reduction in value that a homeowner argues for during the protest process, superscripted with O to denote a proposed *opinion*. At most, she will achieve that change in value; however, the assessor or arbiter may not agree, resulting in a final reduction that is smaller than the protester's proposal. All else equal, this results in a probability of successful reduction that increases in conjunction with the original draw ε_t; in other words, the homeowner is more likely to win if over-assessed by a larger amount. Simultaneously, reductions are censored above the original draw to reflect the fact that in most jurisdictions, property owners are implicitly (if not explicitly) protected against increases resulting from the appeals process. Altogether, homeowners face a stochastic environment that may result in a full, partial, or no reduction vis-a-vis their proposal.

Expected Benefit of Protesting

Additional details concerning the *Stochastic Reduction Model* are detailed in Appendix 1.4.3. Here I highlight the essential features. Defining $A_t^O \equiv V_t + Q(1-e_t)$ as the homeowner's proposed opinion of assessed value, and letting $\tilde{\varepsilon}_t^r = (V_{t-1} + \varepsilon_{t-1}) - (V_t)$ represent the threshold $\tilde{\varepsilon}_t$ draw that separates the gain domain from the loss domain, the expected utility benefit associated with a reduction in assessed value can be described as follows.

Case A(i): $A_t \geq A_{t-1}$, $A_t^O \leq A_{t-1}$

$$(1-e_t^*) \times [\tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t + Q(1-e_t^*))]] + \int_{Q(1-e_t^*)}^{\tilde{\varepsilon}_t^r} \tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t + \tilde{\varepsilon}_t)] \, dF(\tilde{\varepsilon}) + \int_{\tilde{\varepsilon}_t^r}^{\varepsilon_t} \lambda\tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t + \tilde{\varepsilon}_t)] \, dF(\tilde{\varepsilon}) + [1 - F(\varepsilon_t)] \times [\lambda\tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t + \varepsilon_t)]] \quad (1.5)$$

Case A(ii): $A_t \geq A_{t-1}$, $A_t^O \geq A_{t-1}$

$$(1-e_t^*) \times [\lambda\tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t + Q(1-e_t^*))]] + \int_{Q(1-e_t^*)}^{\varepsilon_t} \lambda\tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t + \tilde{\varepsilon}_t)] \, dF(\tilde{\varepsilon}) + [1 - F(\varepsilon_t)] \times [\lambda\tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t + \varepsilon_t)]] \quad (1.6)$$

Case B: $A_t^O < A_t \leq A_{t-1}$

$$(1-e_t^*) \times [\tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t + Q(1-e_t^*))]] + \int_{Q(1-e_t^*)}^{\varepsilon_t} \tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t+\tilde{\varepsilon}_t)] \, dF(\tilde{\varepsilon}) + [1-F(\varepsilon_t)] \times [\tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t+\varepsilon_t)]] \quad (1.7)$$

In each case, the homeowner will only protest if the expected benefit of protesting, net of the cost of effort, is greater than the alternative status quo utility. Setting aside bunching behavior momentarily, an optimal interior solution will choose effort e_t^* satisfying the first order condition that equates the marginal cost of effort to the marginal benefit, which as derived in Appendix 1.4.3, is given by,

$$MB_{e_t}^{A(i)} = \tau(1-e_t^*) \cdot q(1-e_t^*) \quad (1.8)$$

$$MB_{e_t}^{A(ii)} = \lambda\tau(1-e_t^*) \cdot q(1-e_t^*) \quad (1.9)$$

$$MB_{e_t}^{B} = \tau(1-e_t^*) \cdot q(1-e_t^*). \quad (1.10)$$

As is evident, the expected marginal benefit of attempting to achieve a reduction less than the reference point is lower by a factor of λ, as is the case in the simpler minimal models.

The *Stochastic Reduction Model* gives rise to a second bunching prediction.

Opinion Bunching Prediction. *If $\lambda > 1$, homeowners will propose Opinions of Assessed Value equal to their Previous Assessed Value, resulting in a distribution of protester's Opinion of Assessed Value that exhibits bunching at the Previous Assessed Value (the reference point).*

The original, revised final assessed value bunching prediction is preserved because bunching in the distribution of opinions leads to bunching in the distribution of final outcomes. Figure 1.2(D) illustrates the opinion bunching prediction, along with the final-outcome bunching that it generates. It shows the simulated distributions of (i) protesters' *Initial Assessed Value* (in grey), (ii) protesters' *Opinion of Value* (outlined in navy), and (iii) protesters' *Final Assessed Value* (in red). As specified, bunching in the distribution of *Opinion of Value* is necessarily larger than bunching in the distribution of *Final Assessed Value*.

1.2 Alternative Models Operating Through Effort Cost Function

When interpreting empirical evidence, a natural question is whether observed behavior results from property owner loss aversion and not the difficulty of obtaining a revised assessment below its previous value. In this section, I briefly distinguish the behavior predicted of loss averse property owners to the behavior predicted of alternative models in which reference-dependence instead affects the effort cost function. As shown in Chapter 2, the empirical results better align with loss aversion.

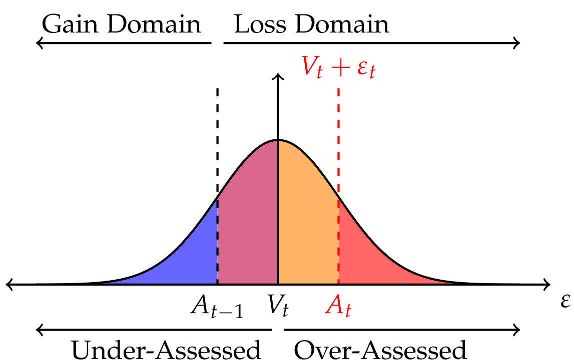
Figure 1.4 shows simulated behavior of property owners who are not loss averse, but who face an effort cost function that ratchets up for reductions sought below the reference point. In other words, one must pay an additional fixed cost if seeking a reduction below the previous value. Everything else about the nature of protesting follows the *Stochastic Reduction Model* outlined in the previous section. As shown, a notch in the effort cost function results in a kink in the probability of protest, but the kink is to the right of the reference point. Similarly, a drop in average conditional reductions occurs to the right of the reference point, but not immediately (as is the case with loss averse property owners). Additionally, there is substantial missing mass below the reference point in the distribution of *Final Assessed Values* as many protesters avoid the additional fixed cost associated with proposing a value below the reference point.

Figure 1.5 shows simulated behavior of property owners who are not loss averse, but who face an effort cost function that kinks—reflecting a discrete increase in the marginal cost of effort for reductions sought below the reference point. Such a model, while producing behavior that is similar to that of the loss averse property owner model, does not exhibit a sharp extensive margin kink in the probability of protesting.

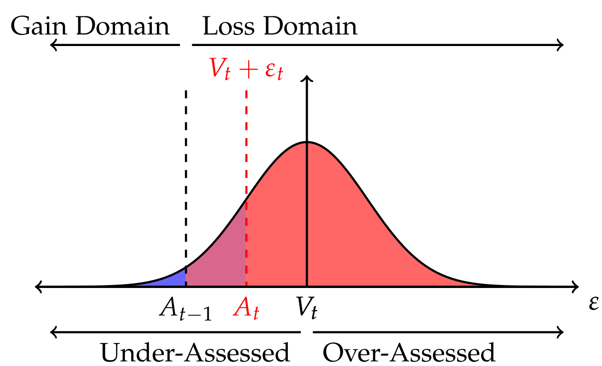
1.3 Figures

Figure 1.1: Illustrations of six assessment cases with a normal noise distribution.

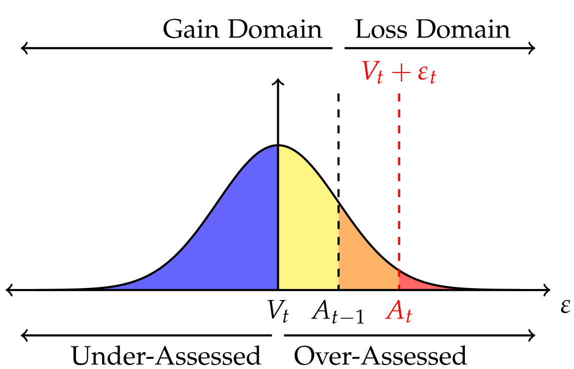
Case 1: Assessed Value Increased, Over-Assessed, True Value in Loss Domain



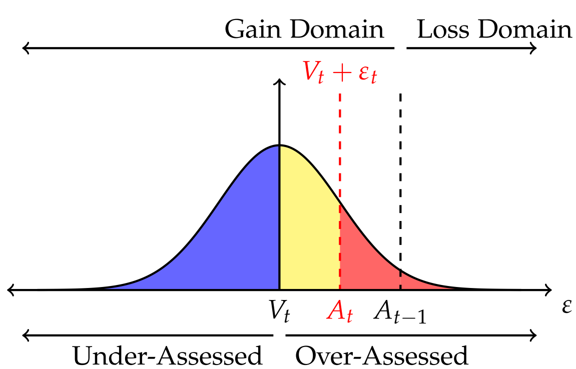
Case 2: Assessed Value Increased, Under-Assessed, True Value in Loss Domain



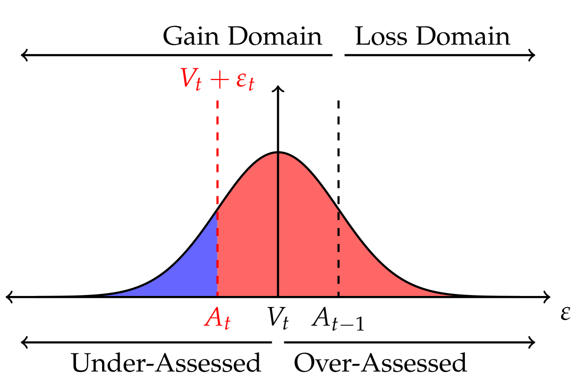
Case 3: Assessed Value Increased, Over-Assessed, True Value in Gain Domain



Case 4: Assessed Value Decreased, Over-Assessed, True Value in Gain Domain



Case 5: Assessed Value Decreased, Under-Assessed, True Value in Gain Domain



Case 6: Assessed Value Decreased, Under-Assessed, True Value in Loss Domain

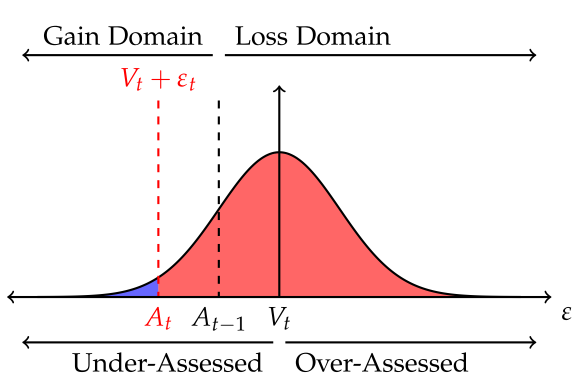
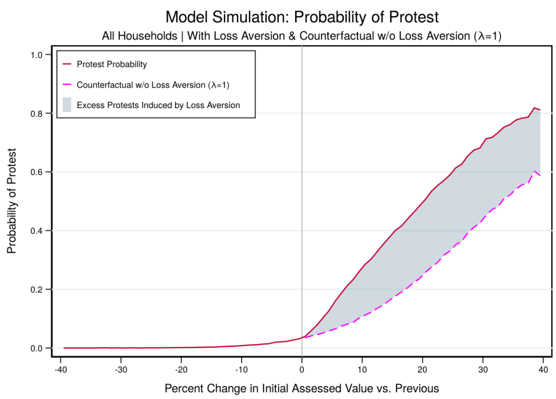
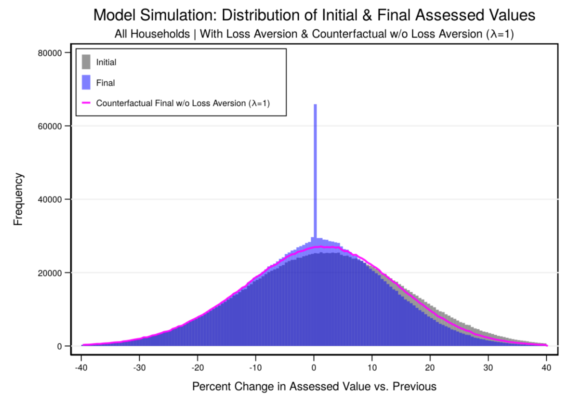


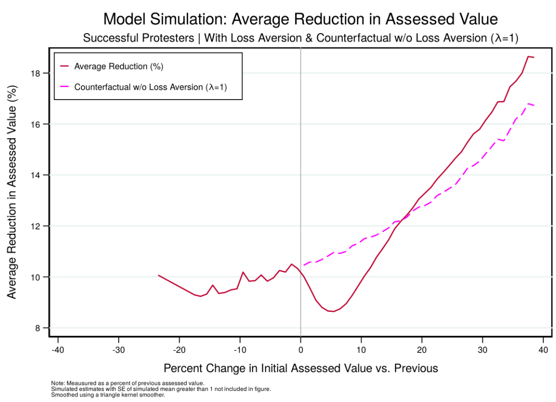
Figure 1.2: Model Simulation: Illustrating the Effect of Loss Aversion on the Probability of Protest, the Distribution of Assessed Values, and the Assessment Value Reductions Received.



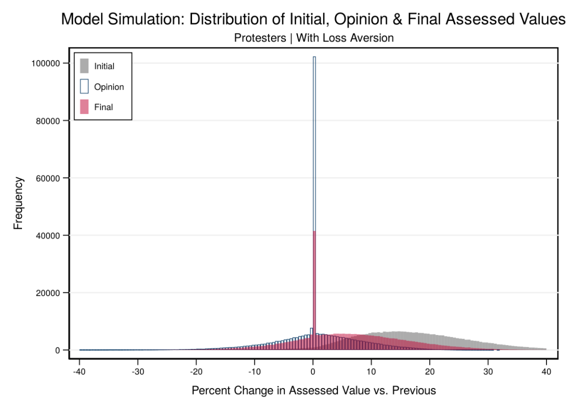
(A) Probability of Protest



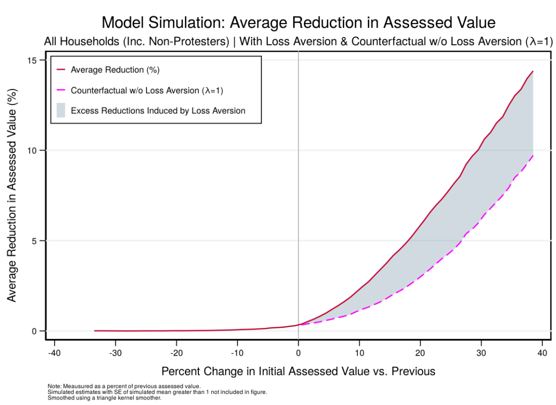
(B) Initial and Final Assessed Values



(C) Average Reduction (%) | Successful Protest



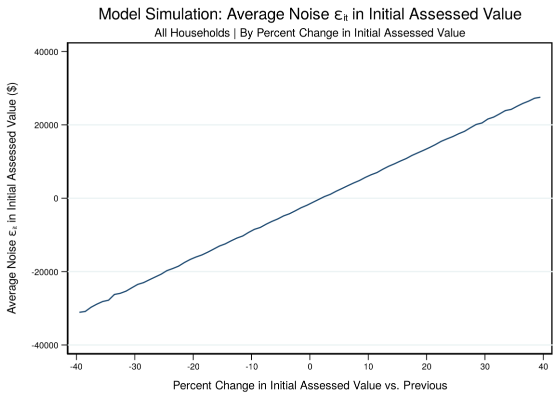
(D) Protesters' Initial, Opinion, and Final Assessed Values



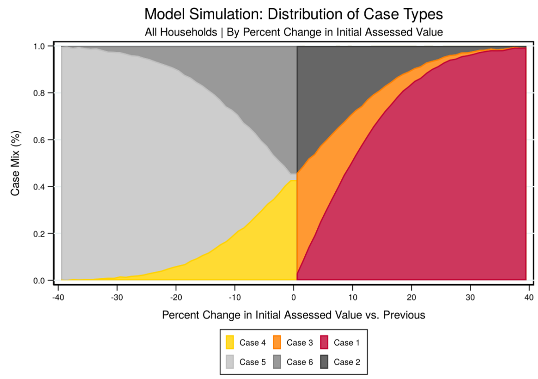
(E) Average Reduction (%) | All Households

Notes: These figures illustrate the results of a simulation ($N = 1,800,000$) of the *Stochastic Reduction Model* outlined in Section 1.1 parameterized as follows: $\tau_t = 0.022$, $A_{t-1} = V_{t-1} = 150,000$, Initial $A_t = V_{t-1} + \Delta V_t + \varepsilon_t$ where $\Delta V_t \sim N(3000, 15000)$ and $\varepsilon_t \sim N(0, 15000)$, and $\lambda \sim N(2.0, 0.3)$. The cost function is given by $\kappa + \phi \times e^{\gamma}$ with $\kappa \sim Lognormal(4.9, 1.5)$, $\phi \sim N(500, 150)$, and $\gamma \sim N(1.3, 0.1)$. In the simulation, 16.4% of agents protest, and 1.8% of agents state an opinion at the *Previous Final Assessed Value* leading to an excess mass of households in the distribution of *Final Assessed Values* at the *Previous Final Assessed Value* equal to 0.7% of all households.

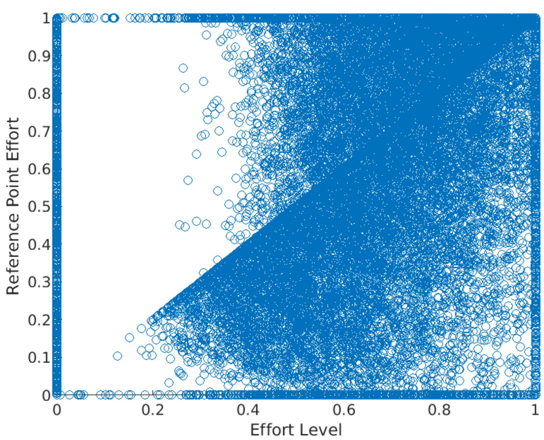
Figure 1.3: Model Simulation: Illustrating the Effects of Loss Aversion.



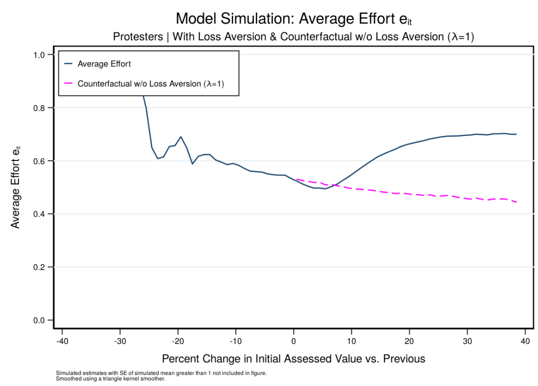
(A) Average Noise in Assessed Value



(B) Case Mix



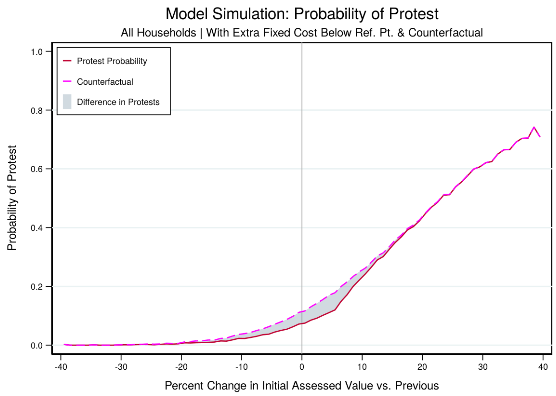
(C) Chosen Effort vs. Reference Point Effect



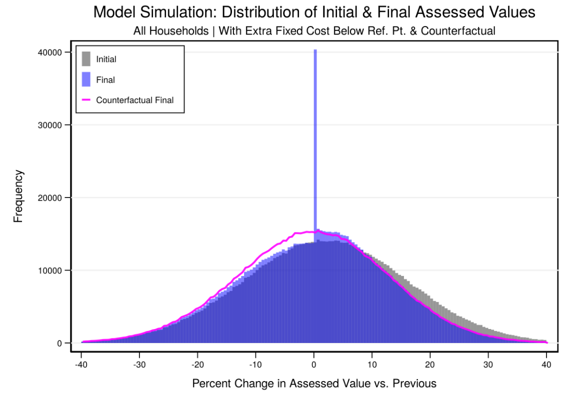
(D) Chosen Effort

Notes: These figures illustrate the results of a simulation ($N = 1,800,000$) of the *Stochastic Reduction Model* outlined in Section 1.1 parameterized as follows: $\tau_t = 0.022$, $A_{t-1} = V_{t-1} = 150,000$, Initial $A_t = V_{t-1} + \Delta V_t + \varepsilon_t$ where $\Delta V_t \sim N(3000, 15000)$ and $\varepsilon_t \sim N(0, 15000)$, and $\lambda \sim N(2.0, 0.3)$. The cost function is given by $\kappa + \phi \times e^{\gamma}$ with $\kappa \sim Lognormal(4.9, 1.5)$, $\phi \sim N(500, 150)$, and $\gamma \sim N(1.3, 0.1)$. In the simulation, 16.4% of agents protest, and 1.8% of agents state an opinion at the *Previous Final Assessed Value* leading to an excess mass of households in the distribution of *Final Assessed Values* at the *Previous Final Assessed Value* equal to 0.7% of all households.

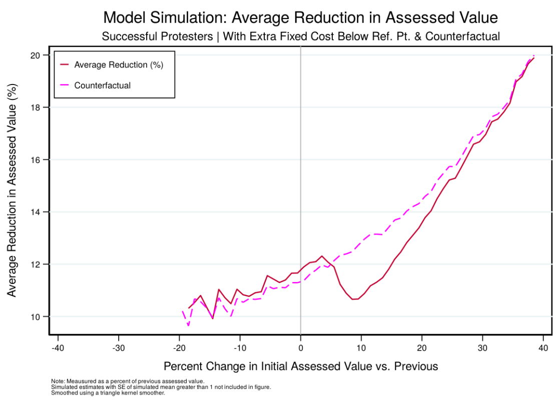
Figure 1.4: Alternate Model Simulation: Additional Fixed Cost Below Reference Point.



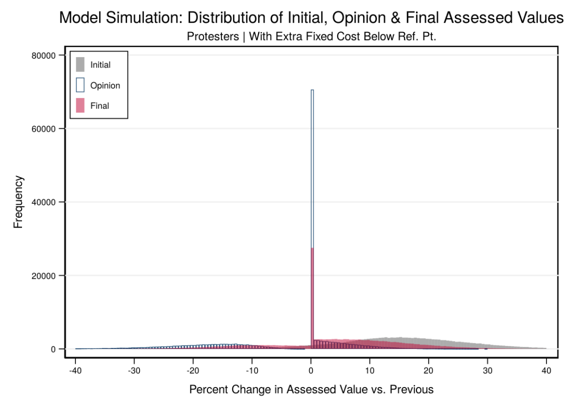
(A) Probability of Protest



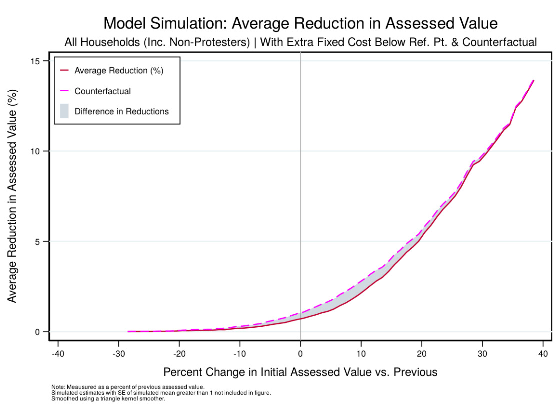
(B) Initial and Final Assessed Values



(C) Average Reduction (%) | Successful Protest



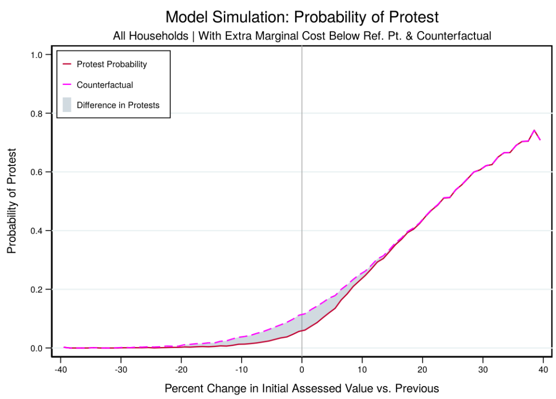
(D) Protesters' Initial, Opinion, and Final Assessed Values



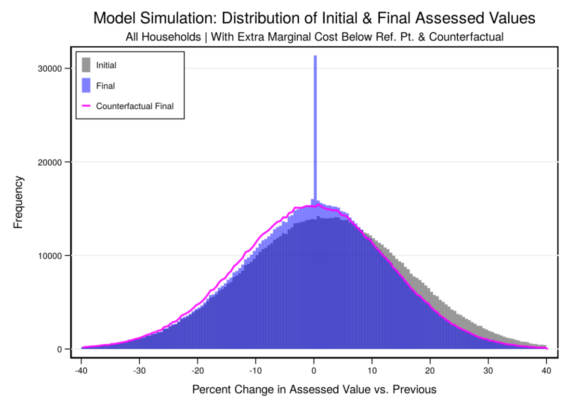
(E) Average Reduction (%) | All Households

Notes: These figures illustrate the results of a simulation ($N = 1,000,000$) of the *Ratchet Cost Stochastic Reduction Model* outlined in Section 1.2 parameterized as follows: $\tau_t = 0.022$, $A_{t-1} = V_{t-1} = 150,000$, Initial $A_t = V_{t-1} + \Delta V_t + \varepsilon_t$ where $\Delta V_t \sim N(3000, 15000)$ and $\varepsilon_t \sim N(0, 15000)$ (and $\lambda = 1$). The cost function is given by $\kappa + \phi \times e^{\gamma}$ above the reference point, and $2 \times \kappa + \phi \times e^{\gamma}$ (strictly) below the reference point with $\kappa \sim Lognormal(4.9, 1.5)$, $\phi \sim N(200, 60)$, and $\gamma \sim N(1.3, 0.1)$. In the simulation, 16.24% of agents protest, and 1.16% of agents state an opinion at the *Previous Final Assessed Value* leading to an excess mass of households in the distribution of *Final Assessed Values* at the *Previous Final Assessed Value* equal to 0.27% of all households.

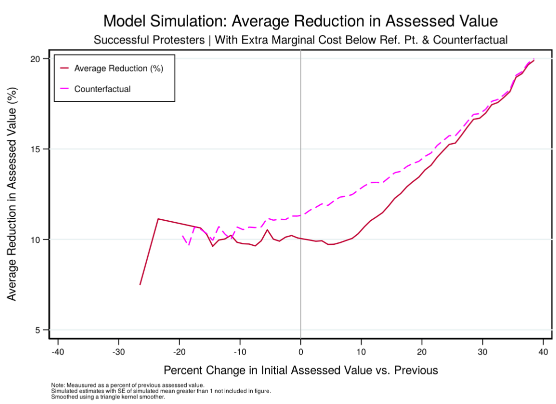
Figure 1.5: Alternate Model Simulation: Additional Marginal Cost Below Reference Point.



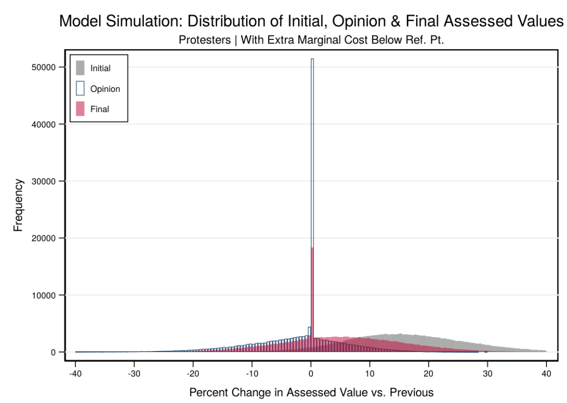
(A) Probability of Protest



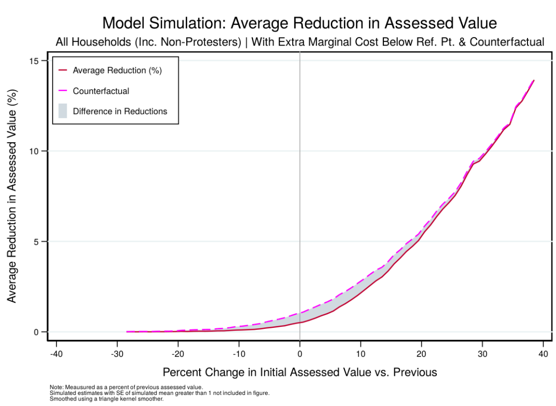
(B) Initial and Final Assessed Values



(C) Average Reduction (%) | Successful Protest



(D) Protesters' Initial, Opinion, and Final Assessed Values



(E) Average Reduction (%) | All Households

Notes: These figures illustrate the results of a simulation ($N = 1,000,000$) of the *Kinked Marginal Cost Stochastic Reduction Model* outlined in Section 1.2 parameterized as follows: $\tau_t = 0.022$, $A_{t-1} = V_{t-1} = 150,000$, Initial $A_t = V_{t-1} + \Delta V_t + \varepsilon_t$ where $\Delta V_t \sim N(3000, 15000)$ and $\varepsilon_t \sim N(0, 15000)$ (and $\lambda = 1$). The cost function is given by $\kappa + \phi \times e^{\gamma}$ above the reference point, and $\kappa + \phi \times e^{\gamma} + \varphi \times (e^{\gamma} - e^{\gamma}_{ref})$ (strictly) below the reference point, with $\kappa \sim \textit{Lognormal}(4.9, 1.5)$, $\phi \sim N(200, 60)$, and $\gamma \sim N(1.3, 0.1)$. In the simulation, 15.93% of agents protest, and 1.51% of agents state an opinion at the *Previous Final Assessed Value* leading to an excess mass of households in the distribution of *Final Assessed Values* at the *Previous Final Assessed Value* equal to 0.34% of all households.

1.4 Model Notes & Derivations

1.4.1 Fixed Cost Noise Removal Model Notes

Table 1.1: Protest Conditions in a *Fixed Cost Noise Removal Model*.

Case	Case-Defining Parameters	Protest Condition	Never
Case 1	$A_t > A_{t-1}$ $\quad \varepsilon_t > 0$ $\quad V_t > A_{t-1}$	$\kappa < \lambda\tau\varepsilon_t$	
Case 2	$A_t > A_{t-1}$ $\quad \varepsilon_t < 0$ $\quad V_t > A_{t-1}$	$\kappa < \lambda\tau\varepsilon_t$	X
Case 3	$A_t > A_{t-1}$ $\quad \varepsilon_t > 0$ $\quad V_t < A_{t-1}$	$\kappa < \lambda\tau\varepsilon_t - (\lambda - 1)\tau\left[(V_{t-1} + \varepsilon_{t-1}) - V_t\right]$	
Case 4	$A_t < A_{t-1}$ $\quad \varepsilon_t > 0$ $\quad V_t < A_{t-1}$	$\kappa < \tau\varepsilon_t$	
Case 5	$A_t < A_{t-1}$ $\quad \varepsilon_t < 0$ $\quad V_t < A_{t-1}$	$\kappa < \tau\varepsilon_t$	X
Case 6	$A_t < A_{t-1}$ $\quad \varepsilon_t < 0$ $\quad V_t > A_{t-1}$	$\kappa < \tau\varepsilon_t + (\lambda - 1)\tau\left[(V_{t-1} + \varepsilon_{t-1}) - V_t\right]$	X

Table 1.1 summarizes the conditions under which a homeowner will protest in a model with a fixed cost of protesting and deterministic assessment reductions that result in the (full) removal of an initial noise term ε_t. The six cases below are illustrated in Figure 1.1.

1.4.2 Effort-Based Noise Reduction Model Notes

Table 1.2: Protest Conditions in a *Effort-Based Noise Reduction Model*.

Case	Case-Defining Parameters	Protest Condition
Case 1	$A_t > A_{t-1}$ $\quad \varepsilon_t > 0$ $\quad V_t > A_{t-1}$	$\kappa + c(e_t^*) < e_t^*\lambda\tau\varepsilon_t$
Case 3A: $\tilde{A}_t < A_{t-1}$	$A_t > A_{t-1}$ $\quad \varepsilon_t > 0$ $\quad V_t < A_{t-1}$	$\kappa + c(e_t^*) < (\lambda - (1 - e_t^*))\tau\varepsilon_t -$ $(\lambda - 1)\tau\left[(V_{t-1} + \varepsilon_{t-1}) - (V_t)\right]$
Case 3B: $\tilde{A}_t \geq A_{t-1}$	$A_t > A_{t-1}$ $\quad \varepsilon_t > 0$ $\quad V_t < A_{t-1}$	$\kappa + c(e_t^*) < e_t^*\lambda\tau\varepsilon_t$
Case 4	$A_t < A_{t-1}$ $\quad \varepsilon_t > 0$ $\quad V_t < A_{t-1}$	$\kappa + c(e_t^*) < e_t^*\tau\varepsilon_t$

Table 1.2 shows the conditions under which a homeowner will protest in a model with a fixed cost protesting, a marginal cost of effort and deterministic assessment reductions that results in removal of an initial noise term ε_t proportional to effort choice such that $\tilde{\varepsilon}_t = (1 - e_t)\varepsilon_t$. The cases are illustrated in Figure 1.1.

1.4.3 Stochastic Reduction Model Notes

Below, I more fully detail the stochastic reduction model introduced in Section 1.1.4, which is also the basis for the simulation figures shown.

Expected Benefit of Reductions

Case 1A: $A_t \geq A_{t-1}$, $A_t^O \leq A_{t-1}$,

$$(1-e_t^*) \times [\tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t + Q(1-e_t^*))]] + \int_{Q(1-e_t^*)}^{\tilde{\varepsilon}_t^r} \tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t + \tilde{\varepsilon}_t)] \, dF(\tilde{\varepsilon}) + \int_{\tilde{\varepsilon}_t^r}^{\varepsilon_t} \lambda\tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t + \tilde{\varepsilon}_t)] \, dF(\tilde{\varepsilon}) + [1 - F(\varepsilon_t)] \times [\lambda\tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t + \varepsilon_t)]] \tag{1.11}$$

or equivalently,

$$\tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t)] + [1 - F(\tilde{\varepsilon}_t^r)] \times [(\lambda - 1)\tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t)]] - \tau(1-e_t^*) \times Q(1-e_t^*) - \int_{Q(1-e_t^*)}^{\tilde{\varepsilon}_t^r} \tau\tilde{\varepsilon}_t dF(\tilde{\varepsilon}) - \int_{\tilde{\varepsilon}_t^r}^{\varepsilon_t} \lambda\tau\tilde{\varepsilon}_t dF(\tilde{\varepsilon}) - [1 - F(\varepsilon_t)] \times [\lambda\tau\varepsilon_t] \tag{1.12}$$

Case 1B: $A_t \geq A_{t-1}$, $A_t^O \geq A_{t-1}$,

$$(1-e_t^*) \times [\lambda\tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t + Q(1-e_t^*))]] + \int_{Q(1-e_t^*)}^{\varepsilon_t} \lambda\tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t + \tilde{\varepsilon}_t)] \, dF(\tilde{\varepsilon}) + [1 - F(\varepsilon_t)] \times [\lambda\tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t + \varepsilon_t)]] \tag{1.13}$$

or equivalently,

$$\lambda\tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t)] - \lambda\tau(1-e_t^*) \times Q(1-e_t^*) - \int_{Q(1-e_t^*)}^{\varepsilon_t} \lambda\tau\tilde{\varepsilon}_t dF(\tilde{\varepsilon}) - [1 - F(\varepsilon_t)] \times [\lambda\tau\varepsilon_t] \tag{1.14}$$

Case 2: $A_t^O < A_t \leq A_{t-1}$,

$$(1-e_t^*) \times [\tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t + Q(1-e_t^*))]] + \int_{Q(1-e_t^*)}^{\varepsilon_t} \tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t + \tilde{\varepsilon}_t)] \, dF(\tilde{\varepsilon}) + [1 - F(\varepsilon_t)] \times [\tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t + \varepsilon_t)]] \tag{1.15}$$

or equivalently,

$$\tau [(V_{t-1}+\varepsilon_{t-1}) - (V_t)] - \tau(1-e_t^*) \times Q(1-e_t^*) - \int_{Q(1-e_t^*)}^{\varepsilon_t} \tau\tilde{\varepsilon}_t dF(\tilde{\varepsilon}) - [1 - F(\varepsilon_t)] \times [\tau\varepsilon_t] \tag{1.16}$$

FOCs and Marginal Benefit

Note that $q(p) = 1/f(Q(p))$. Taking first order conditions of the expected benefit of reductions results in the following.

Case 1A: $A_t \geq A_{t-1}$, $A_t^O \leq A_{t-1}$,

$$\tau \left[Q(1-e_t^*) + (1-e_t^*) \cdot q(1-e_t^*) - Q(1-e_t^*) \cdot f\left(Q(1-e_t^*)\right) \cdot q(1-e_t^*)\right] \tag{1.17}$$

$$MB_{e_t}^{1A} = \tau(1-e_t^*) \cdot q(1-e_t^*) \tag{1.18}$$

Case 1B: $A_t \geq A_{t-1}$, $A_t^O \geq A_{t-1}$,

$$\lambda\tau \left[Q(1-e_t^*) + (1-e_t^*) \cdot q(1-e_t^*) - Q(1-e_t^*) \cdot f\left(Q(1-e_t^*)\right) \cdot q(1-e_t^*)\right] \tag{1.19}$$

$$MB_{e_t}^{1B} = \lambda\tau(1-e_t^*) \cdot q(1-e_t^*) \tag{1.20}$$

Case 2: $A_t^O < A_t \leq A_{t-1}$,

$$\tau \left[Q(1-e_t^*) + (1-e_t^*) \cdot q(1-e_t^*) - Q(1-e_t^*) \cdot f\left(Q(1-e_t^*)\right) \cdot q(1-e_t^*)\right] \tag{1.21}$$

$$MB_{e_t}^{2} = \tau(1-e_t^*) \cdot q(1-e_t^*) \tag{1.22}$$

Protest Conditions

Case 1A: $A_t \geq A_{t-1}$, $A_t^O \leq A_{t-1}$,

Equating marginal benefit to marginal cost, the homeowner will protest with effort e_t^* satisfying,

$$\tau(1-e_t^*) \cdot q(1-e_t^*) = k'(e_t^*), \tag{1.23}$$

if, in addition, the expected benefit of protesting net of cost is better than the alternative,

$$\begin{aligned}(1-e_t^*) \times \tau\left(\lambda\varepsilon_t - Q(1-e_t^*)\right) + \int_{Q(1-e_t^*)}^{\tilde{\varepsilon}_t^r} \tau(\lambda\varepsilon_t - \tilde{\varepsilon}_t) dF(\tilde{\varepsilon}) + \int_{\tilde{\varepsilon}_t^r}^{\varepsilon_t} \lambda\tau\left(\varepsilon_t - \tilde{\varepsilon}_t\right) dF(\tilde{\varepsilon}) \\ - F(\tilde{\varepsilon}_t^r) \times (\lambda-1)\tau\left[(V_{t-1}+\varepsilon_{t-1}) - (V_t)\right] - k(e_t^*) \geq \lambda\tau\left[A_{t-1} - A_t\right].\end{aligned} \tag{1.24}$$

Note that for an opinion exactly at the reference point this collapses to,

$$F(\tilde{\varepsilon}_t^r) \times \lambda\tau\left(\varepsilon_t - \tilde{\varepsilon}_t^r\right) + \int_{\tilde{\varepsilon}_t^r}^{\varepsilon_t} \lambda\tau\left(\varepsilon_t - \tilde{\varepsilon}_t\right) dF(\tilde{\varepsilon}) - k(e_t^*) \geq \lambda\tau\left[A_{t-1} - A_t\right]. \tag{1.25}$$

Case 1B: $A_t \geq A_{t-1}$, $A_t^O \geq A_{t-1}$,

Equating marginal benefit to marginal cost, the homeowner will protest with effort e_t^* satisfying,

$$\lambda\tau(1-e_t^*) \cdot q(1-e_t^*) = k'(e_t^*), \tag{1.26}$$

if, in addition, the expected benefit of protesting net of effort cost is better than the alternative,

$$(1-e_t^*) \times \lambda\tau\left(\varepsilon_t - Q(1-e_t^*)\right) + \int_{Q(1-e_t^*)}^{\varepsilon_t} \lambda\tau\left(\varepsilon_t - \tilde{\varepsilon}_t\right) dF(\tilde{\varepsilon}) - k(e_t^*) \geq \lambda\tau\left[A_{t-1} - A_t\right]. \quad (1.27)$$

Case 2: $A_t^O < A_t \leq A_{t-1}$,

Equating marginal benefit to marginal cost, the homeowner will protest with effort e_t^* satisfying,

$$\tau(1-e_t^*) \cdot q(1-e_t^*) = k'(e_t^*), \quad (1.28)$$

if, in addition, the expected benefit of protesting net of effort cost is better than the alternative,

$$(1-e_t^*) \times \tau\left(\varepsilon_t - Q(1-e_t^*)\right) + \int_{Q(1-e_t^*)}^{\varepsilon_t} \tau\left(\varepsilon_t - \tilde{\varepsilon}_t\right) dF(\tilde{\varepsilon}) - k(e_t^*) \geq \tau\left[A_{t-1} - A_t\right]. \quad (1.29)$$

Chapter 2

Loss Aversion and Property Tax Avoidance

2.1 Introduction

In this Chapter, I test the theoretical predictions of Chapter 1. The empirical analysis examines 8.2 million administrative property assessments associated with 1.6 million appeals from two large Texas counties, home to Houston and Austin.

Figure 2.1 shows appeal rates as a function of percent change in initial assessed value in the sample I study. The efficacy of the property tax is predicated on an initial valuation and subsequent appeals process that together produce final assessments that reflect fair market value. Suppose two properties were both initially over-assessed by $20,000. One might think that both owners would be equally likely to protest, even if one property's assessment increased relative to the prior year, and the other property's assessment decreased. Both owners stand to gain equally—in monetary terms—from correcting the initial over-assessment; however, the evidence highlighted in the figure suggests that in practice, the property owner whose assessment increased is much more likely to protest. Observing the noise in any individual assessment is difficult, but under standard assumptions, we would expect the average noise in assessed values to be smoothly distributed, even if positively correlated with changes in assessed value. Accepting that as given, one might reasonably expect appeal rates to be positively related to changes in assessed value, but similarly, smoothly distributed. Figure 2.1 shows that this does not hold empirically; loss aversion provides an explanation.

I begin by presenting global evidence of a kink using a flexible within-household design. I then formalize the model's main prediction using regression kink discontinuity methods, estimating an elasticity of protesting with respect to change in initial assessed value that, below the reference point, is close to zero, and above the reference point, is between 0.7-1.0. Separately, I estimate excess bunching at the reference point on the order of 1.5% to 4% of all protesting households, and document bunching in protesters' *opinion* of property value that is even larger. These opinions, elicited at the outset of the protest process, provide direct evidence that homeowners target the previous assessed value.[1] Although representative

[1]This provides direct evidence of individuals stating preferences that target a reference point, rather than simply inferring a revealed preference from a final outcome. Only Markle et al. (2015), who show that marathon runners' stated goal times correlate with their finishing times, provide similar field evidence of substantial scale.

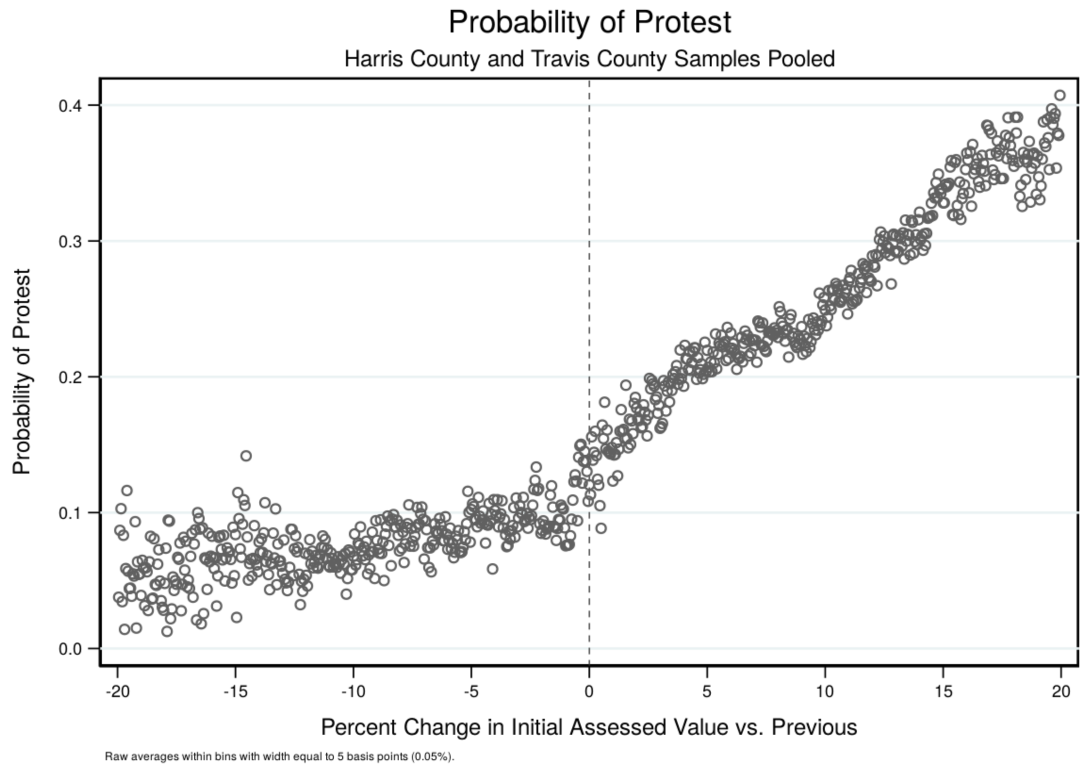


Figure 2.1: The raw probability of protest as a function of percent change in *Initial Assessed Value* pooling Harris County and Travis County samples.

third party agents handle a large fraction of appeals, the effects appear to be driven by owner-protesters, for whom we would expect the reference point to be most meaningful.

Loss aversion induces homeowners who otherwise would *not* protest to seek reductions they would not consider worthwhile if not for loss aversion. As such, we should observe a drop in the average reduction achieved by those at the margin, which I show empirically. Additionally, because the extensive margin has its greatest effect close to the reference point, the probability of protesting conditional on percent change in assessed value is predicted to kink close to the reference point, but can flatten in regions of the loss domain in which fewer households are marginal. This latter prediction is analogous to a theoretical (but not empirical) point made by Engström et al. (2015); I validate the hypothesis empirically.

As a final piece of the analysis, I use a regression kink discontinuity design to quantify the effects of loss aversion in terms of annual tax dollars per property, among other counterfactual outcomes of interest. Unlike Rees-Jones (2018), who infers the revenue effects of loss aversion based on the *final* distribution of (income) taxes owed, I estimate counterfactual behavior based on a homeowner's *initial* (rather than final) assessed value. While the method proposed by Rees-Jones (2018) has the advantage that one need only observe a final distribution, the advantage of the approach I use is that I do not assume the initial distribution's shape. Given available data, and the appropriateness of assumptions in different settings, each approach has different merits. In the present setting, a significant fraction of loss aversion's effect is mediated through the extensive margin. As such, tax dollar effect sizes are best understood conditional on one's position in the loss domain, but unconditional on protesting. Within-property-owner-pair estimates suggest that loss aversion is related to excess tax reductions in the loss domain, averaging $34 per property annually (unconditional on protesting) at the median percent change in initial assessed value. Among properties that had a 10% increase in assessed value, the average annual excess tax reduction is $45. The effects are largely driven by properties in the top quartile of value. For them, the average annual tax reduction attributable to loss aversion is $80 per property at the median percent change in initial assessed value and $115 per property among those that had a 10% increase in assessed value.

The property tax setting is particularly suited for the study of reference dependence. While in other settings, liquidity constraints can produce behavior that may be incorrectly attributed to loss aversion, a property owner who unexpectedly finds that he will owe several hundred dollars more than expected will not need to produce what he owes for several months. Another advantage relates to individual sorting. An income tax filer, for example, has substantial control over the balance he will owe at the end of the tax year, and can affect it by manipulating his automatic withholding or tax payments earlier in the year; by contrast, a property owner has little control over the change in the assessed value of his property, which is instead largely determined by market forces. Because assessors, review arbiters, owners, and agents alike[2] emphasize that tangible and specific evidence warranting a reduction is necessary if a protest is to successfully achieve a reduction, a concern that reductions could conceivably be influenced by actors in the environment other than the taxpayer is minimized.

My findings complement related work that examines reference-dependent behavioral responses to income taxes. Anecdotally, the idea that tax filers exhibit loss aversion with respect to owing taxes at the end of the fiscal year has been documented at least as far back as Carroll (1990); however, the best evidence to date comes from Engström et al. (2015) and Rees-Jones (2018).[3][4] I present evidence on the probability of protesting that parallels the behavior of the income tax filers in Engström et al. (2015) and bunching-based evidence that parallels Rees-Jones (2018). Employing an alternative approach for quantifying the tax liability effects of loss aversion from than that proposed by Rees-Jones (2018), I highlight how the average effect of loss aversion depends on one's position in the loss domain. Altogether, evidence of reference-dependence is both comprehensive and striking. Compared to the income tax setting, the reduced form evidence in this setting is particularly pronounced,[5] while estimated annual tax reductions attributable to loss aversion are of similar magnitude (even though most people pay more in income taxes than property taxes).[6] Given the particular distaste people have for property taxes, it may be less surprising, once considered, that the property

[2] At least in the jurisdictions studied in this paper.

[3] Engström et al. (2018) presents panel evidence similar to cross-sectional evidence in Engström et al. (2015).

[4] Several studies have examined similar questions theoretically or experimentally (e.g. Elffers and Hessing (1997), Yaniv (1999), Dhami and Al-Nowaihi (2007), Dhami and Al-Nowaihi (2010)).

[5] In Engström et al. (2015), the probability of claiming an income tax deduction increases by $\sim$2 percentage points in the loss domain; here, the probability of protesting a property tax assessment increases by $\sim$6 percentage points in the loss domain. In Rees-Jones (2018), an excess $\sim$0.05% of all income tax filers bunch at zero balance due; here, an excess 0.3-1% of all reassessed property owners bunch at the previous assessed value. Several factors could contribute to the difference; for example, in the case of bunching, differences in the ability to target a specific value.

[6] Rees-Jones (2018) estimates $34 of excess income tax reductions in the loss domain.

tax setting is one particularly prone to elicit reference-dependent behavior.

2.2 Data & Setting

2.2.1 Overview & Essential Summary Statistics

My empirical analysis uses 8.2 million annual administrative property assessments and 1.6 million associated protests from two Texas counties: Harris County (home to Houston), and Travis County (home to Austin). For all intents and purposes, the main sample represents all single-family residential property assessments from Harris County from 2005-2016, excluding the *crisis years*, 2008-2010, and the same from Travis County from 2011-2018.

Table 2.1 shows summary statistics for the key variables, separately by county. Three essential pieces of information are available for each property-year observation: (i) the *Initial Assessed Value*, (ii) the *Final Assessed Value*, and (iii) whether the homeowner protested the *Initial Assessed Value*. This allows me to directly measure the behavioral tax avoidance response to each assessment, observing not only the protest choice, but also the exact *Value Reduction* associated with each protest. In total, 19% of *Initial Assessed Values* are protested. Homeowners *Successfully Protest*, achieving a reduction in value, 68% of the time in Harris County and 81% of the time in Travis County. On average, a successful protest achieves a 7-8% reduction in assessed value. With an effective tax rate close to 2.2% of assessed value in both counties, the mean tax reduction is approximately $450 in Harris County, and $750 in Travis County.

2.2.2 Assessment & Protest Records Description

The data come from the Harris County Appraisal District and the Travis Central Appraisal District (HCAD and TCAD, hereafter), the local public offices that, each year, assess the value of all real property in their county.[7] Assessment records provide detailed information on factors used to determine each property's assessed value, taxable value, and tax liability. For each property-year observation, the data include ownership information, property characteristics, neighborhood, applicable taxing jurisdictions and associated jurisdiction-level tax rates.

The records also contain information about each protest. In both counties, homeowners are notified of their *Initial Assessed Value* in early spring. If protesting, a homeowner must file a notice of protest declaring her intent soon thereafter.[8] Pooling both samples, 58% of protests involve the aid of a third-party representative agent. Many protests are resolved informally, with the sides either agreeing to adjust the value, or, alternatively, with the homeowner agreeing that no change in value is warranted. If not resolved informally, the case advances to a formal hearing adjudicated by the county's Appraisal Review Board (ARB, hereafter), an independent three-person panel of arbiters. The homeowner (or agent) and assessor present their opinion of the property's value and the ARB determines a *Final Assessed Value* based on the evidence provided. The ARB does not need to choose one side's proposed value or the other's, and in fact, often settles on a value between the two.

[7] HCAD and TCAD only assess the value of property; they do not collect tax revenue.

[8] Protest deadlines are May 15th (Travis) and May 31st (Harris). Taxes are due January 31st of the following year.

For a selected subset of protests, I observe an *Opinion of Value* stated by the protester, elicited at the time of protest filing. These opinions come from a fill-in-the-blank field that is optional if filing notice of protest offline (by mailing in a physical document), but are required of owners filing notice of protest online. Coverage is superior in the Harris sample, where I observe an *Opinion of Value* for 84% of protests. In the Travis sample, I only observe an opinion for 12% of protests. The difference stems from recordkeeping procedures. Whereas HCAD's records include all opinions supplied by protesters, TCAD's records essentially only reflect opinions entered by owner-protesters who filed notice of protest online .

2.2.3 Harris and Travis Samples: Differences and Comparative Advantages

The Harris County sample spans the years 2005-2016; the Travis County sample spans 2011-2018. I establish the importance of reference-dependence, excluding the *crisis years*, 2008-2010, from the Harris sample; however, I briefly discuss that period in the conclusion.

A key difference between the samples relates to reassessment practices. In Harris County, reassessment occurs approximately every other year but do not adhere to a strict biennial rule. Meanwhile, the vast majority of Travis County properties are reassessed annually. Texas law requires all property to be assessed "at market value" and at minimum, reassessed once every three years; however, county assessors adopt internally-determined standards for reassessment. The Travis sample circumvents a selection process present in the Harris sample that, while unlikely to drive observed effects in the Harris sample, slightly complicates clean identification. In particular, in Harris County, reassessment practices lead to slight differences in observable characteristics of properties near the discontinuity threshold of interest. While possible to control for observable differences using fixed effects, an identification strategy that does not rely upon the inclusion of covariates more readily supports the key assumption of a regression discontinuity design. Travis County's reassessment practices provide variation that does not suffer from covariate imbalance. For the main RKD results, I show that the Harris sample and Travis sample produce similar within-household effects. I also show similar effects in the Travis sample without any controls. Presented together, the Travis sample lends confidence to the main results from both counties.[9]

The samples differ in other dimensions, but in ways that are second-order to understanding the environment. In the Travis sample, the average property value is higher, agents are more commonly used, and more protests are settled informally. In both counties, less than 40% of property-owner pairs protest during the observed tenure. Homeowners *can* challenge an assessment even if the property was not reassessed; however, for much of the analysis, I focus attention on only *reassessed* properties, treating a zero percent change in initial assessed value as fundamentally different from receiving any change in value. While *reassessed* properties reflect a value determined by computer-assisted mass appraisal (CAMA) models, properties that were not reassessed do not reflect a comparably-determined value.[10]

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[9] The appendix briefly discusses covariate imbalance in the Harris sample. Conditional on reassessment and observable differences, there do not appear to be valuation inconsistencies. In supplementary results, I precisely estimate the Harris County CAMA model, and show that there do not appear to be systemic differences in the average residual (measuring the difference between the CAMA value I predict and the assessed value actually assigned by the CAMA model), near the cutoff point of interest, conditional on reassessment.

[10] Reassessment is determined at the neighborhood-level; hence, if a property was not reassessed, it's (typically) because no properties in the neighborhood were reassessed.

2.2.4 Institutional Details

CAMA Assessment Valuation

HCAD and TCAD use proprietary computer-assisted mass appraisal (CAMA) systems to assess property values. Exact modeling specifications differ but follow a similar structure. The total assessed value comprises the value of land, improvements (i.e. buildings and structures), and extra features. For most properties, the value of improvements accounts for the bulk of the total assessed value. CAMA incorporates various improvement characteristics and first estimates the cost of replacement construction. The cost is then depreciated according to a schedule based on the quality of original construction and the age of improvements. To account for demand-side factors, a neighborhood adjustment factor, calibrated using sales ratio tests, uniformly adjusts the value of all property in a neighborhood (inflating or deflating the depreciated value of improvements). Properties are grouped into neighborhoods based not only on proximity, but also homogeneity.[11]

Property Taxes in Texas

Knowing a few institutional details are useful to understand the setting. By Texas law, all taxable property must be assessed equitably and uniformly at its *Market Value* as of January 1st each year. The Texas Comptroller of Public Accounts—a state-level office—certifies county assessor valuations, regularly checking that values pass standardized ratio tests, providing state-level oversight of county assessors. Specific provisions in the state tax code entitle a property owner to assessment relief if she can show that her property is assessed above market value, or if the assessment fails to satisfy "uniform and equal" provisions, including, among others less commonly invoked, one that allows for relief if a property owner can show that the assessed value of the property exceeds the median assessed value of "a reasonable number of comparable properties, appropriately adjusted."[12] Texas is a non-disclosure state, and for that reason, I cannot observe sales prices (except for a small fraction in Travis County which I analyze), which prevents me from conducting sales-assessment ratio analyses, and limits the extent to which I can evaluate assessment practices.[13]

Owner-occupied primary residence properties benefit from a legal provision that restricts the amount by which a property's taxable assessed value may increase in a single year to no greater than 10%. If a property's market value is determined to have increased by more than 10%, the taxable portion can only increase by 10% that year, but may increase the following year to the lesser of the current market value or 10% above the intermediate year's value.[14] To distinguish between these values, I use *Assessed Value* to refer to the underlying *Market Value* of the property and use *Capped Assessed Value* to refer to the taxable portion in instances where they differ. This assessment increase limit introduces a *real kink* in the marginal benefit of protesting near the 10% threshold, in addition to the *psychological kink* that is the focus

[11] Neighborhood changes are rare; nearly all properties are assigned to the same neighborhood for the entire sample period.

[12] Texas Property Tax Code Section 42.26 (a)(3).

[13] HCAD and TCAD collect sales prices from a variety of (primarily proprietary) sources in order to conduct sales-ratio tests that enter their models, but these sales prices are not included in public records.

[14] For example, if the market value of a property is determined to have increased by 15% in year t and by 2% in year $t+1$, the de facto taxable assessed value would increase by 10% in year t and 7% in year $t+1$.

of this paper. For parts of the analysis, I separate the *Cap-Eligible Sample* and *Cap-Ineligible Sample*.

2.2.5 Additional Sample Notes

Each sample excludes a small minority of observations that fail to satisfy a weak set of inclusion criteria. Additionally, I exclude observations in the year of sale, and in years with new construction or remodeling. Additional details are available in the appendix.

2.3 Empirical Analysis of Assessment Protest Behavior

In this section, I test the predictions introduced in Section 1.1, establishing evidence that *Previous Assessed Value* serves as a salient reference point to which property owners are loss averse. As discussed in Section 2.2.3, parts of the analysis focus attention to one county sample or the other, given their respective advantages.

2.3.1 Testing the Kink Prediction

Global Kink Evidence

Figure 2.2 presents straightforward, flexible evidence of a kink in the probability of protesting precisely at the reference point. It plots the coefficients of a linear probability model of protesting as a function of *Percent Change in Initial Assessed Value*, partitioned into evenly-spaced one-percentage-point-width bins with (i) property-owner pair and (ii) year fixed effects. Formally, letting $\ddot{A}_{it} \equiv \log\left(A_{it}^{Init}/A_{i,t-1}^{Final}\right)$, it shows the probability of protest in each of J *Percent Change in Initial Assessed Value* bins Z_j, as estimated by,

$$P_{it} = \sum_{j \in J} \beta_j \cdot \mathbf{1}_{\{\ddot{A}_{it} \in Z_j\}} + \alpha^0 \cdot \mathbf{1}_{\{\ddot{A}_{it}=0\}} + \omega_i + \eta_t + \epsilon_{it} \tag{2.1}$$

where P_{it} indicates that household i protested its *Initial Assessed Value* in year t, ω_i and η_t represent property-owner pair and year fixed effects, respectively, and ϵ_{it} an error term. The coefficients are normalized to the probability of protest given a *Percent Change in Initial Assessed Value* between -1% and 0%.[15] An indicator associated with exactly no change in *Initial Assessed Value* (properties that were *not* reassessed) is included in the estimation to increase the identifying sample for the property-owner pair fixed effects, but excluded from the figure.[16] Indicators associated with a change in *Initial Assessed Value* (i) greater than 40%, and (ii) less than -40% are also included in the estimation but not in the figure.[17] In all

[15] Throughout the empirical analysis, all estimates are based on log points. In many figures, I multiply log points by 100 for ease of communication and information consumption.

[16] Properties with no change in *Initial Assessed Value* were not reassessed, and thus are not valued comparably to reassessed properties. As such, non-reassessed properties can be systematically different from those that are reassessed. The identifying assumption is that properties are comparable, conditional on reassessment.

[17] That is, extreme values are binned at ±40%, respectively. Terms specifying the precise definition of these binned endpoints at ±40% are suppressed in Equation (2.1).

property-year-level regressions, I cluster standard errors at the neighborhood level to allow for correlation in errors both spatially and over time.[18]

Figure 2.2 provides global evidence of a kink in the probability of protest exactly at the reference point in both Harris County (Panel A) and Travis County (Panel B). Below zero percent change in *Initial Assessed Value*—in the *gain domain*—the estimated coefficients are, for the most part, statistically indistinguishable from zero, meaning a homeowner was as likely to protest, for example, an *Initial Assessed Value* that was 10% lower than the *Previous Assessed Value* as they were to protest an *Initial Assessed Value* that was 0.5% lower than their *Previous Assessed Value* (an observation that would be contained in the omitted bin). The Travis County sample shows estimated coefficients that are positive for very large reductions in *Initial Assessed Value*, but as shown by the histogram in Figure 2.6(B)(i), those estimates are based on a portion of the distribution with limited observations. By contrast, immediately to the right of zero percent change in *Initial Assessed Value*—in the *loss domain*—the slope of the conditional expectation increases sharply, indicative of a change in the elasticity of protesting with respect to percent change in *Initial Assessed Value*.

Figure 2.3 contains plots analogous to Figure 2.2, but separates each county sample into a *Cap-Eligible Sub-Sample* and *Cap-Ineligible Sub-Sample*. The reason to do so is twofold. First, it shows that the reference-dependent kink is present among both *Cap-Eligible* homeowners and among *Cap-Ineligible* homeowners, lending confidence to the idea that the psychological kink (near zero) is not somehow related to the real kink associated with the assessment increase limit. Second, as discussed in Section 1.1, a reference-dependent model predicts that the slope of the conditional expectation is steepest close to the reference point, but flattens as the extensive margin effect of loss aversion applies to fewer and fewer property owners. While confounded with the real kink in the benefit of protesting above +10% for *Cap-Eligible* homeowners, the *Cap-Ineligible Sub-Sample* shows a probability that becomes noticeably flatter for larger increases in *Initial Assessed Value*, providing suggestive evidence consistent with a waning extensive margin effect predicted by the reference-dependent model.

Figure 2.4 plots the probability of protesting split along a different dimension, separately estimating owner protests and agent protests. Split this way, it is clear that the kink in the probability of protesting near zero percent change in *Initial Assessed Value* appears strongest for owner-protests. The left-hand panels (Panels 2.4A(i) and 2.4(B)(i)) show a distinct kink in the probability of owner-protests in both counties. Meanwhile, the evidence for agent-protests is somewhat mixed: in the Harris County sample, the probability of an agent protesting (on behalf of an owner) appears to be smooth through the reference point, exhibiting no reference-dependent kink; however, in the Travis County sample, there appears to be a kink. In Section 2.4, I discuss the extent to which the evidence as a whole suggests that observed protest behavior is driven by *homeowners' preferences* (as specified by the model), and not other factors in the environment; these results provide a first piece of evidence favoring that view.

Local Linear Regression Kink Discontinuity (RKD) Estimates

To formally estimate the kink visually evident in Figures 2.2, 2.3, and 2.4, I employ local linear regression kink discontinuity (RKD) methods (*à la* Card et al. (2015)). The selection process governing reassessment in Harris County hinders clean identification of kink in that

[18] Clustering at the property level is inappropriate given that each property's assessed value is partially determined by an annually-calibrated market adjustment factor applied to all properties in a neighborhood.

sample.[19] For that reason, I begin by presenting RKD estimates from the Travis County sample without any controls, and complementary evidence of covariate balance in the Travis County sample. I then go on to present RKD estimates from both counties (separately) that include property-owner pair and year fixed effects, thus aligning with the global evidence previously presented. Presented together, the Travis County no-covariate RKD estimates lend confidence to the within-household RKD estimates from both counties.

The RKD design estimates the (semi-)elasticity of protesting with respect to percent change in *Initial Assessed Value* on either side of the reference point, within a symmetric bandwidth $(-h, h)$ as specified by the local linear model,[20]

$$P_{it} = \mathbf{1}_{\{-h \leq \ddot{A}_{it} \leq 0\}} \cdot \left[\alpha^{Gain} + \overbrace{\beta^{Gain}}^{\substack{\text{Gain Domain} \\ \text{Elasticity}}} \cdot \ddot{A}_{it}\right] + \mathbf{1}_{\{0 < \ddot{A}_{it} \leq h\}} \cdot \left[\alpha^{Loss} + \overbrace{\beta^{Loss}}^{\substack{\text{Loss Domain} \\ \text{Elasticity}}} \cdot \ddot{A}_{it}\right] + \epsilon_{it}. \quad (2.2)$$

As indicated, β^{Gain} identifies the elasticity below the reference point (in the gain domain), and β^{Loss} identifies the elasticity above the reference point (in the loss domain). Estimating the kink amounts to testing for a difference in these elasticities, $\beta^{Loss} - \beta^{Gain} > 0$.

The identifying assumption in the RKD design is that unobserved determinants of protesting are smoothly distributed with respect to the running variable. In the context of the analytical model, this requires that the (unobservable) noise term and effort cost parameters be distributed continuously and with continuous first derivatives in a neighborhood around the reference point. Appendix Figure A.2 and Appendix Table A.1 provide diagnostic covariate balance tests for key variables that determine the CAMA-model-assigned *Initial Assessed Value* in the Travis County sample. By and large, these diagnostic checks provide evidence of covariate balance, and assurance to the RKD design.[21]

Appendix Table A.2 contains the parameter estimates for the RKD design as specified by Equation 2.2 in the Travis County sample with no controls. Appendix Figure A.3 shows the RKD protest elasticity kink estimates for the main sample and sub-samples. Each sub-figure shows a bandwidth sensitivity analysis, plotting the estimated kink, $\beta^{Loss} - \beta^{Gain}$, from separate regressions, each estimated using a different bandwidth $h \in [0.025, 0.10]$. Like in the table, no controls are included in these estimates.[22] Each figure also shows the MSE-optimal bandwidth selected by the procedure suggested by Calonico et al. (2015) (indicated on each sub-figure with a dashed pink line), as well as quadratic-robust confidence intervals suggested

[19]See Section 2.2 and appendix for additional comments. In the main results, property-owner pair fixed effects purge estimates of time-invariant factors, controlling for these differences. If, however, differences in observable characteristics are indicative of differences in time-varying unobservables, properties may not be 'as good as randomly assigned' on either side of the reference point, posing a threat to identification in that sample.

[20]Although a kink in the first derivative could be estimated with a higher order polynomial, Gelman and Imbens (2019) suggest that lower-order polynomial models are less likely to lead to incorrect inference.

[21]Visually, observable property characteristics appear balanced near the threshold of interest. Placebo RD and RKD estimates using the CCT-selected bandwidth from the RKD estimate of the main outcome of interest (presented next) are shown in Appendix Table A.1. Using conventional standard errors (clustered at the neighborhood level), only Year Built has a placebo RD estimate marginally significant at the 5% level; similarly, only Grade shows placebo RKD that is marginally significant at the 5% level. Some covariates have placebo RD estimates that are significant according to the CCT quadratic-robust confidence interval; but none show a significant RKD estimate using the CCT quadratic-robust confidence interval.

[22]The RKD results are estimated using a uniform kernel. The appendix shows robustness variants using: (i) including year fixed effects, and (ii) using a triangular kernel.

by Calonico et al. (2014) for the CCT-bandwidth (overlaying the dashed pink line). Overall, the figures show substantial evidence of a kink, which is strongest among protests by owners (Panel D). Table A.2 shows the estimates underlying four of the kink estimates in Panel A (which includes the full Travis sample). Both β^{Gain} and β^{Loss}—which can be interpreted directly as (semi-)elasticities—are estimated as larger when using a smaller bandwidth, and attenuate at wider bandwidths.

The four left-most columns of Table 2.2 and Figure 2.5 show estimates produced by an RKD design that includes property-owner pair and year fixed effects. To increase the sample identifying the property-owner pair fixed effects, I include observations outside of the kink-estimating bandwidth and properties that were not reassessed, essentially combining Equations (2.1) and (2.2), and estimating,

$$P_{it} = \mathbf{1}_{\{-h \le \ddot{A}_{it} \le 0\}} \cdot \left[\alpha^{Gain} + \beta^{Gain} \cdot \ddot{A}_{it}\right] + \mathbf{1}_{\{0 < \ddot{A}_{it} \le h\}} \cdot \left[\alpha^{Loss} + \beta^{Loss} \cdot \ddot{A}_{it}\right] + \mathbf{1}_{\{\ddot{A}_{it} \notin [-h,h]\}} \cdot \sum_j \beta_j \cdot \mathbf{1}_{\{\ddot{A}_{it} \in Z_j\}} + \alpha^0 \cdot \mathbf{1}_{\{\ddot{A}_{it}=0\}} + \omega_i + \eta_t + \epsilon_{it}. \quad (2.3)$$

Like the standard approach above, $\beta^{Loss} - \beta^{Gain}$ identifies the kink estimated by this within-household procedure. Table 2.2 shows estimates of the kink close to 0.7 in the Harris County sample, and an estimate of the kink that hovers between 0.8 and 1.0 in the Travis County sample . In both samples, estimates of β^{Gain} are close to zero, leading estimates of the kink to be close to estimates of β^{Loss}. Across both samples, β^{Loss} is estimated to be between 0.7-1.0, meaning that to the right of the reference point—in the *loss domain*—a one percent increase in *Initial Assessed Value* is associated with a 0.7-1.0 percentage point increase in the probability of protesting. Altogether, the results from both the no-covariate Travis bandwidth tests, and the within-household bandwidth tests show estimated kinks that suggest a difference in elasticities between approximately 0.6 and 1.0. The eight right-hand columns of Table 2.2 show robustness results discussed Section 2.4.1.

2.3.2 Testing the Bunching Prediction

To test the *Bunching Prediction*, I estimate the excess mass at no change in *Final Assessed Value* in the distribution of changes in *Final Assessed Value* in the *Re-assessed Sub-Sample* using techniques similar to those developed and applied by Saez (2010), Chetty et al. (2011), and Rees-Jones (2018). Partitioning observations into equal-sized bins according to their percent change in *Final Assessed Value*, I estimate the distribution within a bandwidth near the reference point using a symmetric P-degree polynomial, allowing for excess mass at the reference point with,

$$B_j = \sum_{k=0}^{P} \beta_k \cdot \left(Z_j\right)^k + \gamma \cdot \mathbf{1}\left[Z_j = R\right] + \epsilon_j, \quad (2.4)$$

where B_j is a count of households in *Final Assessed Value* bin j, Z_j represents the final assessment bin value, R is the reference point (i.e. the bin associated with no change in *Final Assessed Value*), and ϵ_j an error term. The excess mass is identified by γ. I use a 7th-degree polynomial, 0.10 log point bandwidth, and a bin width of 5 basis points (0.05%), which translates to approximately one tax dollar for the median Harris County property, and approximately two tax dollars for the median Travis County property; results are not sensitive to those choices.

Table 2.3 contains estimates of excess bunching at the reference point in the distribution of (i) all households, (ii) protesters, and (iii) successful protesters, as well as for (iv) owner protesters and (v) agent protesters. For each sub-sample, I show estimates of excess mass both in terms of the raw number of properties, and as a percent of the relevant sub-sample's distribution. All estimates are highly significant, and precisely estimated using block-bootstrapped standard errors clustered at the neighborhood level. Figure 2.7 illustrates the estimation underlying the estimated excess mass for two of the specifications in the table. The top panel shows the final distribution of Harris County protesters; the bottom panel shows the final distribution of Travis County protesters. Both show unambiguous bunching at the *Previous Assessed Value*. Turning back to Table 2.3, in the Harris County sample, the excess mass represents 0.85% of all reassessed households, or equivalently, 3.90% of (reassessed) protesters, or 5.04% of (reassessed) successful protesters. In the Travis County sample, the excess mass represents 0.32% of all reassessed households, 1.51% of (reassessed) protesters, and 1.83% of (reassessed) successful protesters. Owner-protesters are more likely to end at their *Previous Assessed Value* than agent protesters, and notably, the excess mass is larger in the Harris County sample.

2.3.3 Testing the Opinion Bunching Prediction

Turning to the *Opinion Bunching Prediction*, I examine protesters' stated *Opinion of Value*, elicited at the time of protest filing *before* informal or formal review. While an imperfect measure, protesters' *Opinion of Value* provides evidence that homeowner preferences drive the patterns observed. In Section 1.1, I introduce A_t^O as the homeowner's proposed opinion of assessed value into the stochastic analytical model, assuming a particular structure and role. Using the structure of the model as a guide, I view empirically-observed homeowner opinions as, at bare minimum, correlated with their model counterpart. Coverage of *Opinion of Value* is imperfect in both samples, but far superior in Harris County. In both counties, the observed sample is selected, as providing an *Opinion of Value* is optional at the time of protest. Furthermore, due to recordkeeping procedures, coverage of *Opinion of Value* is low in the Travis County sample, even conditional on supplying an opinion. Most observed opinions come from owner-protests filed electronically (rather than on paper). Agent provided opinions are rarely recorded in the Travis sample.

With those caveats in mind, evidence clearly points to strong bunching tendencies. Table 2.4 and Figure 2.8 show estimates of excess bunching at the *Previous Assessed Value* in the distribution of protesters' *Opinion of Value* using the same estimation strategy as the previous bunching results. Limiting to their respective *Re-assessed, Opinion-Stated Sub-Samples*, Table 2.4 shows estimates of excess bunching among (i) all protesters, (ii) owner protesters, and (iii) agent protesters, in the Harris sample, and for all protesters in the Travis sample. In the Harris County sample, among those that stated an opinion, the estimated excess mass represents 10.63% of all protesters, 12.30% of owner protesters, and 9.18% of agent protesters. Exercising more caution with the Travis sample, evidence still points to substantial bunching, with 5.53% of all opinion-stated protesters bunching at the *Previous Assessed Value*. Like the final-outcome bunching results, all estimates are highly significant and precisely estimated.

Appendix Figure A.7 further reinforces the importance of *Previous Assessed Value* for protesters' valuations. The left-hand panel shows a histogram of *Opinion of Value* relative to the *Previous Assessed Value* in dollars (rather than percent differences); the right-hand panel shows a histogram of *Opinion of Value* relative to the *Initial Assessed Value*. Comparing these histograms and the associated statistics, protesters are much more likely to state an *Opinion of Value* that is an exact round-dollar-amount multiple (e.g. $10,000, or $5,000) away from the *Previous Assessed Value* than they are to state an *Opinion of Value* that is an exact round-dollar-amount multiple away from their *Initial Assessed Value*. While perhaps also indicative of a heuristic anchoring-and-adjustment process, this provides clear evidence that *Previous Assessed Value* is at the fore of protesters' attention.

Notably, there is more bunching in the *Opinion of Value* distribution than in the *Final Assessed Value* distribution. The model makes the same prediction, and furthermore predicts that bunching in the distribution of *Final Assessed Value* is a direct consequence of opinion bunching. Appendix Table A.3 shows correlational regression estimates from the Harris sample that relate bunching in the distribution of *Final Assessed Value* to opinions. While there exists bunching in the distribution of *Final Assessed Value* among protesters that did not state an opinion equal to their *Previous Assessed Value*, the estimates clearly show that final value bunching is more common among protesters that did state an opinion equal to their *Previous Assessed Value*. Column (4) contains the preferred specification, showing that opinion-bunchers are twice as likely to be final value-bunchers. It also shows that those who received a full reduction (achieving a final assessment equal to their opinion) were also more as likely to be final value-bunchers, which is also consistent with what the reference-dependence model predicts. Furthermore, both of these effects are stronger among owner-protesters.

2.3.4 Conditional Average Assessment Reductions Near the Reference Point

Figure 2.9 plots the average percent reduction received by successful protesters,[23] estimated analogously to Equation (2.1) with individual and year fixed effects, where larger values correspond to larger reductions. Coefficients are normalized to the average reduction given a percent change in *Initial Assessed Value* between -1% and 0%. The top panel shows successful protesters in the Harris sample; the bottom panel shows successful owner-protesters in the Travis sample. Both plots show that the average reduction received by successful protesters drops for those just barely in the loss domain, consistent with an *extensive* margin effect induced by loss aversion. The Travis County sample excludes agent-protesters, as the effect is only pronounced when the sample is limited to owner-protesters.

An assumption of the model is that the average noise in assessments is smoothly distributed around the reference point. If, arbitrarily, properties that increased in value were disproportionately more likely to be over-assessed by a greater amount, we would expect a kink in the probability of protesting at the reference point, but we would also expect those homeowners to receive larger reductions on average. Instead, we see the opposite, a result consistent with the reference-dependence framework.

2.3.5 Kink in Unconditional Average Assessment Reductions

In Section 2.5, I examine reductions received *unconditional* on protesting to conduct counterfactual analysis. Table 2.5 and Figure 2.10 show regression kink discontinuity es-

[23] Percent reductions defined as $100 \cdot \log\left(A_{it}^{Init} / A_{it}^{Final}\right)$.

timates analogous to Equation 2.3 but with assessment reductions received unconditional on protesting as the dependent variable. Appendix Figure A.13 shows kink bandwidth sensitivity tests estimated from regressions analogous to Equation 2.2 (without fixed effects or any other controls). Similar to the protest kink results, the within-property-owner-pair estimates provide evidence of a stably estimated kink. The effect size is indicative of average reductions—unconditional on protesting—that are approximately 0.8 (Harris) and 0.5 (Travis) percentage points (of *Initial Assessed Value*) higher per 10% increase in *Initial Assessed Value* in the loss domain.

2.4 Robustness of Results & Alternative Mechanisms

Having established the principal evidence, I now address the robustness of results and the extent to which alternative mechanisms warrant consideration.

2.4.1 Robustness to Proxy Controls for the Noise Term

Ideally, one would observe and control for the noise term in an *Initial Assessed Value*. In addition to relieving concerns that results are driven by the distribution of noise in assessments, controlling for an assessment's noise term would mitigate concerns that results are driven by reviewers, who, being both experienced and quite familiar with the law, are likely to act in accordance with it. Idiosyncratic sources of noise will always be unobservable, but features of the Texas property tax code make it possible to construct proxies for certain sources of noise. As discussed in Section 2.2, a "uniform and equal" provision affords property owners the right to a reduction if they can show that the assessed value of their property exceeds the median assessed value of a reasonable number of comparable properties.[24]

Guided by the practices of a private firm which provides property tax protest services in both counties, I estimate the potential reductions available from pursuing a uniform and equal grounded protest. For each property-year, I identify comparable properties in the same neighborhood, and compare the assessed value per square foot of improvements on that property to the median assessed value per square foot of improvements on comparable properties, provided at least five comparable properties can be identified. Using this strategy (detailed in Appendix A.3), I construct a uniform and equal noise proxy, η_{it}^{UE}, for 91.4% of Harris County properties and 85.3% of Travis County properties. The eight right-hand columns of Table 2.2 and Table 2.5, and Appendix Figures A.9, A.10, and A.11, show the results from this analysis. As before, I show within-property-owner-pair results for Harris County, and results for Travis County with and without property-owner pair fixed effects. The evidence can be summarized as follows: (i) as predicted by the model, the U&E noise proxy appears positively and linearly related to one's percent change in *Initial Assessed Value*, (ii) the proxy appears valid in the sense that it is positively related to the reductions achieved, (iii) the kink in the probability of protesting is robust to controlling for the U&E noise proxy (both linearly, and allowing for a kink in the proxy's effect for positive values of the proxy), and (iv) the kink in the average reduction achieved unconditional on protesting (discussed further in the Section 2.5), is robust to controlling for the U&E noise proxy (again, both

[24] Most protesters give themselves the option to protest on the basis that both (i) the *Initial Assessed Value* does not reflect *Market Value*, and that (ii) the *Initial Assessed Value* is not assessed uniformly and equally (83% in Travis County). I cannot separate the reason(s) for which a reduction was ultimately granted.

controlling linearly, and allowing for a kink in the proxy's effect for positive values of the proxy).

A similar provision affords property owners the right to a reduction if they can show that the assessed value of their property is not reflective of market value. Sales prices are not publicly available in Texas, limiting my ability to construct an analogous comparable sales noise proxy; however, TCAD's records include a very small fraction of non-confidential, non-random sale prices. Using a similar strategy (detailed in Appendix A.3), I construct a comparable sales noise proxy for 1.9% of Travis County properties. Given the available data, the comparable sales proxy is noisier, more likely to be biased, and, unlike the U&E proxy, based on data that may or may not have been available to property owners or third-party agents at the time of their protest. Furthermore, there is insufficient variation to examine effects within-property-owner-pair. That said, results available in Appendix Figure A.12 mirror that of the U&E noise proxy analysis, providing suggestive evidence that the kink-based results are robust to controlling for a comparable sales noise proxy.

2.4.2 Owner vs. Agent Preferences

Third-party agent representatives handle more than half of all protests. Conceivably, agents could themselves be loss averse. While interesting in and of itself, one would expect the reference point to weigh most heavily on homeowners; if there were evidence suggesting the contrary, that might give pause to the purported theory. I do not attempt to separate the preferences of agents from the preferences of the homeowners they represent in agent-protested cases, but we can examine differences between agent-protested cases and owner-protested cases. In particular, (i) the extensive margin evidence is most clear in owner-protested cases (kinks in Figures 2.4 and A.3, and average reductions in Figure 2.9), (ii) owner-protesters are more likely to achieve a *Final Assessed Value* at the *Previous Assessed Value* (Table 2.3), and, (iii) at least in Harris County, owners are more likely to state that their *Opinion of Value* is equal to their *Previous Assessed Value* (Table 2.4). Together, while not ruling out the possibility that reference-dependence has some bearing for agents, on balance, evidence points to reference-dependent actions being most associated with owners. In fact, this evidence could suggest that third-party agents in fact *de-bias* property owners, influencing them to act less loss averse than they otherwise might.

2.4.3 Reviewer Preferences & the Probability of Successfully Protesting

The kink and bunching evidence could result from the protest process itself if it is difficult to convince a reviewer (be it an assessor or review board) to lower an assessment below the *Previous Assessed Value*. Appendix Figure A.6 plots the probability of winning, conditional on protesting, with property-owner pair and year fixed effects. Coefficients are normalized to the probability of winning given a change in *Initial Assessed Value* between -1% and 0%. In both county samples, there appears to be a slight increase in the probability of winning a protest to the right of the reference point, particularly in the Travis sample. While seemingly indicative of a potential dynamic involving differences in the marginal cost of achieving a reduction above the *Previous Assessed Value*, it is important to recognize that the baseline probability of winning is quite high. Choosing 2011 as a common base year, the baseline probabilities of success are 77% in Harris and 83% in Travis. Given the high baseline likelihood of winning, differences in the probability of winning on either side of the reference point are unlikely to drive the observed pattern in the probability of protesting, especially in the Harris County sample, where the difference is minimal. Furthermore, differences in the probability of winning near the kink could also *result* from homeowner loss aversion. While in my analytical model effort does not affect the probability of winning a protest, one could imagine a margin for effort that influences the probability of winning. In fact, some evidence directly suggests that effort is higher among those in the loss domain: in the Harris County sample, I can observe if a protester did not show up to a scheduled meeting or hearing (resulting in forfeiture). As shown in Appendix Figure A.6(A)(ii), the slight increase in the probability of winning (among those in the loss domain) is partly attributable to the fact that those in the loss domain are less likely to miss a scheduled meeting or hearing.

2.4.4 Salience, Heuristics & Previous Assessed Value as a Bargaining Point

The amount of bunching generated from reference-dependent behavior depends on the ability to target a specific value. In the present context, bunching is quite substantial. In part, the observed bunching may be biased to the extent that the process determining final values (or opinions too, for that matter) disproportionately yields a final value (or opinion) that is, in one way or another, heuristically determined. Appendix Figure A.7 shows that there is excess bunching at round-dollar-amount multiples away from both the *Previous Assessed Value* and *Initial Assessed Value*. That said, bunching at the *Previous Assessed Value* dwarfs bunching at other notable values.

Without complementary evidence on protesters' *Opinion of Value*, one might wonder if final outcome bunching at the *Previous Assessed Value* is driven by reviewer preferences. Certainly, strategic concerns may influence some protesters' opinions; however, because reductions need to be accompanied by supporting evidence, the margin for bargaining is limited in practice. Appendix Figure A.8 shows how *Final Assessed Value* compares to both the *Initial Assessed Value* and *Opinion of Value* in the Harris sample. Splitting the difference between *Opinion of Value* and *Initial Assessed Value* appears to occur slightly more that randomness would predict (as indicated by the excess mass at 0.5), but it is certainly not the norm. Overall, the large and significant amount of excess bunching in protester *Opinion of Value* suggests that protester preferences significantly impact the amount of bunching observed in the distribution of *Final Assessed Value*.

Intricacies introduced by these additional dynamics warrant future research, but their impact is likely marginal, and furthermore, limited to the intensive margin.

2.4.5 Liquidity Constraints

Liquidity constraints could seemingly drive similar results if households do not budget for potential property tax increases. Three reasons make this an unlikely explanation. First, property assessments must be challenged in the beginning of the fiscal year, but property taxes are not paid until the end. A liquidity constrained income tax filer who, close to the filing deadline, unexpectedly discovers that she owes income tax in excess of what was already withheld, may only have a few weeks or days to absorb the shock and come up with the necessary payment; by contrast, a property tax filer will have several months. Second, a reference-dependence framework predicts a probability of protesting that may eventually flatten, as I show empirically. A model with liquidity constraints would instead produce a probability of protesting that continually increases. Finally, in the next section, I point out that owners of more valuable properties, who we would expect to be less likely to be liquidity constrained, are much more likely to protest.

2.5 Contextualizing the Ultimate Effects of Loss Aversion

To contextualize and quantify the ultimate impact of loss aversion, I now shift my focus to counterfactual analysis. For this exercise, I use only the Travis County sample to avoid any issues arising from selection into reassessment, potentially present in the Harris sample. The aim is to provide first-order approximations of estimates for several outcomes of interest: (i) the excess protests induced by loss aversion, (ii) the revenue lost due to loss aversion, (iii) an effect size in both assessed value reductions and tax dollar reductions per property-year observation, and (iv) the administrative wage burden of handling excess protests. The essence is to first empirically estimate areas equivalent to the shaded regions shown in simulation Figures 1.2(A) and 1.2(E), and then to use those estimates to calculate the aforementioned outcomes. Note that the shaded region in Figure 1.2(E) shows the excess percent reduction in property value among *all households*, not just those that protest; consequently, revenue and tax estimates derived from estimations of this area will reflect a total effect size, inseparably consisting of both an intensive and extensive margin effect associated with loss aversion.

I restrict attention to, and only calculate counterfactuals for, a region of the distribution close to the reference point. Because these counterfactuals rely on estimated behavior in the gain domain extrapolated into the loss domain, one might reasonably disagree about the bandwidth within which we can confidently estimate counterfactuals that reasonably reflect the true counterfactual. That said, evidence presented shows a stably estimated kink except at very small bandwidths (e.g. Figure 2.10). With that caveat in mind, I proceed with the analysis, choosing as a bandwidth those properties for which the percent change in *Initial Assessed Value* was between $\pm 10\%$. Intentionally, this represents the region of the loss domain below the 10% cap in assessed value (and a symmetric region of the gain domain). Simultaneously it strikes a balance between refraining from extrapolation far from the reference point, while still covering a substantial portion of the distribution.

The approach is straightforward and builds off of the RKD analysis in Section 2.3. Like before, I present estimates that (i) do not include any controls, and (ii) that include both year and property-owner pair fixed effects. I begin by estimating the probability of protest as previously specified (Equations 2.2 and 2.3). I then extrapolate the fitted values from the gain domain to predict a counterfactual probability of protesting in the loss domain,

$$\hat{P}_{it}^{CF:\lambda\equiv 1} \equiv \hat{P}_{it} + \left(\beta^{Gain} - \beta^{Loss}\right) \cdot \ddot{A}_{it} + \left(\alpha^{Gain} - \alpha^{Loss}\right) \qquad \text{if } \ddot{A}_{it} \text{ in Loss Domain} \tag{2.5}$$

The excess probability of protest $\hat{\mu}_{it}^{P}$ is then defined as the deviation between the estimated probability of protest and the counterfactual,

$$\hat{\mu}_{it}^{P} \equiv \hat{P}_{it} - \hat{P}_{it}^{CF:\lambda=1} \qquad \text{if } \ddot{A}_{it} \text{ in Loss Domain}$$

The excess percent reduction achieved is calculated in parallel fashion, first estimating the average percent reduction analogously to Equations 2.2 and 2.3, then extrapolating the fitted values from the gain domain to predict a counterfactual in the loss domain,

$$\widehat{\Delta A}_{it}^{CF:\lambda\equiv 1} \equiv \widehat{\Delta A}_{it} + \left(\beta^{Gain,Red.} - \beta^{Loss,Red.}\right) \cdot \ddot{A}_{it} + \left(\alpha^{Gain,Red.} - \alpha^{Loss,Red.}\right) \quad \text{if } \ddot{A}_{it} \text{ in Loss Domain} \tag{2.6}$$

and defining the excess percent reductions $\hat{\mu}^{\Delta A_{it}}$ as the difference between the predicted reduction and the counterfactual,

$$\hat{\mu}_{it}^{\Delta A} = \widehat{\Delta A}_{it} - \widehat{\Delta A}_{it}^{CF:\lambda\equiv 1} \qquad \text{if } \ddot{A}_{it} \text{ in Loss Domain}$$

Combining $\hat{\mu}_{it}^{P}$ and $\hat{\mu}_{it}^{\Delta A}$ (both percentages) with the underlying distribution of A_{it} and τ_{it}, one can readily calculate aggregate and average-per-property effect sizes, translated into assessed value and tax dollar terms.[25]

Figure 2.11 illustrates the intuition for this exercise, showing the estimated counterfactuals and average excess in the loss domain among all reassessed households in Travis County (binned into 0.05% bins in the figure, but estimated on the underlying data) without controls. Panel (A) of Figure 2.11 shows the counterfactual and excess probability of protest. Figure 2.11(B) shows the counterfactual and excess average percent reduction in assessed value in the loss domain among all reassessed households. Panel 2.11(C) shows how the estimated excess assessment reductions translate to an estimated annual average excess tax reduction per property-year observation.

Table 2.6 (estimated from micro-data without controls) and Table 2.7 (estimated from micro-data with property-owner pair and year fixed effects) show the estimated effect sizes. For both, I show neighborhood-clustered block bootstrap standard errors. In each table, the left-most column shows estimates for all reassessed properties. In both tables, the full-sample estimates are highly significant. Throughout this section, it's important to keep in mind that all estimates refer only to the portion of the loss domain below a 10% increase in assessed value. In total, this bandwidth covers 55% of all reassessed properties. Accounting for the underlying distribution of properties, I estimate that loss aversion increases the number of protests filed (above the counterfactual estimated for this portion of the loss domain). With no controls, I estimate that protests increase by 50.32%, representing an additional 4,999 protests *per year* and 4.41% of all households in the bandwidth. Making rough, but reasoned assumptions, I estimate that each additional protest incurs an administrative labor cost (to the county) of at least \$14.38; under that assumption, excess protests induced by loss aversion burdens Travis county with an administrative wage cost of at least \$72,000 annually.[26] With property-owner pair and year fixed effects (Table 2.7), I estimate that protests increase by 38.52%, representing an additional 4,494 protests *per year*, and an administrative wage cost of at least \$65,000 annually.

[25]For example, Annual Excess Protests $\equiv \sum_{it} \hat{\mu}_{it}^{P} / N_{Years}$, and Average Annual Tax Reductions in Loss Domain $\equiv \sum_{it} \hat{\mu}_{it}^{\Delta A} \times A_{it} \times \tau_{i,t-1} / N_{Obs} | \ddot{A}_{it}$ in Loss Domain. Note that following the analytical model, I calculate *estimated* taxes using the previous year's tax rate.

[26]The cost-per protest estimate is based upon a handling time I assume, and actual labor costs (see Appendix A.3). It surely understates the true administrative cost of a protest, which, if more comprehensively estimated, would also include non-labor expenses. For example, ARB members must be trained, and hearings require office space–in 2019, TCAD purchased 72,720 square feet of office space specifically acquired to handle the large volume of protest cases.

Continuing with the preferred estimates in Table 2.7 (with year and property-owner pair fixed effects), I estimate that loss aversion increases the value of reductions received by 39.60% in the loss domain. The counterfactual difference in terms of assessed value averages $79.83 million per year, or, in terms of tax dollars, $1.91 million per year. Overall, estimates suggest that loss aversion induces property owners in *this portion* of the loss domain to secure reductions in their tax liability averaging $26 annually, *unconditional on protesting*; however, that singular estimate is a bit misleading. As shown in Figure 2.12(A), the average effect of loss aversion depends substantially upon one's position in the loss domain. Close to the reference point there is no effect. At the median percent change in *Initial Assessed Value* in the full, unrestricted sample (indicated in the figure with the dashed vertical line), the average annual effect size is $34. Among properties that experienced a 10% increase in assessed value—a substantial, but not extraordinary increase—the average annual effect size is close to $45.

In both Tables, I repeat the same exercise, but calculate estimates separately by quartile of *Initial Assessed Value*, assigned within-year. Figures A.16 and 2.12, and Appendix Figures A.17 and A.18 correspond to the by-quartile-of-value estimates. This sub-sample analysis reveals that the effects are largely concentrated among properties that constitute the top two quartiles. The median *Initial Assessed Value* in these quartiles is $313,311 and $533,770, respectively. Together these properties account for 72% of all protests. Comparing the estimates across quartiles in Tables 2.6 and 2.7, estimated excess protests and estimated excess assessed value reductions are both substantially higher among properties in the third and fourth quartile. As a result, revenue differences attributable to loss aversion are almost entirely driven by owners of more expensive properties.

This fact is readily apparent from the calculated effect sizes per property-year (which recall, are stated *unconditional on protesting*). Overall, the average annual tax reduction attributable to loss aversion is negligible among properties constituting the lower two quartiles of value: the estimated effect sizes are $5 and $9 (without fixed effects), and $5 and $2 (with fixed effects), respectively. Among properties constituting the top two quartiles of value, the average annual tax reduction attributable to loss aversion is substantially larger, precisely estimated, and economically meaningful: $39 and $112 (without fixed effects), and $10 and $57 (with fixed effects), respectively. Figure A.16(B)-(E) reiterates the importance of one's position in the loss domain when considering the average unconditional effect of loss aversion. Near the reference point the effect size is close to zero. At the median percent change in *Initial Assessed Value* for top quartile properties, the estimated annual effect size is $80 (estimated with fixed effects). Among households that experienced a 10% increase in assessed value, the average effect size is $25 for third quartile-of-value properties and close to $115 for top quartile-of-value properties (estimated with fixed effects).

2.6 Discussion & Conclusion

This paper unveils the importance of reference-dependence and loss aversion in understanding property tax avoidance. In doing so, I add to an emerging literature in public finance that examines psychological bias and tax morale as a determinant of tax compliance.

Compared to other taxes, morale for the property tax is especially low. Between 1988 and 2005 (the most recent year available), the fraction of survey respondents in a Gallup poll that cited the property tax as the worst or least fair tax rose from 24% to 42%. In all likelihood, the increasing dislike relates to the substantial increase in home prices (and corresponding property taxes) that occurred during that period. That tax increases are disliked is hardly surprising; however, recognizing the acute role played by loss aversion helps to explain why contempt for property taxes is particularly emotive. Indirectly, the findings in this paper suggest further explanation for the popularity of property tax limit measures, such as California's famous Proposition 13, because they not only allow taxpayers to avert taxes but also limit feelings of loss. Furthermore, by setting expectations for future tax increases, feelings of loss are ameliorated.

The extent to which loss aversion influences avoidance may be substantially greater in the property tax setting as compared with an income tax setting for the simple reason that with property taxes, individuals are more likely to find themselves in the loss domain. Whereas the majority of income tax filers receive a refund at the end of the year, even without any avoidance measures, historically, housing prices have steadily increased, leading to a distribution of value changes that, more often than not, is centered in the loss domain.

Unearthing reference-dependence as both critical and transparently observable in the property tax setting could also aid the future research of reference-dependence more generally. Protest behavior from the *crisis years* 2008-2010 provides suggestive evidence of a partially-adaptive reference point during that period. While beyond the scope of this paper, in future research the property tax setting may prove useful in further understanding the endogeneity of reference points, or the simultaneous influence of multiple reference points.

Understanding the psychology of reference dependence and loss aversion could inform policy-relevant practices that subvert its effects. Assessment notices prominently feature the property's *Previous Assessed Value*. Including additional, equally prominent reference points on assessment notices may significantly affect household protest behavior. For example, a homeowner upset that his taxes have increased, may be less upset if his notice also makes clear that his neighbors' taxes have increased as well. Indeed, similar strategies have been shown to change behavior in residential energy usage (Allcott, 2011). Conversely, to ensure fairness and, potentially, to increase trust in the institution, it might be prudent to remind homeowners on their tax notice that a property may still be overvalued despite a decline in assessment, and hence warrant protest.

Establishing loss aversion's significance may also shed new light on open questions related to property tax appeals and administration. For example, if people have systematic differences in the tendency to behave in a manner consistent with loss aversion, it may lead to nonuniform or inequitable assessments. Finally, a question this research raises is whether any localities attempt to exploit loss aversion to raise additional revenue, perhaps especially if financially strained. In principle, a tax assessor could systematically over-assess property that has decreased in value, leveraging the fact that households are unlikely to protest assessments as long as they do not increase. In all likelihood, this would place undue burden on households that are already financially strained.

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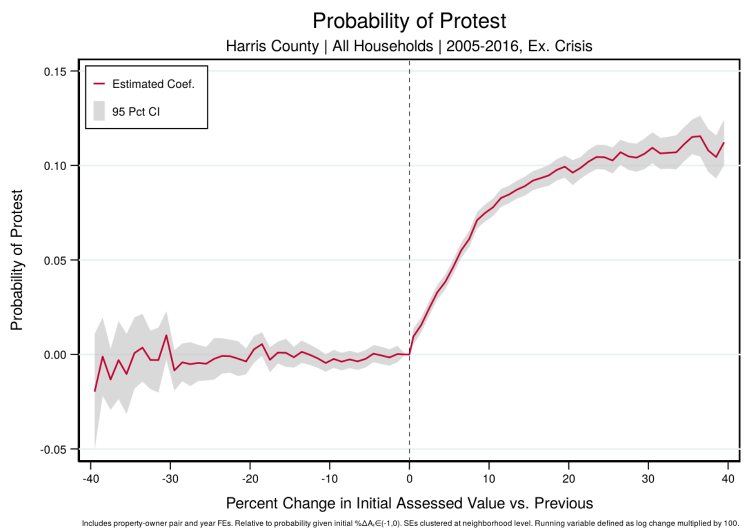
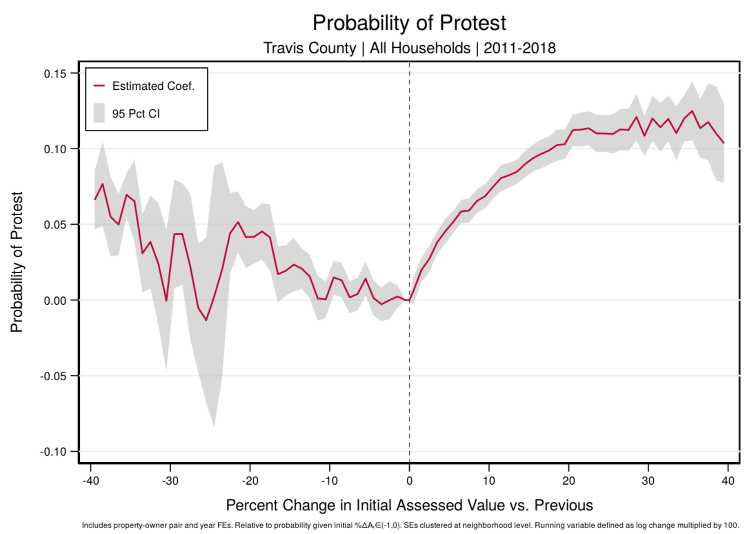
2.7 Figures

Figure 2.2: Probability of Protest by Percent Change in *Initial Assessed Value*.



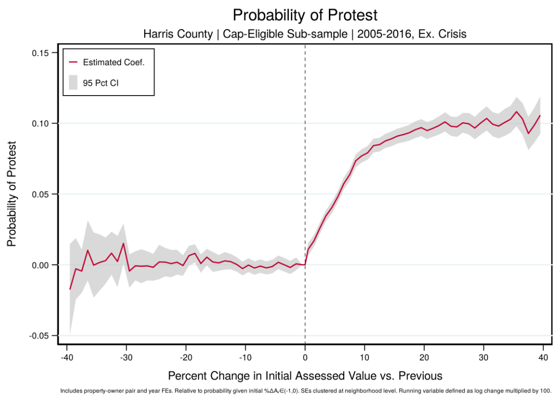
(A) Harris County



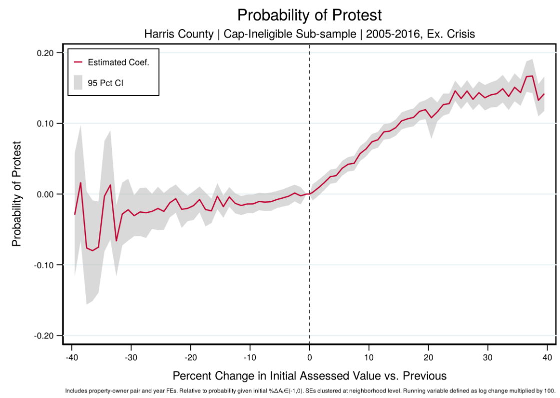
(B) Travis County

Notes: Estimated coefficients from a linear probability model of protesting given percent change in *Initial Assessed Value*, binned into one percentage point bins, with property-owner pair and year fixed effects. Coefficients are normalized to the probability of protest given a percent change in *Initial Assessed Value* between -1% and 0%. An indicator associated with exactly no change in *Initial Assessed Value* is included in the regression to increase the identifying sample for the individual fixed effects, but is omitted from the figure; likewise, indicators associated with a change in *Initial Assessed Value* (i) greater than 40%, and (ii) less than -40% are included in the regression but not in the figure (i.e. extreme values are binned at ±40%, respectively). Crisis years defined as 2008-2010. Standard errors are clustered at the neighborhood level.

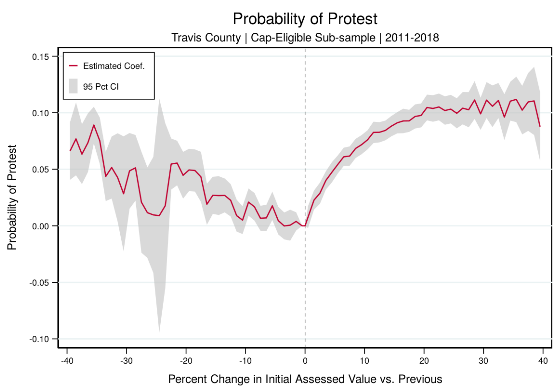
Figure 2.3: Probability of Protest by Percent Change in *Initial Assessed Value* splitting Cap-Eligible and Cap-Ineligible properties.



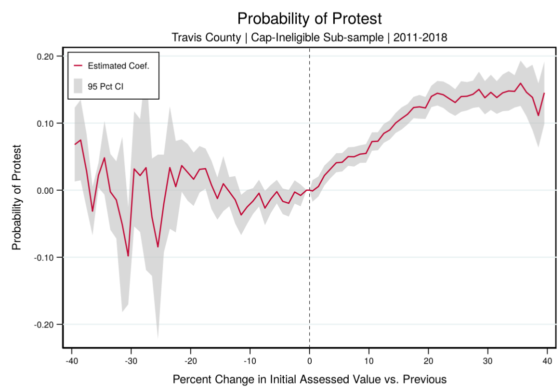
(A) (i) Harris County: *Cap-Eligible Sub-sample*



(A) (ii) Harris County: *Cap-Ineligible Sub-sample*



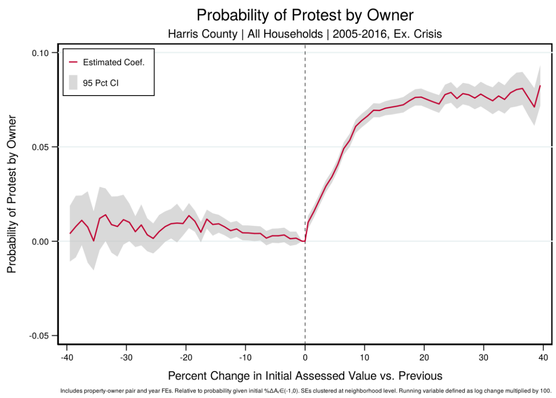
(B) (i) Travis County: *Cap-Eligible Sub-sample*



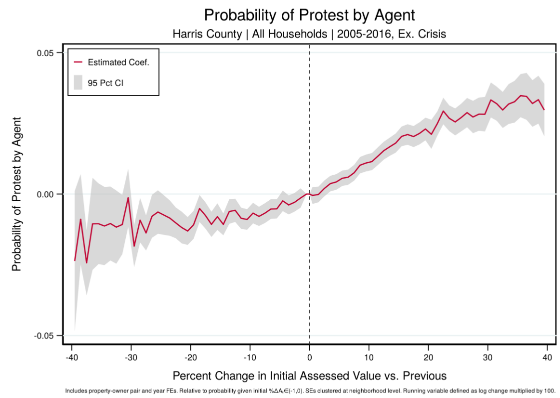
(B) (ii) Travis County: *Cap-Ineligible Sub-sample*

Notes: Analogous to Figure (2.2) but splitting homeowners into sub-samples that are (i) eligible to benefit from a capped assessed value provision (at 10%), and (ii) ineligible to benefit from a capped assessed value. Estimated coefficients from a linear probability model of protesting given percent change in *Initial Assessed Value*, binned into one percentage point bins, with property-owner pair and year fixed effects. Coefficients are normalized to the probability of protest given a percent change in *Initial Assessed Value* between -1% and 0%. An indicator associated with exactly no change in *Initial Assessed Value* is included in the regression to increase the identifying sample for the individual fixed effects, but is omitted from the figure; likewise, indicators associated with a change in *Initial Assessed Value* (i) greater than 40%, and (ii) less than -40% are included in the regression but not in the figure (i.e. extreme values are binned at $\pm$40%, respectively). Crisis years defined as 2008-2010. Standard errors are clustered at the neighborhood level.

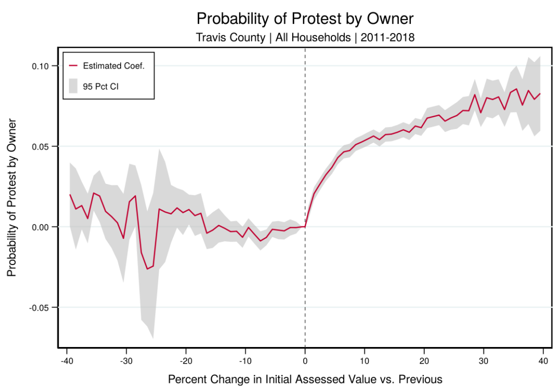
Figure 2.4: Probability of Protest by Percent Change in *Initial Assessed Value* splitting Owner-Protested and Agent-Protested Cases.



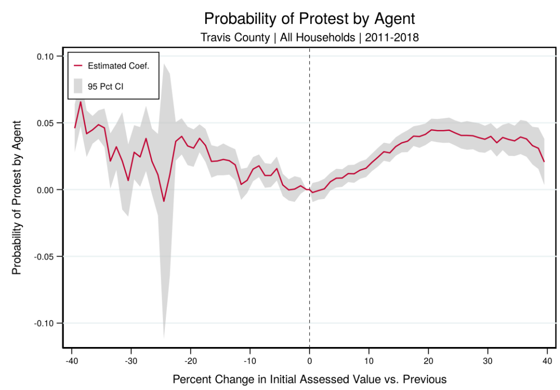
(A) (i) Harris County: *Protests by Owners*



(A) (ii) Harris County: *Protests by Agents*



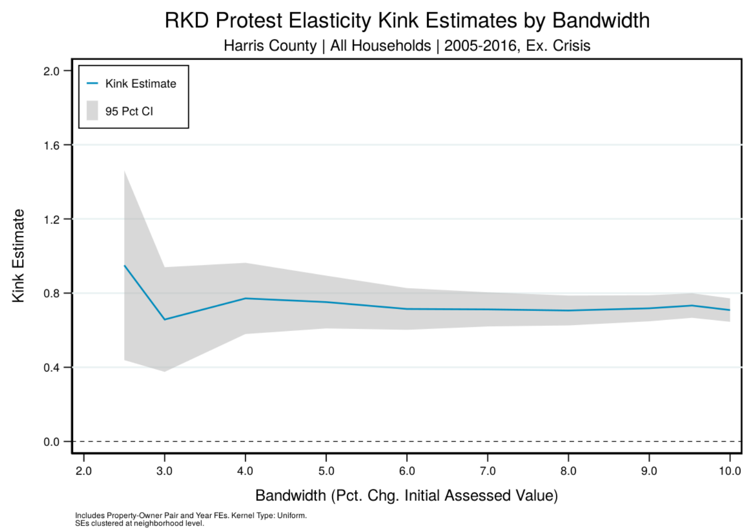
(B) (i) Travis County: *Protests by Owners*



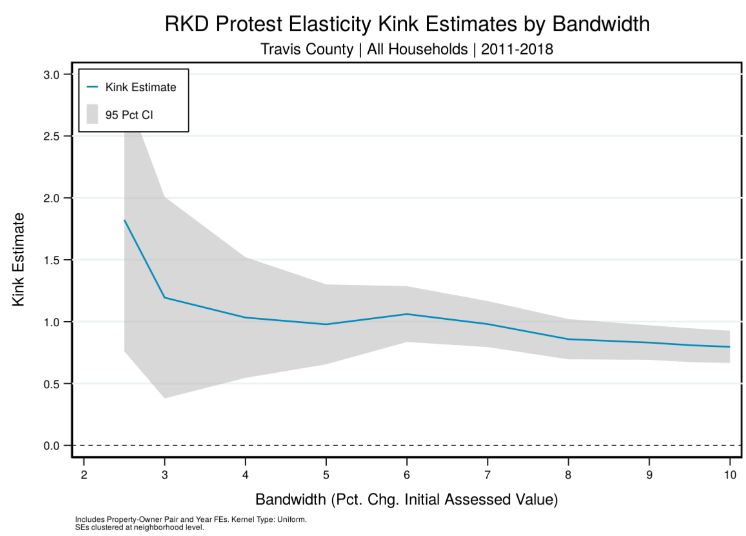
(B) (ii) Travis County: *Protests by Agents*

Notes: Analogous to Figure (2.2) but splitting protests into those that are (i) protested by owners, and (ii) protested by representing agents. Estimated coefficients from a linear probability model of protesting given percent change in *Initial Assessed Value*, binned into one percentage point bins, with property-owner pair and year fixed effects. Coefficients are normalized to the probability of protest given a percent change in *Initial Assessed Value* between -1% and 0%. An indicator associated with exactly no change in *Initial Assessed Value* is included in the regression to increase the identifying sample for the individual fixed effects, but is omitted from the figure; likewise, indicators associated with a change in *Initial Assessed Value* (i) greater than 40%, and (ii) less than -40% are included in the regression but not in the figure (i.e. extreme values are binned at $\pm$40%, respectively). Crisis years defined as 2008-2010. Standard errors are clustered at the neighborhood level.

Figure 2.5: Regression Kink Design Estimates of the Difference in the Elasticity of Protesting with respect to Percent Change in *Initial Assessed Value* with Property-Owner Pair and Year Fixed Effects.



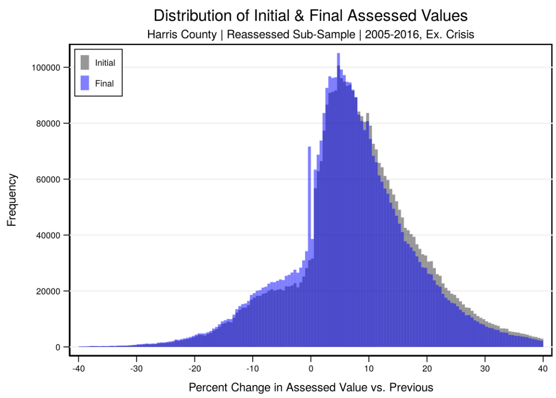
(A) Harris County



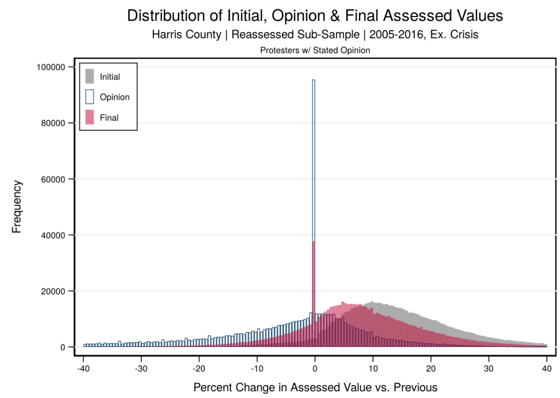
(B) Travis County

Notes: The figures above show regression kink design (RKD) estimates from regressions that include both individual and year fixed effects, showing the *difference* in the elasticity of protesting above and below the reference point. Both plots show a bandwidth sensitivity test, showing the RKD estimates of separate regressions at symmetric bandwidths $k \in [2.5\%, 10\%]$ around the reference point. In each underlying regression, values outside of the kink-estimating bandwidth are included (modeled flexibly by binning observations into one percentage point bins by percent change in *Initial Assessed Value* outside of the kink-estimating bandwidth) in order to increase the sample identifying the individual fixed effects; similarly, an indicator associated with exactly no change in *Initial Assessed Value* is included in the regression to increase the identifying sample for the individual fixed effects, but is excluded from the kink estimate. Standard errors are clustered at the neighborhood level; uniform kernel. Corresponds to Equation 2.3 and Table 2.2.

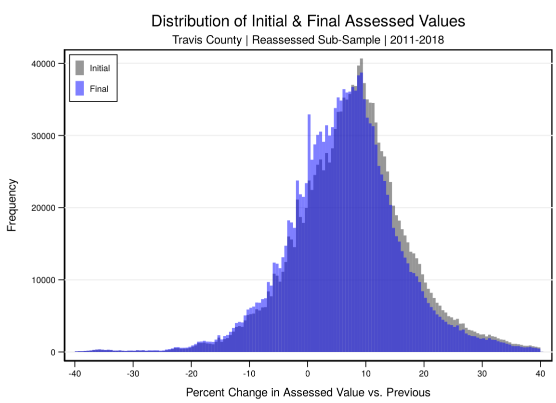
Figure 2.6: The distribution changes in *Initial Assessed Value* and *Final Assessed Value* among all reassessed households, and separately among reassessed households that protested and stated an *Opinion of Value*.



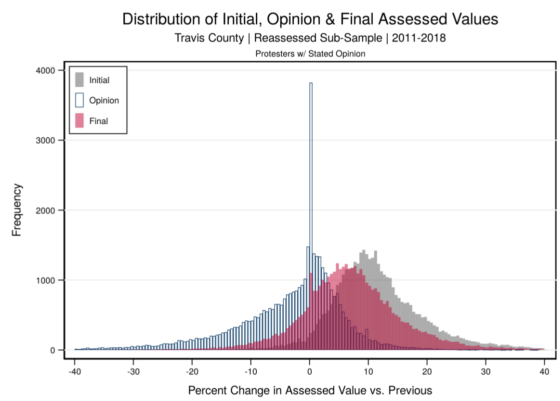
(A) (i) Harris County: *Reassessed Households*



(A) (ii) Harris County: *Reassessed, Opinion-Stated Protesters*



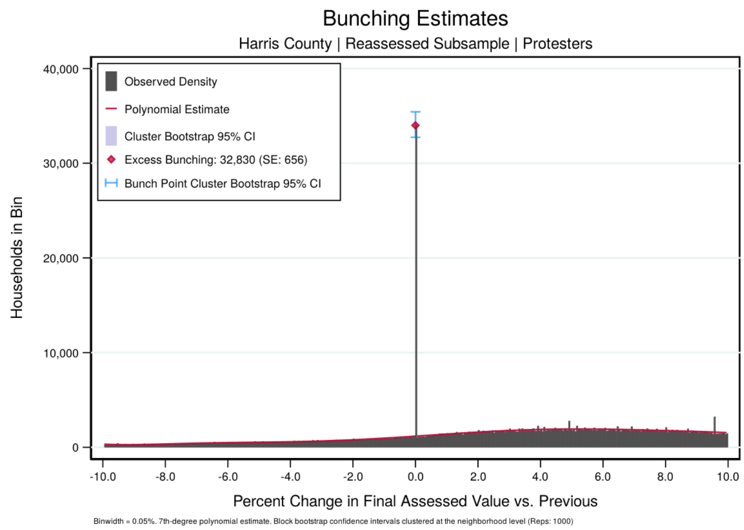
(B) (i) Travis County: *Reassessed Households*



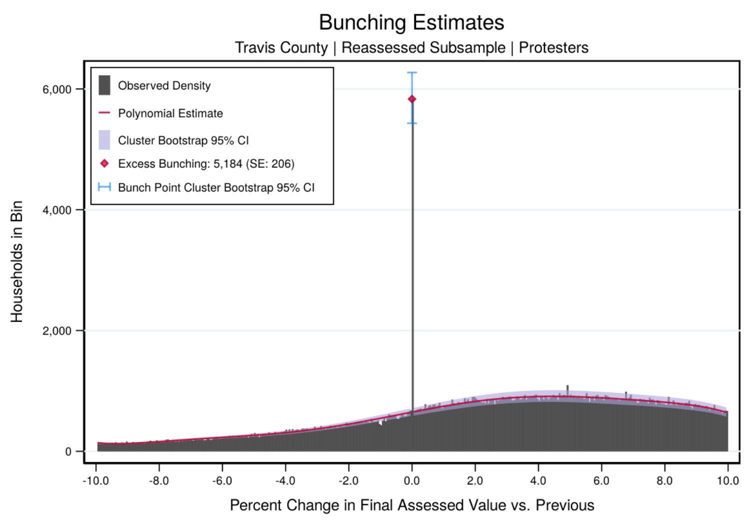
(B) (ii) Travis County: *Reassessed, Opinion-Stated Protesters*

Notes: The left-hand panel shows both (i) the distribution of percent change in *Initial Assessed Value*, and (ii) the distribution of percent change in *Final Assessed Value*, among all reassessed households (excluding property which mechanical received no change in *Initial Assessed Value*). The right-hand panel shows (i) the distribution of percent change in *Initial Assessed Value*, and (ii) the distribution of percent change in *Final Assessed Value*, and (iii) the distribution of percent change in *Opinion of Value* relative to *Initial Assessed Value*, among protesters for whom an *Opinion of Value* is observed (constituting 84% of Harris protests, and 12% of Travis protests).

Figure 2.7: Distribution of *Final Assessed Value* and Estimated Bunching at *Previous Final Assessed Value* among protesters in the *Reassessed Subsample*.



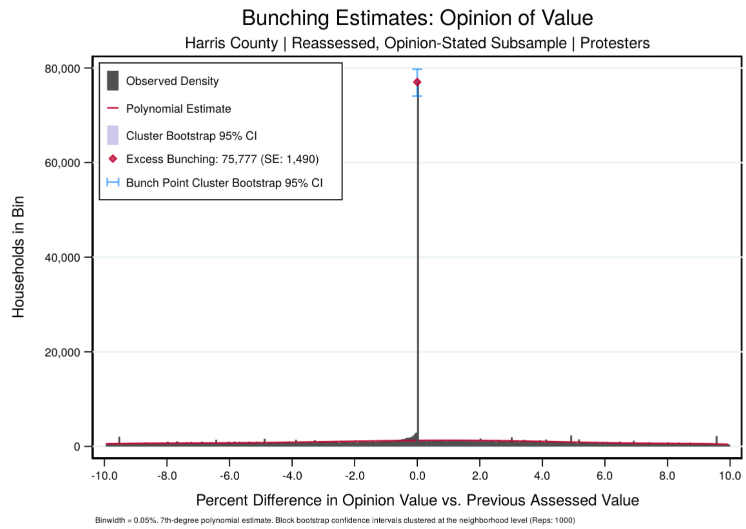
(A) Harris County



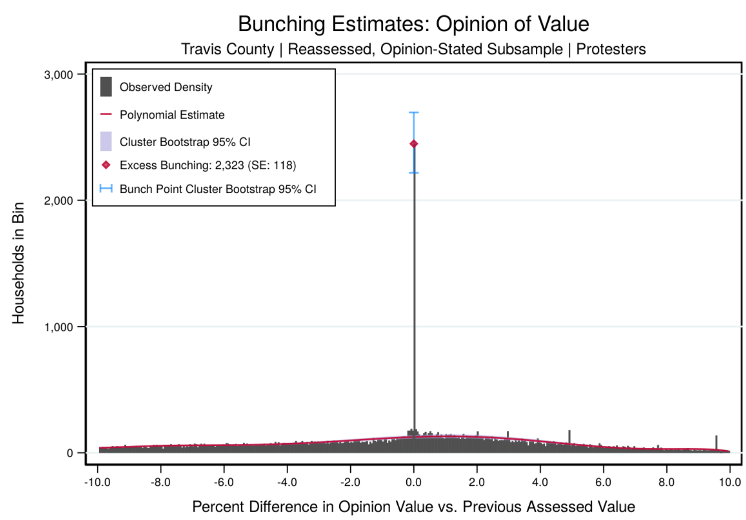
(B) Travis County

Notes: The figure plots (i) the distribution of $100 \times \log($*Final Assessed Value*/*Previous Final Assessed Value*$)$ within 0.10 log points of the *Previous Assessed Value*, and (ii) a 7th-degree polynomial estimate of this distribution symmetrically-fitted on either side of the reference point, allowing for excess mass at the reference point. Bin size 5 basis points. Block bootstrapped standard errors in parentheses clustered at the neighborhood level (1000 replications). *Reassessed Subsample* (excludes properties with no initial change).

Figure 2.8: Distribution of *Opinion of Value* and Estimated Bunching at *Previous Final Assessed Value* in *Reassessed Subsample*.



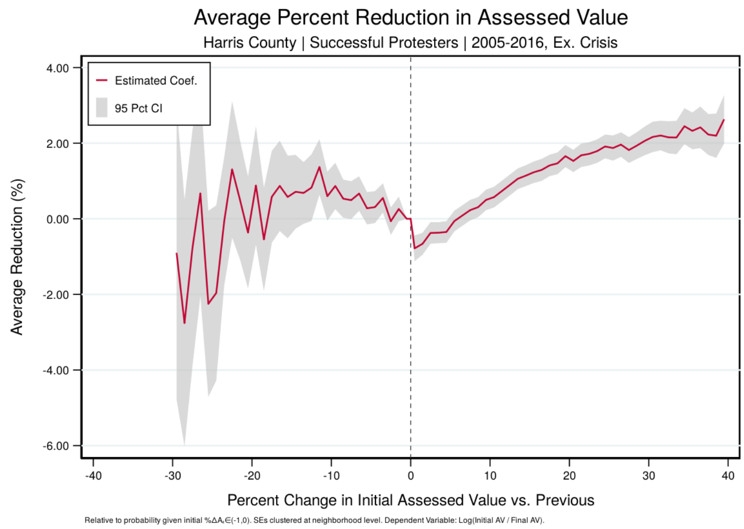
(A) Harris County



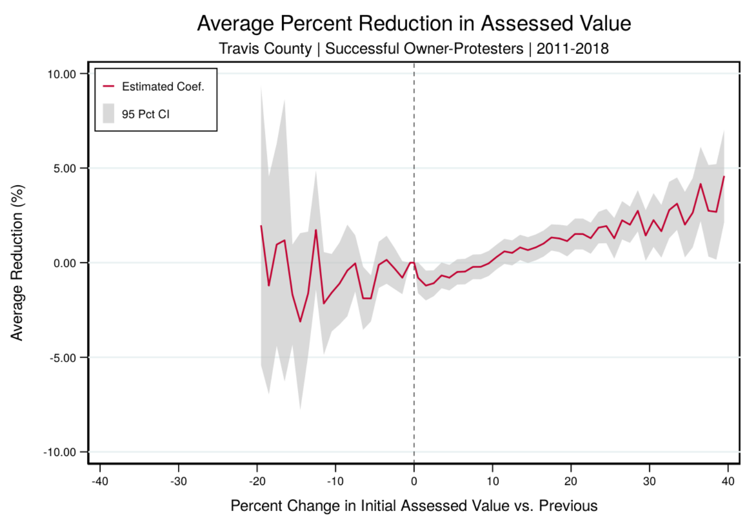
(B) Travis County

Notes: The figure plots (i) the distribution of 100 $\times$ log(*Opinion of Value*/*Previous Final Assessed Value*) within 0.10 log points of the *Previous Assessed Value*, and (ii) a 7th-degree polynomial estimate of this distribution symmetrically-fitted on either side of the reference point, allowing for excess mass at the reference point. Bin size 5 basis points. Block bootstrapped standard errors in parentheses clustered at the neighborhood level (1000 replications). Bin size 5 basis points. *Reassessed Subsample* (excludes properties with no initial change). Note that *Opinion of Value* is only observed for 84% of Harris protests, and 12% of Travis protests.

Figure 2.9: Average Reduction of Successful Protesters by Percent Change in *Initial Assessed Value*.



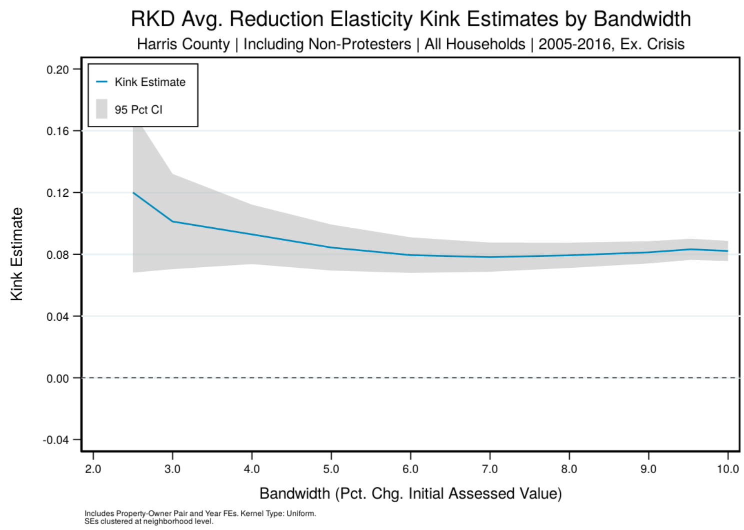
(A) Harris County: Successful Protesters



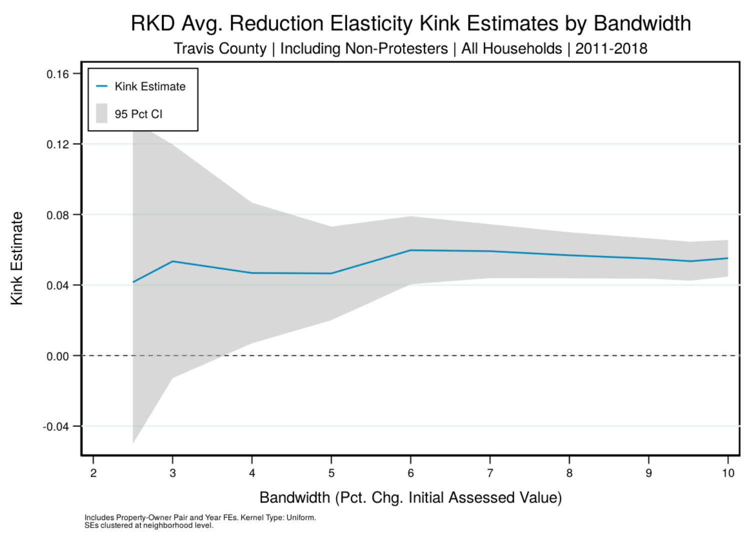
(B) Travis County: Successful Owner-Protesters

Notes: Outcome variable is 100 $\times$ log(*Initial Assessed Value* / *Final Assessed Value*), which measures percent reduction in value (with higher values associated with larger reductions). Coefficients show estimated size of reduction (conditional on winning) given a percent change in *Initial Assessed Value*, binned into one percentage point bins, with individual and year fixed effects. Coefficients are normalized to the average reduction given a percent change in *Initial Assessed Value* between -1% and 0%. The coefficient associated with no change in *Initial Assessed Value* is omitted. Standard errors are clustered at the neighborhood level. The top panel shows all successful protesters in Harris County; the bottom panel shows successful owner-protesters in Travis County.

Figure 2.10: Regression Kink Design Estimates of the Difference in the Elasticity of Reductions *unconditional on protesting* with respect to Percent Change in *Initial Assessed Value* with Property-Owner Pair and Year Fixed Effects.



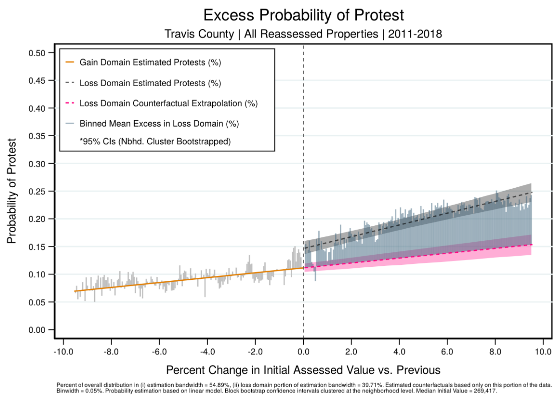
(A) Harris County



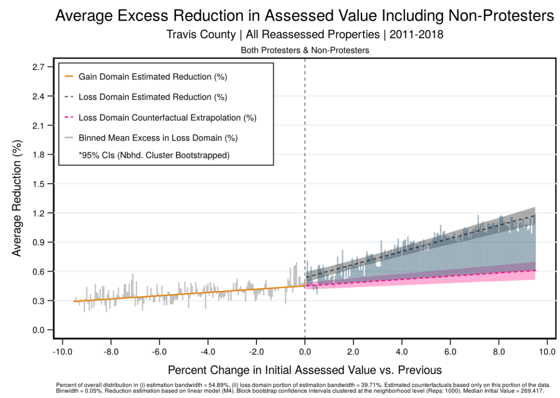
(B) Travis County

Notes: The figures above show regression kink design (RKD) estimates from regressions that include both individual and year fixed effects, showing the *difference* in the elasticity of reductions received *unconditional on protesting* above and below the reference point. Both plots show a bandwidth sensitivity test, showing the RKD estimates of separate regressions at symmetric bandwidths $k \in [2.5\%, 10\%]$ around the reference point. In each underlying regression, values outside of the kink-estimating bandwidth are included (modeled flexibly by binning observations into one percentage point bins by percent change in *Initial Assessed Value* outside of the kink-estimating bandwidth) in order to increase the sample identifying the individual fixed effects; similarly, an indicator associated with exactly no change in *Initial Assessed Value* is included in the regression to increase the identifying sample for the individual fixed effects, but is excluded from the kink estimate. Standard errors are clustered at the neighborhood level; uniform kernel. Analogous to Equation 2.3; corresponds to Table 2.5.

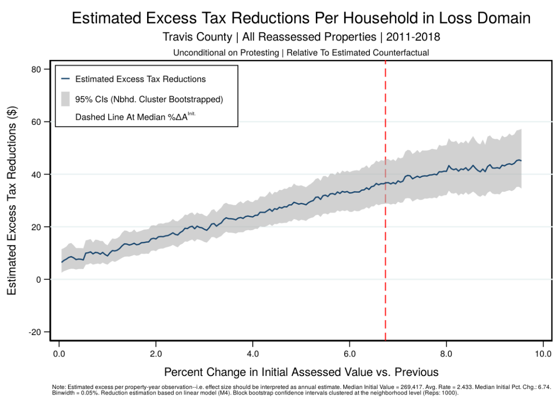
Figure 2.11: Counterfactual Estimates and (i) Excess Protests, (ii) Excess Assessed Value Reductions, and (iii) Excess Tax Reductions in the Loss Domain estimated in a 10% bandwidth around the reference point using the *Reassessed Sub-sample* from *Travis County*.



(A) Excess Protests in the Loss Domain



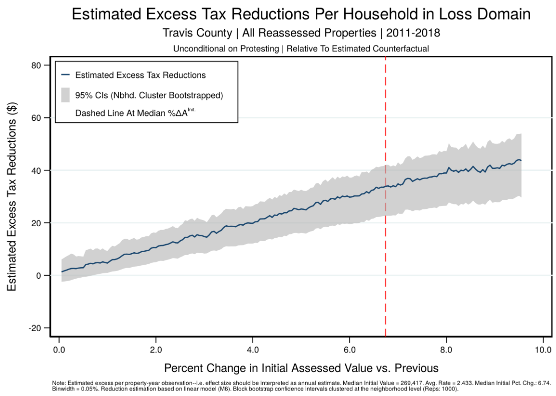
(B) Excess Assessed Value Reductions in the Loss Domain



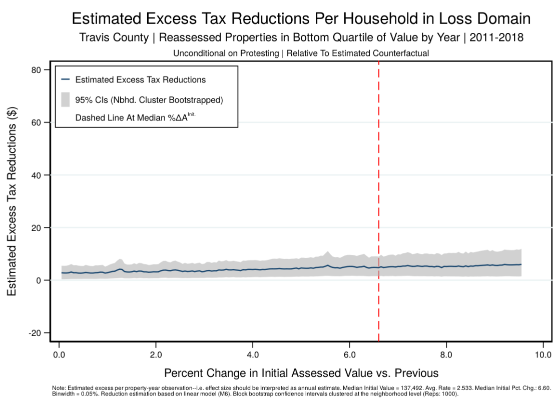
(C) Excess Tax Reductions per Household in the Loss Domain

Notes: These figures illustrate counterfactual estimates of the ultimate impact of loss aversion as detailed in Section 2.5 and corresponding to Table 2.6. Panel (A) illustrates the estimated counterfactual probability of protest and excess probability of protest in the loss domain. Panel (B) illustrates the estimated counterfactual average assessed value reduction and excess average reduction, from which counterfactual revenue estimates (overall and per household) can be calculated. All reductions are estimated including both protesters and non-protesters, capturing both an intensive and extensive margin effect induced by loss aversion. Panel (C) illustrates the estimated annual reductions per household (unconditional on protesting), translated into tax dollars. All estimates based on underlying micro-data; the figures show binned average effects. All estimates are based only on the portion of the distribution of assessed value changes shown (i.e. changes in *Initial Assessed Value* between -10% and +10%), which contains 55% of the reassessed distribution. Block bootstrapped confidence intervals clustered at the neighborhood level (1000 replications). Bin size 5 basis points (0.05%).

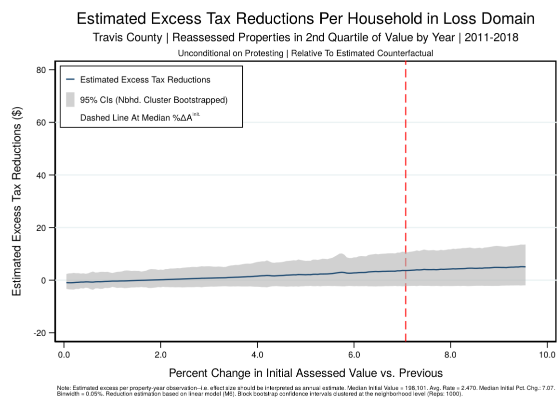
Figure 2.12: Estimates of Annual Excess Tax Reductions per Household in the Loss Domain (including Non-Protesters) Estimated Including Property-Owner Pair and Year Fixed Effects by Quartile of Property Value in the Travis County *Re-assessed Sub-Sample*.



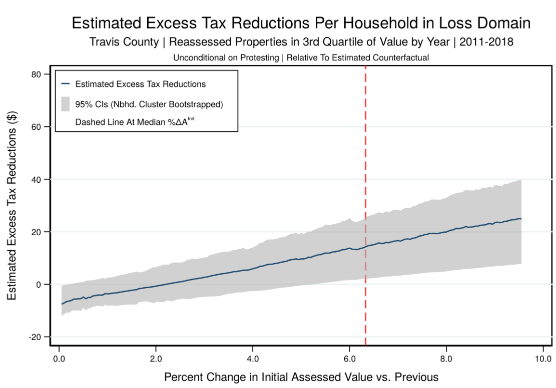
(A) All Reassessed Properties



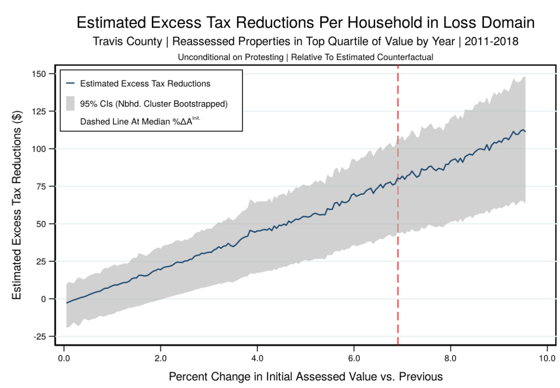
(B) Bottom Quartile



(C) 2nd Quartile



(D) 3rd Quartile



(E) Top Quartile

Notes: These figures illustrate the estimated annual reductions per household (unconditional on protesting) translated into tax dollars. Panel (A) shows estimates for the full sample; Panels (B)-(E) show estimates separately by quartile of *Initial Assessed Value* (quartile defined within year). Estimates derived from a model that includes property-owner pair and year fixed effects, as detailed in Section 2.5 and corresponding to Table 2.7. All reductions are estimated including both protesters and non-protesters, capturing both an intensive and extensive margin effect induced by loss aversion. All estimates based on underlying micro-data; the figures show binned average effects. All estimates are based only on the portion of the distribution of assessed value changes shown (i.e. changes in *Initial Assessed Value* between -10% and +10%). Block bootstrapped confidence intervals clustered at the neighborhood level (1000 replications). Samples restricted to only *Re-assessed* properties. Bin size 5 basis points (0.05%).

2.8 Tables

Table 2.1: Summary statistics for the key variables of interest in the Harris County and Travis County samples.

	Harris County 2005-2016 (Ex. Crisis Years)					**Travis County** 2011-2018				
Observations										
Property-Year Pairs	6.54 Million					1.65 Million				
Property-Owner Pairs	1.34 Million					0.34 Million				
Protests	1.25 Million					0.36 Million				
	Mean	**SD**	**P25**	**Median**	**P75**	**Mean**	**SD**	**P25**	**Median**	**P75**
Property-Year Level										
Initial Assessed Value (1000s)	181.7	207.2	92.0	127.7	190.7	327.8	274.3	173.4	255.2	392.7
Pct. Chg. *Initial Assessed Value*, $Log(A_t^{Init} / A_{t-1}^{Final})$	0.051	0.098	0.000	0.000	0.097	0.070	0.100	0.000	0.067	0.125
Pct. Chg. *Initial Assessed Value* | Reassessed	0.085	0.115	0.026	0.078	0.146	0.076	0.101	0.012	0.075	0.130
Reassessed	0.60	0.49				0.93	0.25			
Protested	0.19	0.39				0.22	0.42			
Cap-Eligible	0.87	0.34				0.83	0.38			
Property-Owner Pair Level										
Property-Owner Pair Years	4.9	2.9	2	5	8	4.8	2.7	2	5	8
Ever Protested	0.34	0.47				0.38	0.49			
Total Protests	0.93	1.80	0	0	1	1.07	1.88	0	0	1
Protest Level										
Successful Protest	0.68	0.47				0.81	0.39			
Owner-Protested (vs. Representing Agent)	0.45	0.50				0.33	0.47			
Ended At Informal Stage	0.39	0.49				0.71	0.46			
Opinion of Value Observed	0.84	0.36				0.12	0.32			
Conditional on Successful Protest										
Assessment Reduction (1000s)	-21.0	39.6	-22.6	-11.2	-5.4	-35.1	55.5	-40.8	-22.0	-10.8
Assessment Reduction (Log Chg.)	-0.075	0.066	-0.100	-0.059	-0.030	-0.068	0.050	-0.091	-0.058	-0.033

Notes: Crisis years excluded from the main Harris County sample defined as 2008-2010. Neighborhood counts in each county are 5,329 (Harris) and 2,672 (Travis).

Table 2.2: RKD estimates of the elasticity of Protesting with respect to Percent Change in *Initial Assessed Value*.

	Harris County Sample N=6,335,862				**Harris County Sample Robustness Results** N=5,788,349							
Bandwidth (Log Points)	0.025	0.05	0.07	0.0953	0.025	0.05	0.07	0.0953	0.025	0.05	0.07	0.0953
β^{Gain}	-0.487	0.007	0.050	0.031	-0.378	0.053	0.067	0.036	-0.377	0.054	0.067	0.036
	(0.158)	(0.054)	(0.035)	(0.024)	(0.166)	(0.057)	(0.036)	(0.025)	(0.166)	(0.057)	(0.036)	(0.025)
β^{Loss}	0.463	0.759	0.763	0.764	0.403	0.716	0.727	0.738	0.403	0.716	0.726	0.738
	(0.170)	(0.044)	(0.028)	(0.021)	(0.177)	(0.045)	(0.028)	(0.021)	(0.177)	(0.045)	(0.028)	(0.021)
Jump, $\alpha^{Loss} - \alpha^{Gain}$	0.010	0.005	0.004	0.004	0.009	0.004	0.004	0.003	0.009	0.004	0.004	0.003
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Kink, $\beta^{Loss} - \beta^{Gain}$	0.950	0.752	0.712	0.733	0.781	0.663	0.660	0.702	0.780	0.662	0.659	0.702
	(0.261)	(0.073)	(0.047)	(0.034)	(0.273)	(0.076)	(0.049)	(0.035)	(0.273)	(0.076)	(0.049)	(0.035)
UE Noise Proxy, η_{it}^{UE}					0.295	0.295	0.295	0.297				
					(0.010)	(0.010)	(0.010)	(0.010)				
UE Noise Proxy (-), $\eta_{it}^{UE} \| \eta_{it}^{UE} < 0$									0.277	0.277	0.277	0.279
									(0.013)	(0.013)	(0.013)	(0.013)
UE Noise Proxy (+), $\eta_{it}^{UE} \| \eta_{it}^{UE} \geq 0$									0.324	0.324	0.324	0.327
									(0.014)	(0.014)	(0.014)	(0.014)
Flexible $\ddot{A}_{it}$ Bins Outside BW	X	X	X	X	X	X	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Property-Owner Pair FEs	X	X	X	X	X	X	X	X	X	X	X	X

	Travis County Sample N=1,599,961				**Travis County Sample Robustness Results** N=1,361,755							
Bandwidth (Log Points)	0.025	0.05	0.07	$0.0953^{\dagger}$	0.025	0.05	0.07	0.0953	0.025	0.05	0.07	0.0953
β^{Gain}	-0.882	-0.035	-0.143	-0.149	-0.765	-0.061	-0.180	-0.180	-0.758	-0.059	-0.178	-0.179
	(0.333)	(0.145)	(0.084)	(0.058)	(0.369)	(0.157)	(0.091)	(0.064)	(0.370)	(0.157)	(0.091)	(0.064)
β^{Loss}	0.941	0.943	0.838	0.660	0.984	0.895	0.788	0.620	0.981	0.895	0.788	0.619
	(0.370)	(0.086)	(0.054)	(0.038)	(0.397)	(0.091)	(0.057)	(0.041)	(0.397)	(0.091)	(0.057)	(0.041)
Jump, $\alpha^{Loss} - \alpha^{Gain}$	0.010	0.004	0.008	0.012	0.008	0.004	0.008	0.012	0.008	0.004	0.008	0.011
	(0.006)	(0.004)	(0.004)	(0.003)	(0.007)	(0.005)	(0.004)	(0.004)	(0.007)	(0.005)	(0.004)	(0.004)
Kink, $\beta^{Loss} - \beta^{Gain}$	1.823	0.978	0.980	0.809	1.749	0.956	0.969	0.800	1.740	0.954	0.966	0.798
	(0.542)	(0.165)	(0.095)	(0.070)	(0.584)	(0.180)	(0.102)	(0.076)	(0.586)	(0.180)	(0.102)	(0.076)
UE Noise Proxy, η_{it}^{UE}					0.505	0.504	0.504	0.511				
					(0.024)	(0.024)	(0.024)	(0.024)				
UE Noise Proxy (-), $\eta_{it}^{UE} \| \eta_{it}^{UE} < 0$									0.427	0.427	0.427	0.432
									(0.032)	(0.032)	(0.032)	(0.032)
UE Noise Proxy (+), $\eta_{it}^{UE} \| \eta_{it}^{UE} \geq 0$									0.594	0.593	0.593	0.602
									(0.037)	(0.037)	(0.037)	(0.037)
Flexible $\ddot{A}_{it}$ Bins Outside BW	X	X	X	X	X	X	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Property-Owner Pair FEs	X	X	X	X	X	X	X	X	X	X	X	X

Notes: This table shows estimates of the elasticity of protesting above and below the reference point within the specified bandwidth, as well as the estimated kink, as specified by Equation 2.3. Binary dependent variable. The left-hand columns in the top and bottom panel show estimates from four of the regressions that underly Figure 2.5 (running variable multiplied by 100 in figure). The right-hand columns show robustness to the inclusion of a U&E noise proxy, η_{it}^{UE}, discussed in Section 2.4.1; robustness samples restricted to those for which a U&E noise proxy, η_{it}^{UE}, can be constructed (91.4% (Harris) and 85.3% (Travis) of property-year observations). U&E noise proxies have mean -0.24% (Harris) and -0.18% (Travis) and standard deviation 6.73% (Harris) and 5.91% (Travis). All regressions include property-owner pair and year fixed effects. Standard errors are clustered at the neighborhood level. Note that the log point bandwidth 0.0953 corresponds to a 10% increase.

Table 2.3: Estimates of excess bunching at the reference point in distribution of *Final Assessed Value* among (i) *All Households*, (ii) *Protesters*, and (iii) *Successful Protesters*, (iv) *Owner Protesters* and (v) *Agent Protesters* in the *Re-assessed Sub-sample* by number of households and as a percent of the distribution.

	Harris County		**Travis County**	
	Excess HHs	Excess Pct.	Excess HHs	Excess Pct.
All Households	32,828	0.851	4,780	0.322
	(641)	(0.017)	(340)	(0.023)
Protesters	32,830	3.900	5,184	1.506
	(656)	(0.078)	(206)	(0.060)
Successful Protesters	32,829	5.037	5,200	1.831
	(629)	(0.097)	(214)	(0.075)
Owner Protesters	18,500	4.512	1,821	1.617
	(379)	(0.093)	(81)	(0.072)
Agent Protesters	14,331	3.318	3,362	1.452
	(339)	(0.079)	(169)	(0.073)

Notes: Estimates of excess bunching at the reference point in the distribution of log(*Final Assessed Value*/*Previous Final Assessed Value*) by number of households and as a percent of the distribution. Block bootstrapped standard errors in parentheses clustered at the neighborhood level (1000 replications). Symmetric 0.10 log change bandwidth. Bin size 5 basis points (0.05%). Samples restricted to only *Re-assessed* properties.

Table 2.4: Estimates of excess bunching at the reference point in distribution of *Opinion of Value* in the *Re-assessed, Opinion-Stated Sub-Sample* by number of households and as a percent of the distribution.

	Harris County		**Travis County**†	
	Excess HHs	Excess Pct.	Excess HHs	Excess Pct.
Protesters	75,777	10.626	2,323	5.528
	(1,490)	(0.209)	(118)	(0.280)
Owner Protesters	40,688	12.297		
	(379)	(0.093)		
Agent Protesters	35,088	9.180		
	(838)	(0.219)		

Notes: Estimates of excess bunching at the reference point in the distribution of log(*Opinion of Value*/*Previous Final Assessed Value*) by number of households and as a percent of protesters with stated value opinions. Travis County results do not separate owner-protesters and agent-protesters; nearly all observed opinions in the Travis sample come from owner-protesters (see Section 2.2). Block bootstrapped standard errors in parentheses clustered at the neighborhood level (1000 replications). Symmetric 0.10 log change bandwidth. Bin size 5 basis points (0.05%). Samples restricted to only *Re-assessed*, *Opinion-Stated* properties.

Table 2.5: RKD estimates of the average reduction received *unconditional on protesting* with respect to Percent Change in *Initial Assessed Value*.

	Harris County Sample N=6,335,862				**Harris County Sample Robustness Results** N=5,788,349							
Bandwidth (Log Points)	0.025	0.05	0.07	0.0953	0.025	0.05	0.07	0.0953	0.025	0.05	0.07	0.0953
β^{Gain}	-0.039	-0.031	-0.018	-0.015	-0.016	-0.019	-0.015	-0.013	-0.018	-0.020	-0.016	-0.014
	(0.017)	(0.006)	(0.004)	(0.003)	(0.017)	(0.006)	(0.004)	(0.003)	(0.017)	(0.006)	(0.004)	(0.003)
β^{Loss}	0.081	0.053	0.060	0.069	0.065	0.041	0.045	0.053	0.065	0.041	0.045	0.053
	(0.016)	(0.004)	(0.003)	(0.002)	(0.017)	(0.004)	(0.003)	(0.002)	(0.017)	(0.004)	(0.003)	(0.002)
Jump, $\alpha^{Loss} - \alpha^{Gain}$	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Kink, $\beta^{Loss} - \beta^{Gain}$	0.120	0.084	0.078	0.083	0.081	0.060	0.060	0.066	0.083	0.061	0.061	0.067
	(0.026)	(0.008)	(0.005)	(0.003)	(0.026)	(0.008)	(0.005)	(0.003)	(0.026)	(0.008)	(0.005)	(0.003)
UE Noise Proxy, η_{it}^{UE}					0.156	0.156	0.156	0.156				
					(0.002)	(0.002)	(0.002)	(0.002)				
UE Noise Proxy (-), $\eta_{it}^{UE} \mid \eta_{it}^{UE} < 0$									0.180	0.180	0.180	0.180
									(0.002)	(0.002)	(0.002)	(0.002)
UE Noise Proxy (+), $\eta_{it}^{UE} \mid \eta_{it}^{UE} \geq 0$									0.116	0.117	0.117	0.117
									(0.003)	(0.003)	(0.003)	(0.003)
Flexible $\ddot{A}_{it}$ Bins Outside BW	X	X	X	X	X	X	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Property-Owner Pair FEs	X	X	X	X	X	X	X	X	X	X	X	X

	Travis County Sample N=1,599,961				**Travis County Sample Robustness Results** N=1,361,755							
Bandwidth (Log Points)	0.025	0.05	0.07	0.0953†	0.025	0.05	0.07	0.0953	0.025	0.05	0.07	0.0953
β^{Gain}	-0.022	0.020	0.004	0.003	-0.015	0.017	-0.003	-0.001	-0.012	0.018	-0.002	-0.001
	(0.024)	(0.012)	(0.007)	(0.005)	(0.025)	(0.012)	(0.007)	(0.005)	(0.026)	(0.012)	(0.007)	(0.005)
β^{Loss}	0.020	0.067	0.063	0.057	0.032	0.050	0.049	0.045	0.031	0.050	0.049	0.045
	(0.035)	(0.008)	(0.005)	(0.004)	(0.035)	(0.008)	(0.005)	(0.004)	(0.035)	(0.008)	(0.005)	(0.003)
Jump, $\alpha^{Loss} - \alpha^{Gain}$	0.001	-0.000	0.000	0.000	0.000	-0.000	0.000	0.000	0.000	-0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)
Kink, $\beta^{Loss} - \beta^{Gain}$	0.042	0.047	0.059	0.054	0.046	0.033	0.052	0.047	0.043	0.032	0.051	0.046
	(0.047)	(0.014)	(0.008)	(0.006)	(0.046)	(0.014)	(0.008)	(0.006)	(0.046)	(0.014)	(0.008)	(0.006)
UE Noise Proxy, η_{it}^{UE}					0.107	0.107	0.107	0.108				
					(0.005)	(0.005)	(0.005)	(0.005)				
UE Noise Proxy (-), $\eta_{it}^{UE} \mid \eta_{it}^{UE} < 0$									0.078	0.078	0.078	0.079
									(0.005)	(0.005)	(0.005)	(0.005)
UE Noise Proxy (+), $\eta_{it}^{UE} \mid \eta_{it}^{UE} \geq 0$									0.141	0.141	0.141	0.141
									(0.007)	(0.007)	(0.007)	(0.007)
Flexible $\ddot{A}_{it}$ Bins Outside BW	X	X	X	X	X	X	X	X	X	X	X	X
Year FEs	X	X	X	X	X	X	X	X	X	X	X	X
Property-Owner Pair FEs	X	X	X	X	X	X	X	X	X	X	X	X

Notes: This table shows estimates of the average reductions received above and below the reference point *unconditional on protesting* within the specified bandwidth, as well as the estimated kink, analogous to Equation 2.3. Dependent variable defined as $\log\left(A_{it}^{Init} / A_{it}^{Final}\right)$. The left-hand columns in the top and bottom panel show estimates from four of the regressions that underly Figure 2.10 (running variable multiplied by 100 in figure). The right-hand columns show robustness to the inclusion of a U&E noise proxy, η_{it}^{UE}, discussed in Section 2.4.1; robustness samples restricted to those for which a U&E noise proxy, η_{it}^{UE}, can be constructed (91.4% (Harris) and 85.3% (Travis) of property-year observations). U&E noise proxies have mean -0.24% (Harris) and -0.18% (Travis) and standard deviation 6.73% (Harris) and 5.91% (Travis). All regressions include property-owner pair and year fixed effects. Standard errors are clustered at the neighborhood level. Note that the log point bandwidth 0.0953 corresponds to a 10% increase.

Table 2.6: Estimates of Annual Excess (i) Protests, (ii) Assessed Value Reductions, (iii) Property Tax Reductions, and (iv) Administrative Wage Costs vs. Estimated Counterfactual without Loss Aversion in the Travis County *Re-assessed Sub-Sample*. Estimated without controls.

		Separately Estimated By Quartile of Property Value (by Year)			
Estimates of Annual Excess vs. Estimated Counterfactual	All Reassessed Properties	Bottom	2nd	3rd	Top
Protests	4999	513	607	2119	2893
	(555.72)	(108.57)	(139.09)	(249.86)	(386.13)
As Pct. of All Reassessed HHs	4.90	2.36	2.37	7.48	11.00
	(0.55)	(0.50)	(0.54)	(0.88)	(1.47)
As Pct. Inc. Over CF in Loss Domain	50.32	72.97	36.39	91.83	70.16
	(7.80)	(27.87)	(11.33)	(16.34)	(14.57)
Assessed Value (AV) Reductions ($ Mil.)	90.37	3.10	6.44	34.55	94.30
	(10.40)	(0.91)	(1.74)	(4.81)	(12.46)
As Pct. Inc. Over CF in Loss Domain	65.10	72.90	43.20	118.40	85.90
	(10.10)	(45.42)	(16.11)	(30.16)	(18.88)
Tax Revenue ($ Mil.)	2.17	0.08	0.16	0.82	2.22
	(0.25)	(0.02)	(0.04)	(0.11)	(0.29)
Avg. AV Reduction per Prop. in Loss Domain ($)	1224.54	209.90	352.65	1646.73	4761.48
	(140.04)	(61.05)	(92.06)	(193.71)	(578.42)
Avg. Tax Reduction per Prop. in Loss Domain ($)	29.34	5.35	8.68	39.10	112.07
	(3.33)	(1.56)	(2.27)	(4.63)	(13.60)
Avg. Tax Reduction per Prop. at Median* $\ddot{A}_{it}$ ($)	36.75	5.70	11.50	48.80	154.08
	(4.33)	(1.75)	(2.66)	(5.62)	(16.86)
Admin Wage Cost ($ 1,000s)	71.90	7.40	8.70	30.50	41.60
	(7.99)	(1.56)	(2.00)	(3.59)	(5.55)
Median Initial Assessed Value	269,417	137,492	198,101	313,310	533,770
Average Tax Rate per Property	2.433	2.533	2.470	2.387	2.364
Pct. of Reassessed Distribution in					
(i) Estimation Bandwidth (BW)	54.89	48.40	53.74	59.27	57.88
(ii) Loss Domain Portion of BW	39.71	32.80	38.32	43.91	43.59

†Estimates based on, and refer only to, 10% symmetric bandwidth on either side of the reference point.
*Median $\ddot{A}_{it}$ refers to at median percent change in *Initial Assessed Value* in unrestricted sample (by quartile).

Notes: Annual estimates of the ultimate impact of loss aversion based on the counterfactual procedure outlined in Section 2.5 and corresponding to Figures 2.11 and A.16 and Appendix Figures A.17 and A.18. Estimates based only on, and refer only to, 10% symmetric bandwidth (BW) on either side of the reference point (i.e. changes in *Initial Assessed Value* between -10% and +10%). Assessment and tax reductions estimates are unconditional on protesting, capturing both the intensive and extensive margin effect induced by loss aversion. Block bootstrapped standard errors in parentheses clustered at the neighborhood level (1000 replications). Samples restricted to only *Re-assessed* properties.

Table 2.7: Estimates of Annual Excess (i) Protests, (ii) Assessed Value Reductions, (iii) Property Tax Reductions, and (iv) Administrative Wage Costs vs. Estimated Counterfactual without Loss Aversion in the Travis County *Re-assessed Sub-Sample*. Estimated with property-owner pair and year fixed effects.

		Separately Estimated By Quartile of Property Value (by Year)			
Estimates of Annual Excess vs. Estimated Counterfactual	All Reassessed Properties	Bottom	2nd	3rd	Top
Protests	4494	213	444	1102	1438
	(521.38)	(75.94)	(116.52)	(180.49)	(205.65)
As Pct. of All Reassessed HHs	4.41	0.98	1.74	3.89	5.47
	(0.51)	(0.35)	(0.46)	(0.64)	(0.78)
As Pct. Inc. Over CF in Loss Domain	38.52	17.53	19.66	28.97	21.87
	(5.23)	(7.09)	(6.18)	(5.04)	(3.08)
Assessed Value (AV) Reductions ($ Mil.)	79.83	2.68	1.83	8.84	47.91
	(13.22)	(1.13)	(1.99)	(4.53)	(11.72)
As Pct. Inc. Over CF in Loss Domain	39.60	29.30	6.50	12.20	22.90
	(8.34)	(15.54)	(7.80)	(6.93)	(6.41)
Tax Revenue ($ Mil.)	1.91	0.07	0.05	0.21	1.13
	(0.32)	(0.03)	(0.05)	(0.11)	(0.28)
Avg. AV Reduction per Prop. in Loss Domain ($)	1082.04	181.38	100.17	421.67	2419.33
	(171.63)	(72.94)	(109.35)	(213.66)	(555.82)
Avg. Tax Reduction per Prop. in Loss Domain ($)	25.93	4.62	2.47	10.01	56.95
	(4.11)	(1.85)	(2.70)	(5.07)	(13.16)
Avg. Tax Reduction per Prop. at Median* $\ddot{A}_{it}$ ($)	33.93	4.77	3.68	14.48	80.41
	(4.95)	(1.90)	(3.30)	(6.00)	(16.31)
Admin Wage Cost ($ 1,000s)	64.60	3.10	6.40	15.80	20.70
	(7.50)	(1.09)	(1.67)	(2.60)	(2.96)
Median Initial Assessed Value	269,417	137,492	198,101	313,311	533,770
Average Tax Rate per Property	2.433	2.533	2.470	2.387	2.364
Pct. of Reassessed Distribution in					
(i) Estimation Bandwidth (BW)	54.89	48.40	53.74	59.27	57.88
(ii) Loss Domain Portion of BW	39.71	32.80	38.32	43.91	43.59

†Estimates based on, and refer only to, 10% symmetric bandwidth on either side of the reference point.
*Median $\ddot{A}_{it}$ refers to at median percent change in *Initial Assessed Value* in unrestricted sample (by quartile).

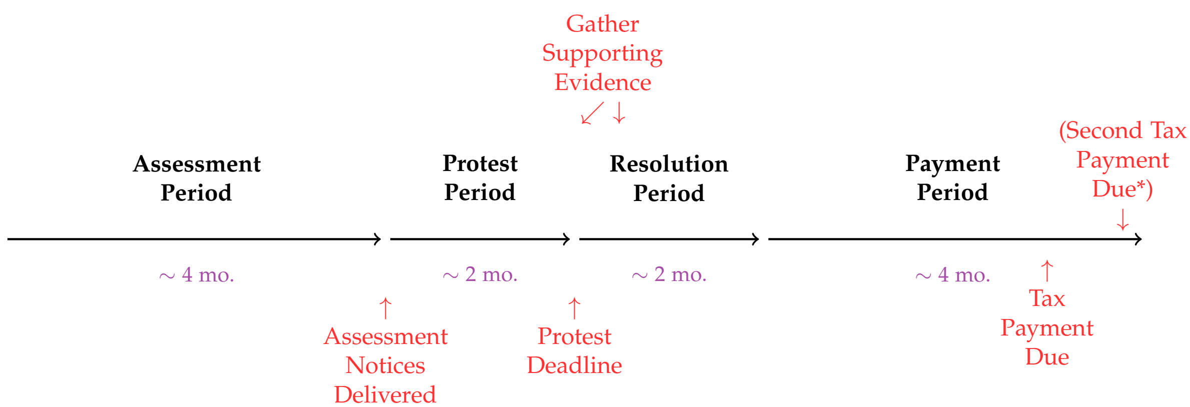
Notes: Annual estimates of the ultimate impact of loss aversion based on the counterfactual procedure outlined in Section 2.5 and corresponding to Figure 2.12. Estimates based only on, and refer only to, 10% symmetric bandwidth (BW) on either side of the reference point (i.e. changes in *Initial Assessed Value* between -10% and +10%). Assessment and tax reductions estimates are unconditional on protesting, capturing both the intensive and extensive margin effect induced by loss aversion. Block bootstrapped standard errors in parentheses clustered at the neighborhood level (1000 replications). Samples restricted to only *Re-assessed* properties.

Appendix A

Appendix

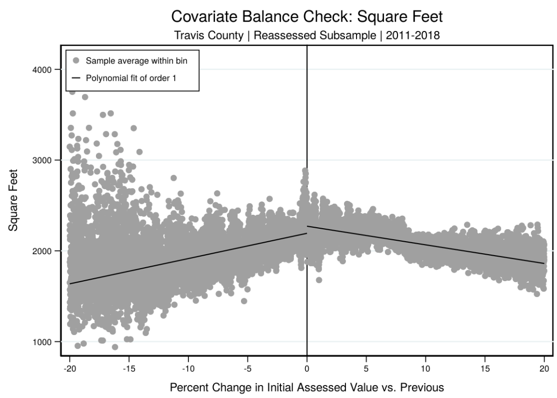
A.1 Appendix Figures

Figure A.1: A Typical Property Assessment Cycle.

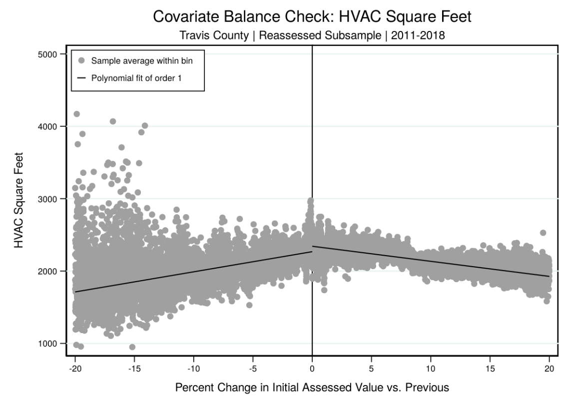


Notes: This diagram illustrates a typical assessment cycle as discussed in Section 0.1. In most places, property taxes are due in either one or two payments at the end of the tax year.

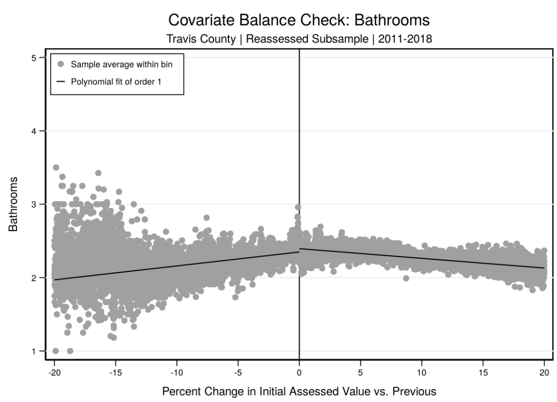
Figure A.2: Travis County RKD diagnostic checks for covariate balance near zero percent change in *Initial Assessed Value*.



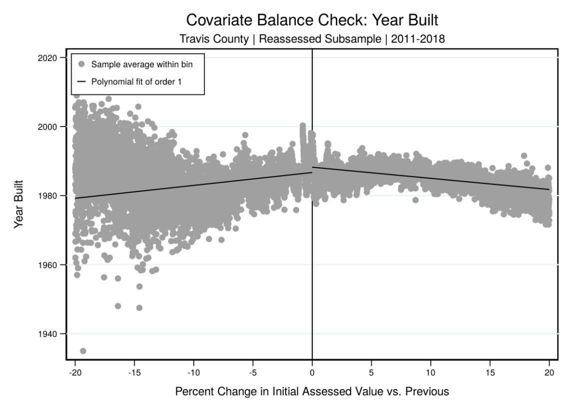
(A) Covariate Balance: Square Feet



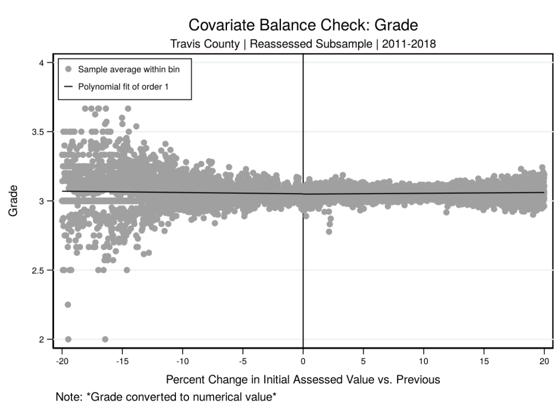
(B) Covariate Balance: HVAC Square Feet



(C) Covariate Balance: Number of Bathrooms

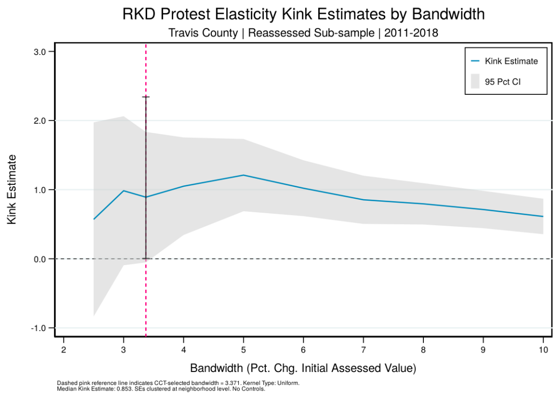


(D) Covariate Balance: Year Built

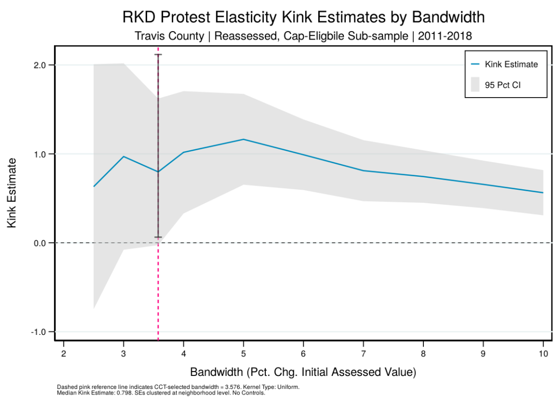


(E) Covariate Balance: Grade (Numeric Conversion)

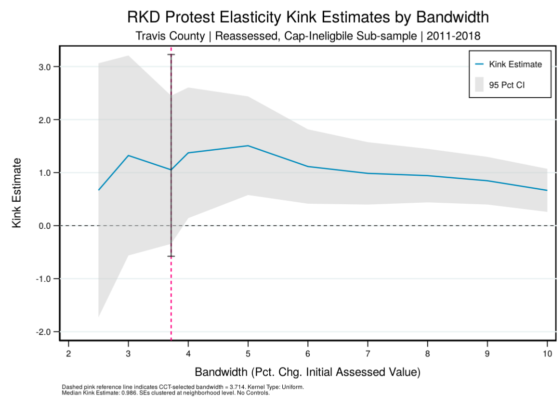
Figure A.3: Regression Kink Discontinuity Estimates of the Difference in the Elasticity of Protesting with respect to Percent Change in *Initial Assessed Value* in the Travis County sample.



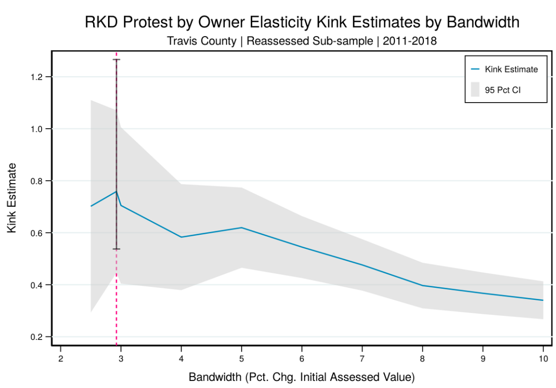
(A) Travis County



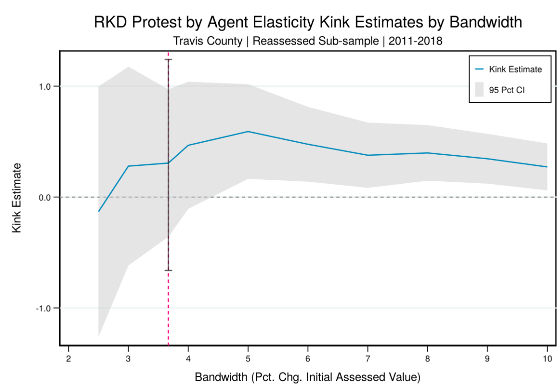
(B) (i) Travis County: Cap-Eligible Sub-Sample



(B) (ii) Travis County: Cap-Ineligible Sub-Sample



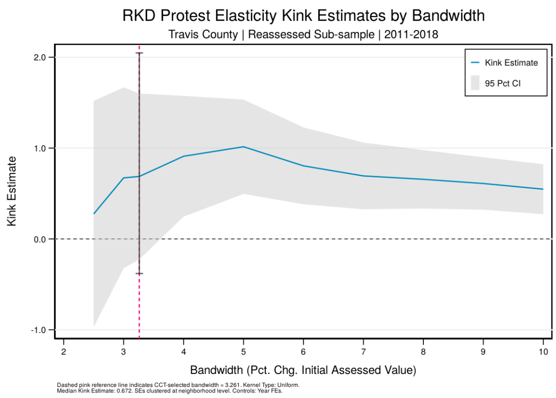
(C) (i) Travis County: Protests by Owner



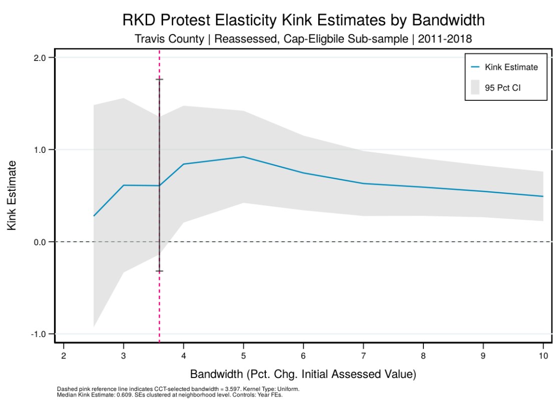
(C) (ii) Travis County: Protests by Representing Agents

Notes: The figures above show regression kink discontinuity (RKD) estimates of the *difference* in the elasticity of protesting above and below the reference point. Each plot is a bandwidth sensitivity test, showing the RKD estimates of separate regressions at symmetric bandwidths $k \in [2.5\%, 10\%]$ around the reference point. The CCT-selected bandwidth and (quadratic) robust confidence intervals are shown at the dashed-pink line (Calonico et al., 2014). No controls included in regression estimates; standard errors are clustered at the neighborhood level; uniform kernel.

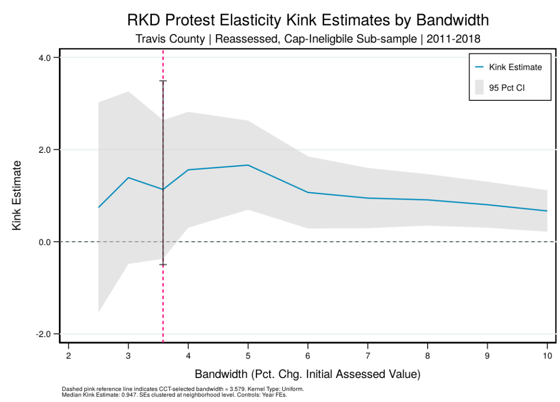
Figure A.4: Regression Kink Discontinuity Bandwidth Test: Difference in the Elasticity of Protesting with respect to Percent Change in *Initial Assessed Value* [Robustness Check: Including Year Fixed Effects].



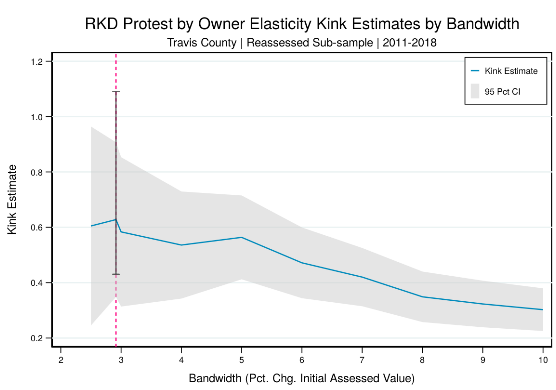
(A) Travis County



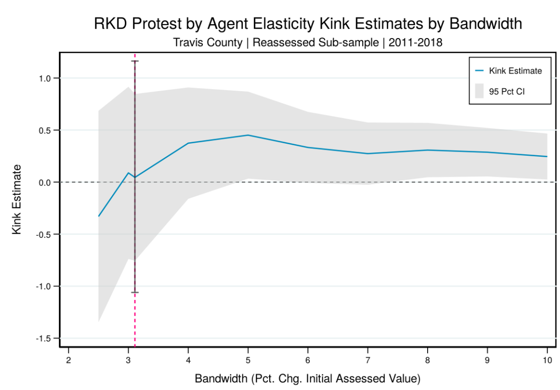
(B) (i) Travis County: Cap-Eligible Sub-Sample



(B) (ii) Travis County: Cap-Ineligible Sub-Sample



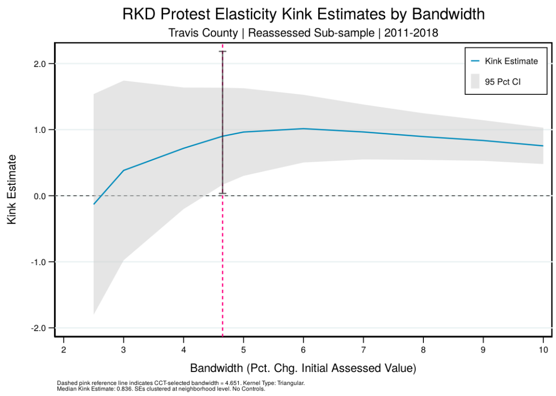
(C) (i) Travis County: Protests by Owner



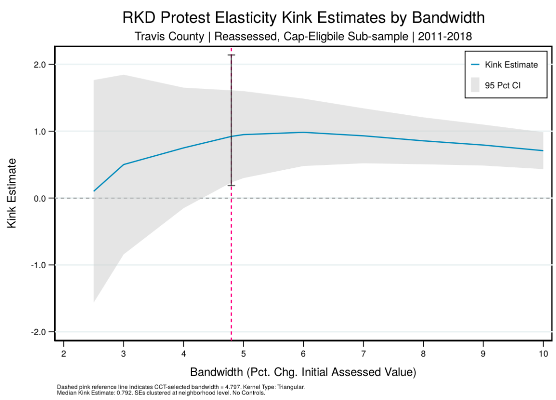
(C) (ii) Travis County: Protests by Representing Agents

Notes: Robustness figure analogous to Figure A.3, but including year fixed effects in RKD estimates. The figures above show regression kink discontinuity (RKD) estimates of the *difference* in the elasticity of protesting above and below the reference point. Each plot is a bandwidth sensitivity test, showing the RKD estimates of separate regressions at symmetric bandwidths $k \in [2.5\%, 10\%]$ around the reference point. The CCT-selected bandwidth and (quadratic) robust confidence intervals are shown at the dashed-pink line (Calonico et al., 2014). Year fixed effects included in regression estimates; standard errors are clustered at neighborhood level; uniform kernel.

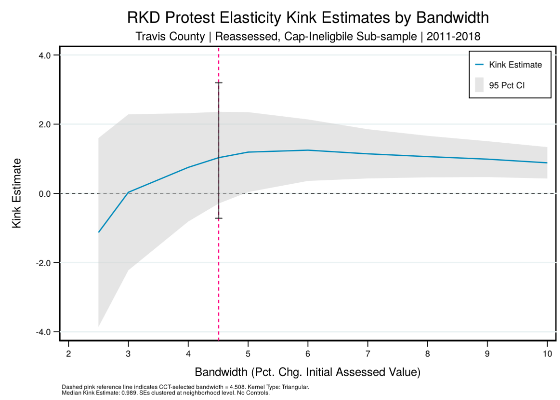
Figure A.5: Regression Kink Discontinuity Bandwidth Test: Difference in the Elasticity of Protesting with respect to Percent Change in *Initial Assessed Value* [Robustness Check: Triangular Kernel].



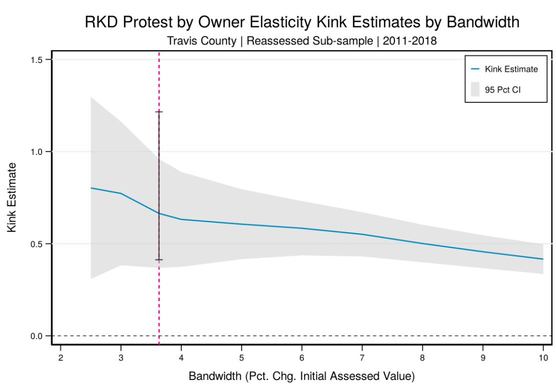
(A) Travis County



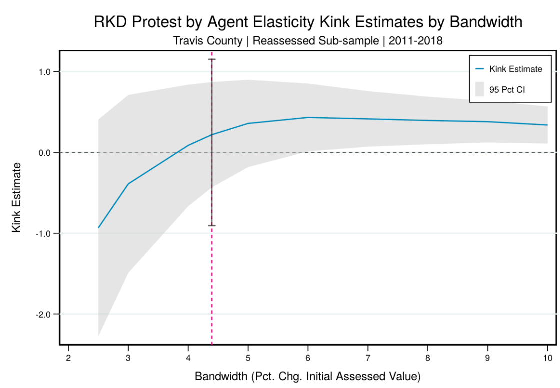
(B) (i) Travis County: Cap-Eligible Sub-Sample



(B) (ii) Travis County: Cap-Ineligible Sub-Sample



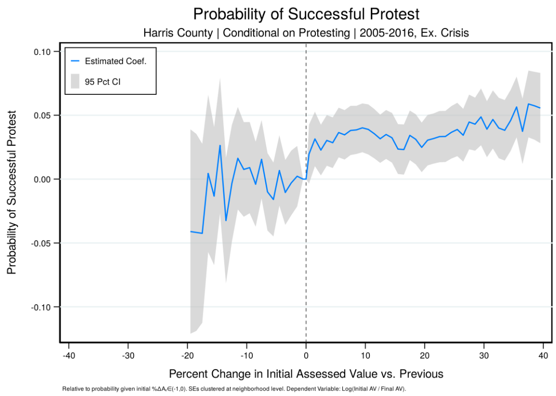
(C) (i) Travis County: Protests by Owner



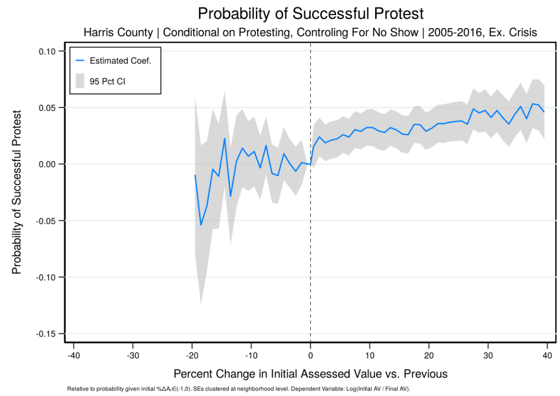
(C) (ii) Travis County: Protests by Representing Agents

Notes: Robustness figure analogous to Figure A.3, but using a triangular kernel for RKD estimates. The figures above show regression kink discontinuity (RKD) estimates of the *difference* in the elasticity of protesting above and below the reference point. Each plot is a bandwidth sensitivity test, showing the RKD estimates of separate regressions at symmetric bandwidths $k \in [2.5\%, 10\%]$ around the reference point. The CCT-selected bandwidth and (quadratic) robust confidence intervals are shown at the dashed-pink line (Calonico et al., 2014). No controls included in regression estimates; standard errors are clustered at neighborhood level; triangular kernel.

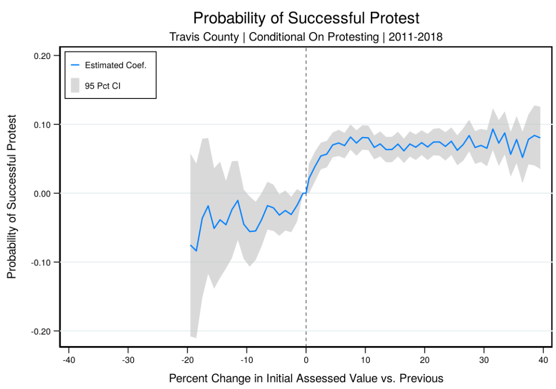
Figure A.6: Probability of Successful Protest by Percent Change in *Initial Assessed Value*.



(A)(i) Harris County
Controls: FEs Only



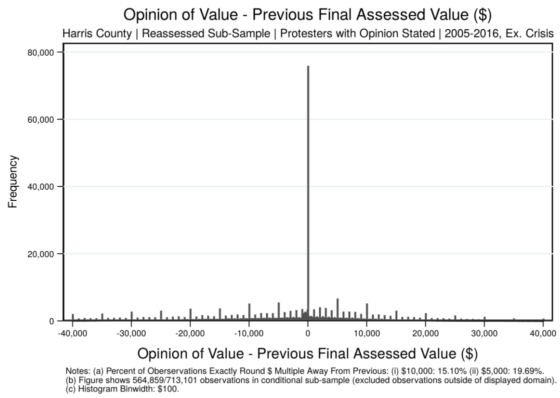
(A)(ii) Harris County
Controls: FEs, No Show Indicator



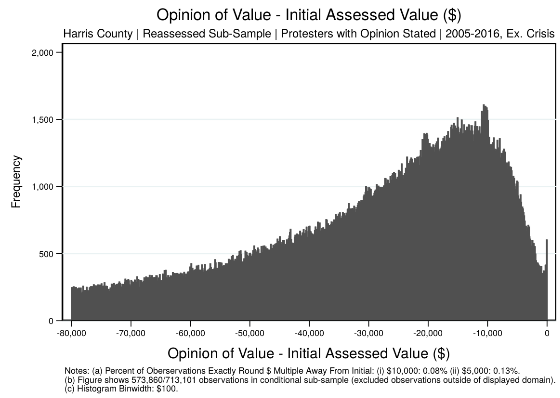
(B) Travis County
Controls: FEs Only

Notes: Estimated coefficients from a linear probability model of successfully achieving a reduction in value, conditional on protesting, given a percent change in *Initial Assessed Value*, binned into one percentage point bins, with individual and year fixed effects. Coefficients are normalized to the probability of winning given a percent change in *Initial Assessed Value* between -1% and 0%. The coefficient associated with no change in *Initial Assessed Value* is omitted. Standard errors are clustered at the neighborhood level. Choosing 2011 as a based year, the baseline probabilities in the omitted bin are, (A) 0.77 and (B) 0.83.

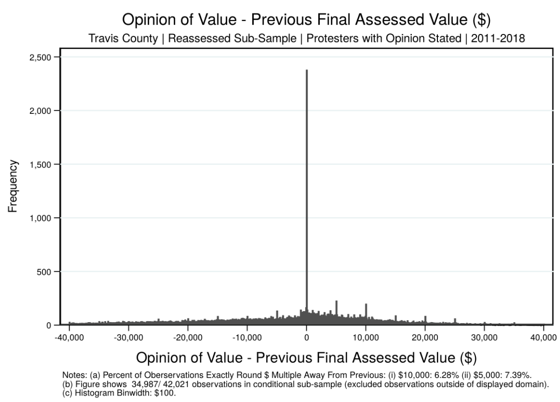
Figure A.7: Histograms of (i) *Opinion of Value* minus *Previous Final Assessed Value*, and (ii) *Opinion of Value* minus *Initial Assessed Value* among *Opinion-Stated Protesters* in the *Reassessed Sub-sample* (separately by county).



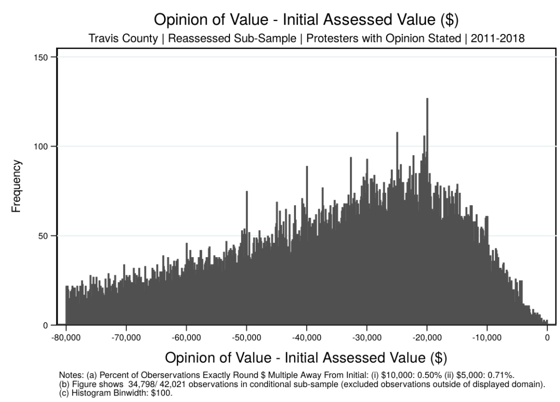
(A) (i) Harris County: *Opinion of Value* minus *Previous Final Assessed Value*



(A) (ii) Harris County: *Opinion of Value* minus *Initial Assessed Value*



(B) (i) Travis County: *Opinion of Value* minus *Previous Final Assessed Value*



(B) (ii) Travis County: *Opinion of Value* minus *Initial Assessed Value*

Notes: The left-hand panels show histograms of protesters' *Opinion of Value* relative to their *Previous Final Assessed Value*. The right-hand panels show histograms of protesters' *Opinion of Value* relative to their *Initial Assessed Value*. Protesters are much more likely to state an *Opinion of Value* that is an exact round-dollar-amount multiple away from the *Previous Final Assessed Value* than they are to state an *Opinion of Value* that is an exact round-dollar-amount multiple away from their (new) *Initial Assessed Value* (e.g. *Anchor Value* $\pm k \times \$10,000$). Binwidth: $100.

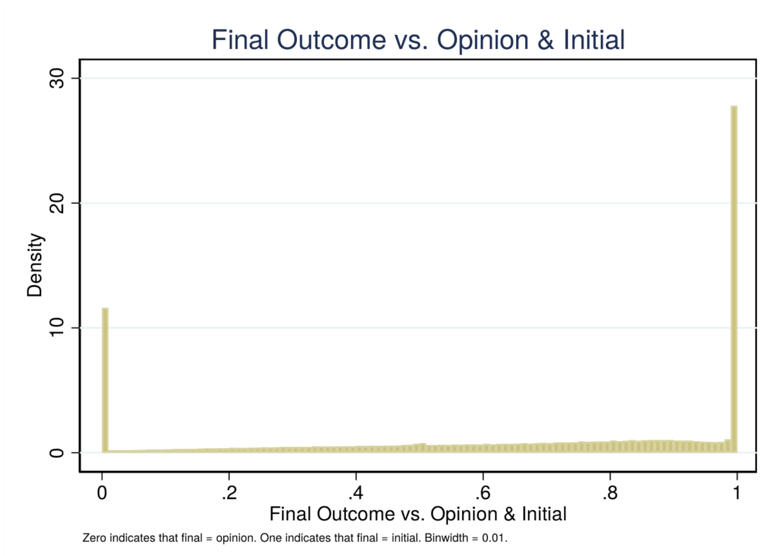
A(i): Percent of observations exact round-dollar-amount multiple away from *Previous Final Assessed Value*: (i) $10,000: 15.10%, (ii) $5,000: 19.69%

A(ii): Percent of observations exact round-dollar-amount multiple away from *Initial Assessed Value*: (i) $10,000: 0.08%, (ii) $5,000: 0.13%

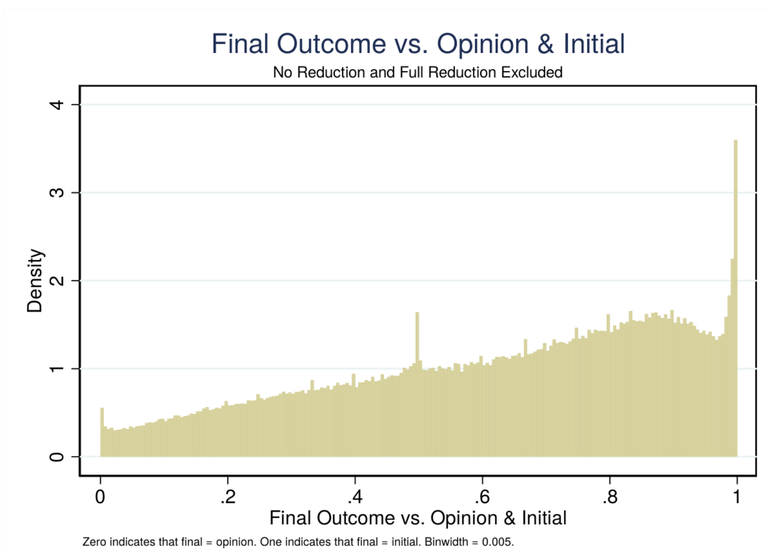
B(i): Percent of observations exact round-dollar-amount multiple away from *Previous Final Assessed Value*: (i) $10,000: 6.28%, (ii) $5,000: 7.39%

B(ii): Percent of observations exact round-dollar-amount multiple away from *Initial Assessed Value*: (i) $10,000: 0.51%, (ii) $5,000: 0.71%

Figure A.8: *Final Assessed Value* vs. *Opinion of Value* and *Initial Assessed Value* in *Harris County* sample.



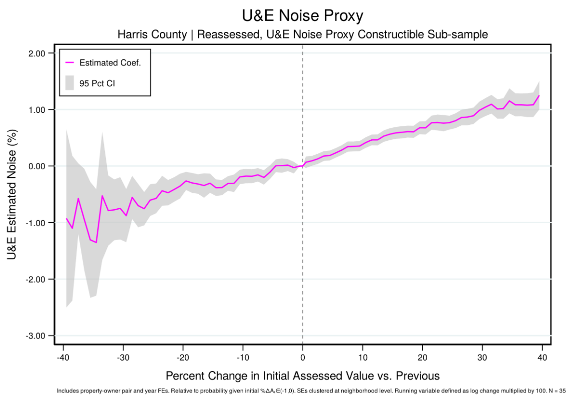
(A) All Values in [0,1]



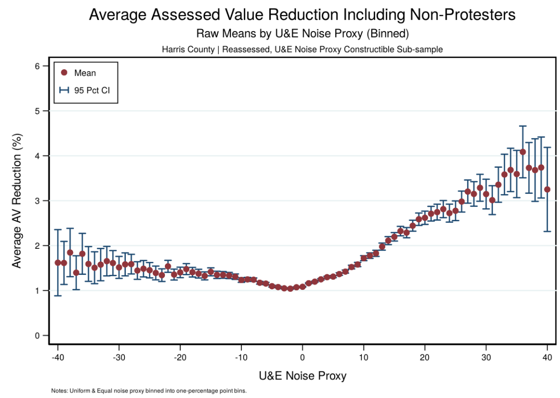
(B) Only Values in (0,1)

Notes: Histogram of (*Opinion of Value* - *Final Assessed Value*) divided by (*Opinion of Value* - *Initial Assessed Value*). A value of one indicates that *Final Assessed Value* equals *Initial Assessed Value*; in other words, no reduction was achieved. A value of zero indicates that *Final Assessed Value* equals *Opinion of Value*; in other words, the property owner received a "full reduction," insofar as their stated opinion is concerned. *Opinion-Stated Sub-Sample*. Top Panel: 1.53% of observations with a value less than zero are omitted from figure. Binwidth is 0.01. Bottom Panel: Values 0 and 1 also excluded. Binwidth is 0.005.

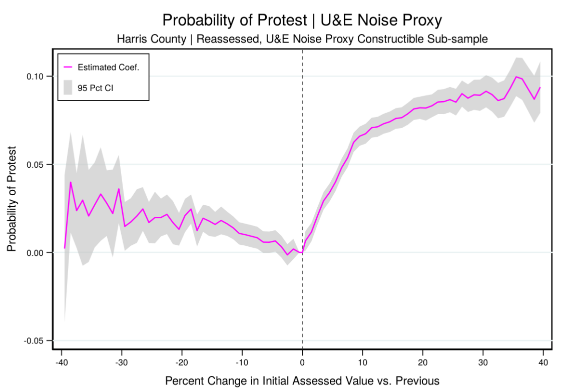
Figure A.9: Robustness to Uniform & Equal (U&E) Estimated Noise Proxy in the *Harris County* sample.



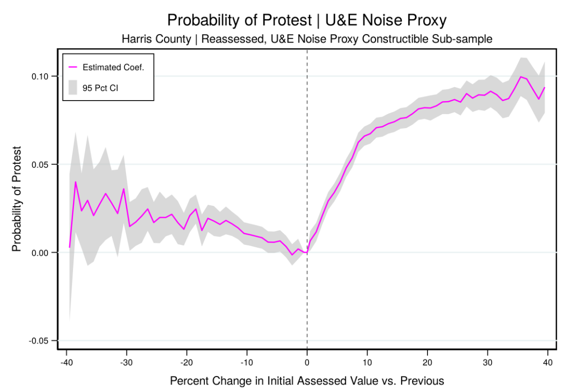
(A) U&E Estimated Noise Proxy by Pct. Chg. *Initial Assessed Value* with Property-Owner Pair FEs



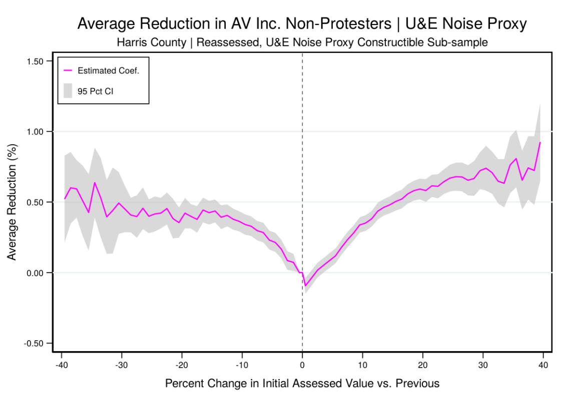
(B) Average Reduction (Inc. Non-Protesters) by U&E Noise Proxy



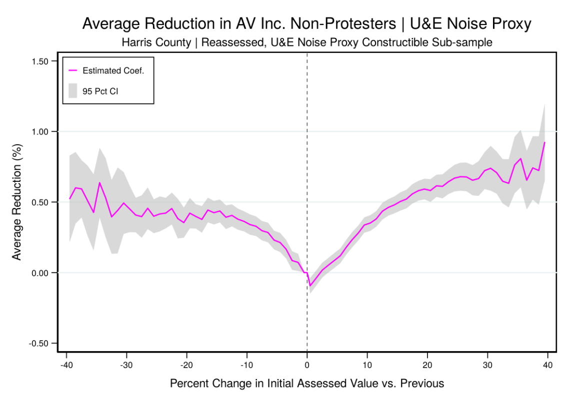
(C) Probability of Protest with Property-Owner Pair FEs Conditional on U&E Noise Proxy (Linear Control)



(D) Probability of Protest with Property-Owner Pair FEs Conditional on U&E Noise Proxy (Kinked Control)



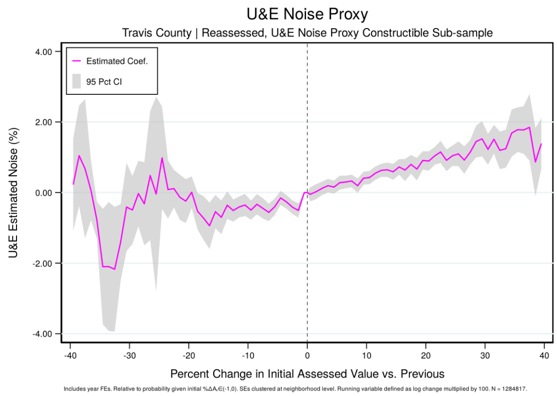
(E) Average Reduction (Inc. Non-Protesters) by Pct. Chg. *Initial Assessed Value* with Property-Owner Pair FEs
Conditional on U&E Noise Proxy (Linear Control)



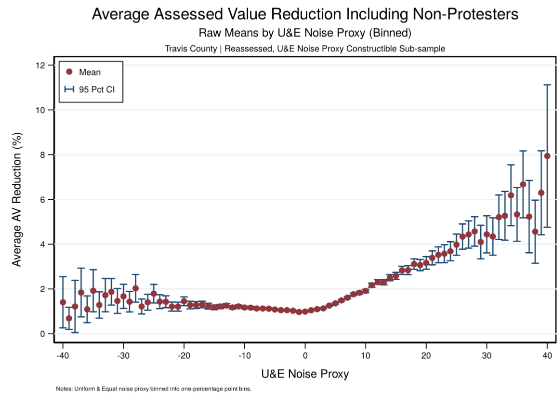
(F) Average Reduction (Inc. Non-Protesters) by Pct. Chg. *Initial Assessed Value* with Property-Owner Pair FEs
Conditional on U&E Noise Proxy (Kinked Control)

Notes: Sample restricted to those for which a U&E noise proxy, η_{it}^{UE}, can be constructed (91.4% of property-year observations in the Harris County sample). Harris County U&E noise proxy has mean -0.24% and standard deviation 6.73%. Linear control estimates RKD (analogous to Equation 2.3) including η_{it}^{UE} as a control. Kinked control estimates RKD (analogous to Equation 2.3) including both η_{it}^{UE} and $\eta_{it}^{UE}|\eta_{it}^{UE} > 0$ as separate controls, allowing for differential marginal effects for values of the noise proxy that are positive. All underlying regressions include year fixed effects. Coefficients are normalized to the value given a percent change in *Initial Assessed Value* between -1% and 0%. Standard errors are clustered at the neighborhood level.

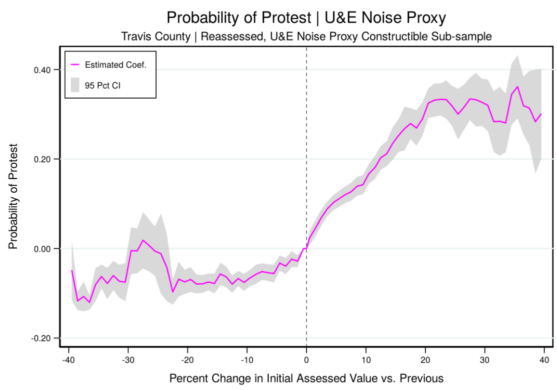
Figure A.10: Robustness to Uniform & Equal (U&E) Estimated Noise Proxy in the *Travis County* sample [Without Property-Owner Pair Fixed Effects].



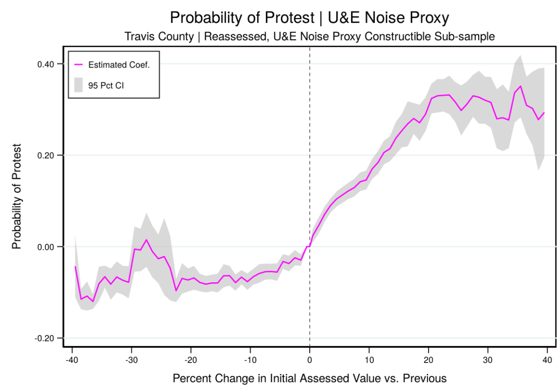
(A) U&E Estimated Noise Proxy by Pct. Chg. *Initial Assessed Value*



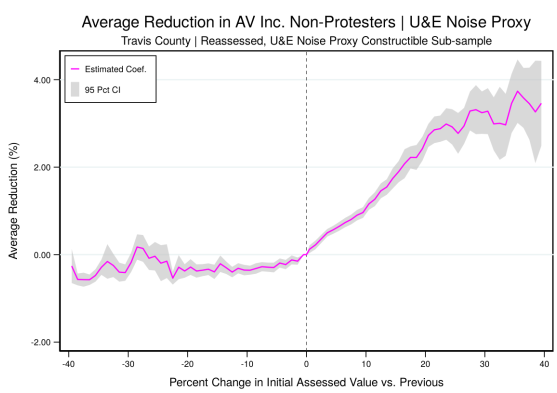
(B) Average Reduction (Inc. Non-Protesters) by U&E Noise Proxy



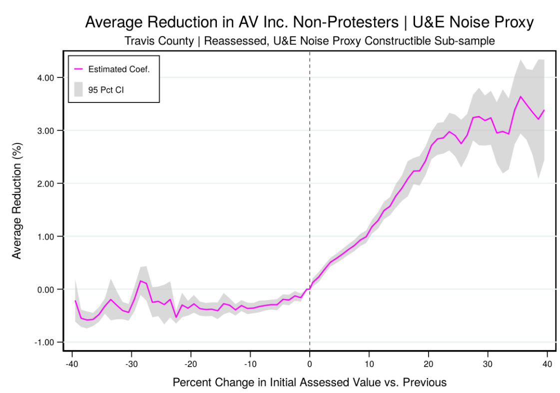
(C) Probability of Protest Conditional on U&E Noise Proxy (Linear Control)



(D) Probability of Protest Conditional on U&E Noise Proxy (Kinked Control)



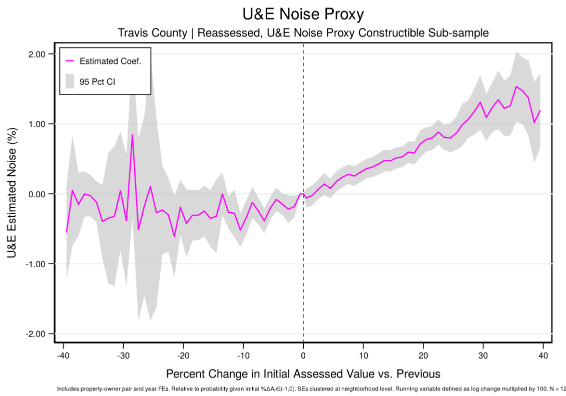
(E) Average Reduction (Inc. Non-Protesters) by Pct. Chg. *Initial Assessed Value* Conditional on U&E Noise Proxy (Linear Control)



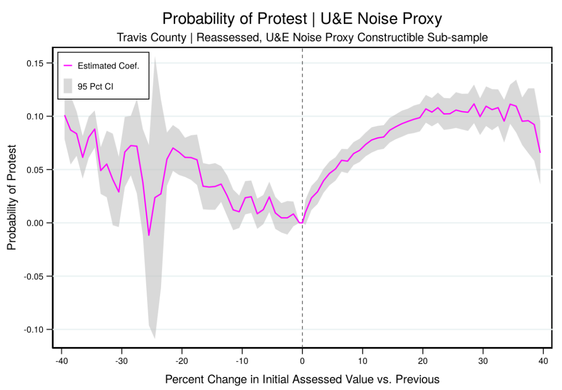
(F) Average Reduction (Inc. Non-Protesters) by Pct. Chg. *Initial Assessed Value* Conditional on U&E Noise Proxy (Kinked Control)

Notes: Sample restricted to those for which a U&E noise proxy, η_{it}^{UE}, can be constructed (85.3% of property-year observations in the Travis County sample). Travis County U&E noise proxy has mean -0.18% and standard deviation 5.91%. Linear control estimates RKD (analogous to Equation 2.2) including η_{it}^{UE} as a control. Kinked control estimates RKD (analogous to Equation 2.2) including both η_{it}^{UE} and $\eta_{it}^{UE}|\eta_{it}^{UE} > 0$ as separate controls, allowing for differential marginal effects for values of the noise proxy that are positive. All underlying regressions include year fixed effects. Coefficients are normalized to the value given a percent change in *Initial Assessed Value* between -1% and 0%. Standard errors are clustered at the neighborhood level.

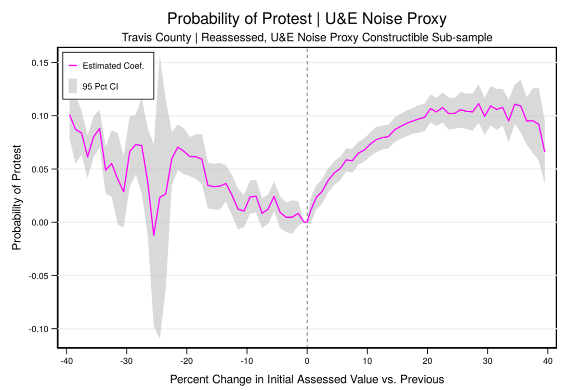
Figure A.11: Robustness to Uniform & Equal (U&E) Estimated Noise Proxy in the *Travis County* sample.



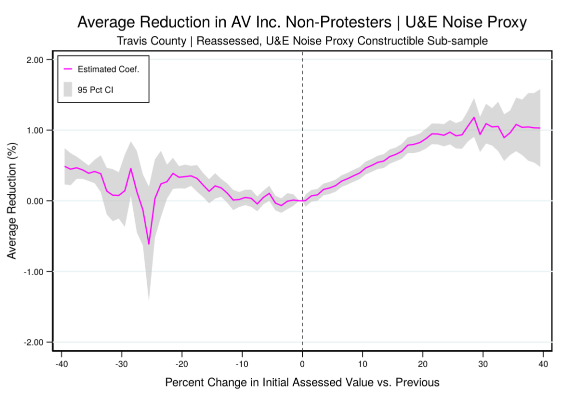
(A) U&E Estimated Noise Proxy by Pct. Chg. *Initial Assessed Value* with Property-Owner Pair FEs



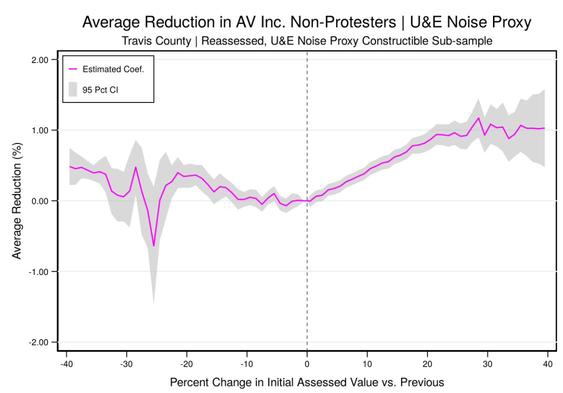
(B) Probability of Protest with Property-Owner Pair FEs Conditional on U&E Noise Proxy (Linear Control)



(C) Probability of Protest with Property-Owner Pair FEs Conditional on U&E Noise Proxy (Kinked Control)



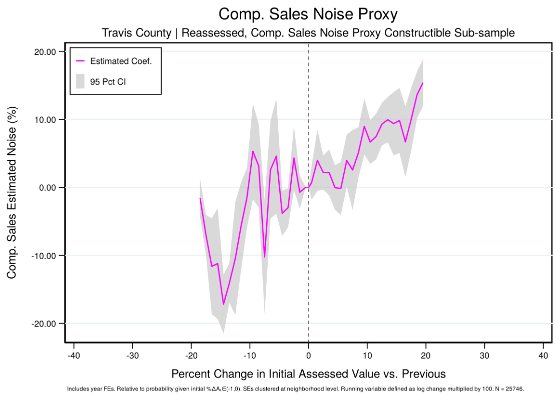
(E) Average Reduction (Inc. Non-Protesters) with Property-Owner Pair FEs Conditional on U&E Noise Proxy (Linear Control)



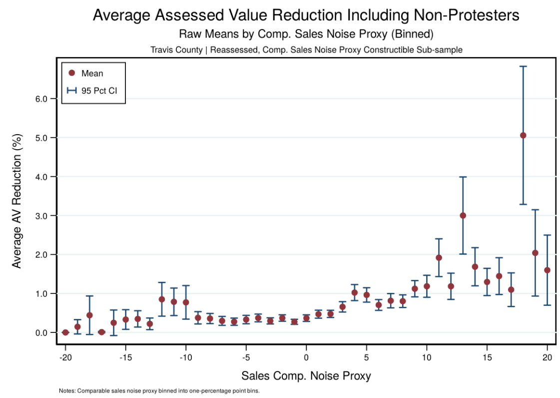
(F) Average Reduction (Inc. Non-Protesters) with Property-Owner Pair FEs Conditional on U&E Noise Proxy (Linear Control)

Notes: Sample restricted to those for which a U&E noise proxy, η_{it}^{UE}, can be constructed (85.3% of property-year observations in the Travis County sample). Travis County U&E noise proxy has mean -0.18% and standard deviation 5.91%. Linear control estimates RKD (analogous to Equation 2.3) including η_{it}^{UE} as a control. Kinked control estimates RKD (analogous to Equation 2.3) including both η_{it}^{UE} and $\eta_{it}^{UE}|\eta_{it}^{UE} > 0$ as separate controls, allowing for differential marginal effects for values of the noise proxy that are positive. All underlying regressions include year fixed effects. Coefficients are normalized to the value given a percent change in *Initial Assessed Value* between -1% and 0%. Standard errors are clustered at the neighborhood level.

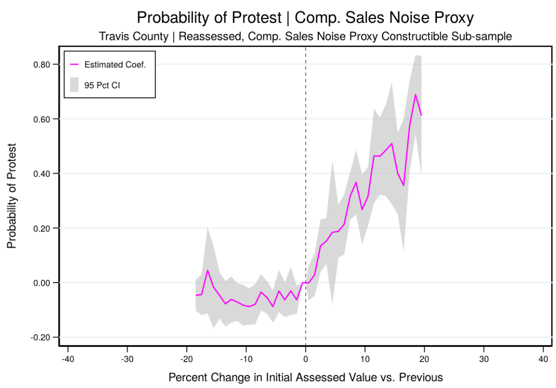
Figure A.12: Robustness to Comparable Sales Estimated Noise Proxy in the *Travis County* Sample. [Without Property-Owner Pair Fixed Effects]



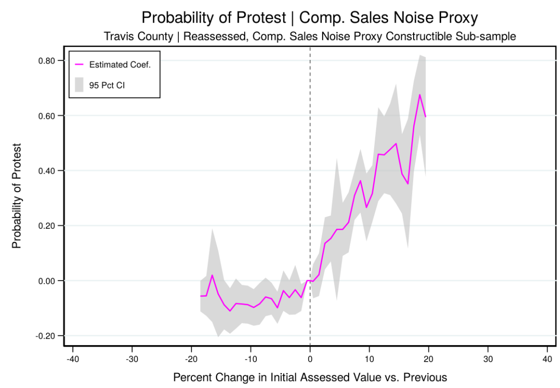
(A)Comp. Sales Estimated Noise Proxy by Pct. Chg. *Initial Assessed Value*



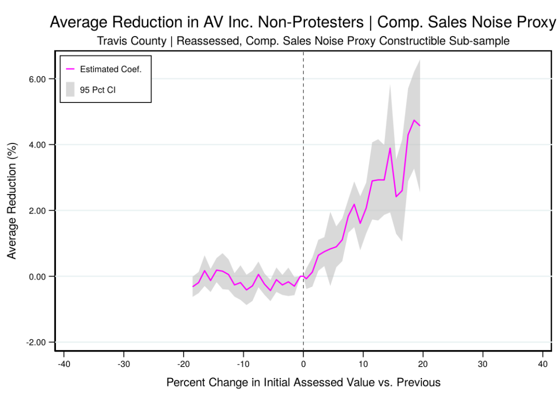
(B) Average Reduction by Comp. Sales Noise Proxy (All)



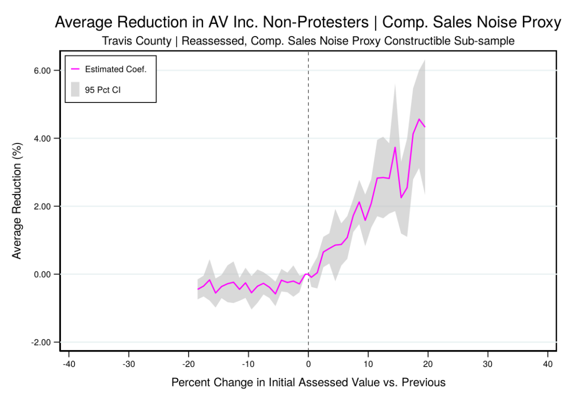
(C) Probability of Protest Conditional on Comp. Sales Noise Proxy (Linear)



(D) Probability of Protest Conditional on Comp. Sales Noise Proxy (Kinked)



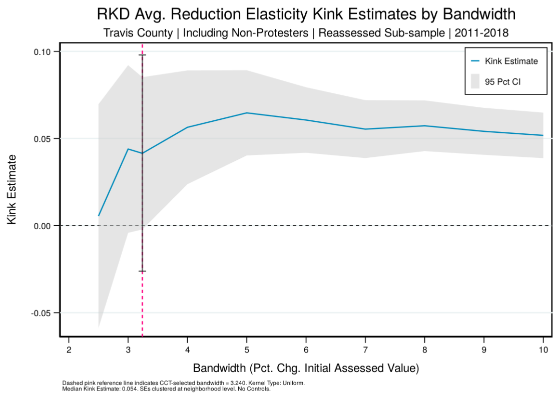
(E) Average Reduction (Inc. Non-Protesters) by Pct. Chg. *Initial Assessed Value* Cond. on Comp. Sales Noise Proxy (Linear)



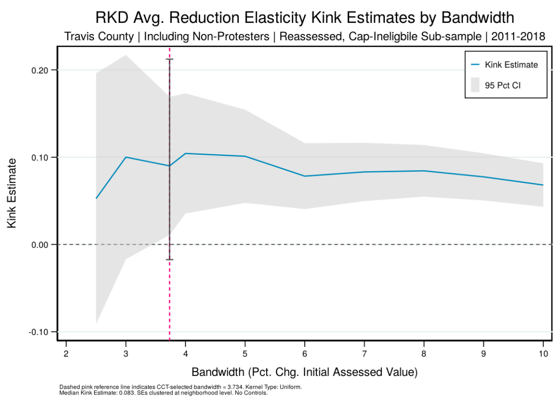
(F) Average Reduction (Inc. Non-Protesters) by Pct. Chg. *Initial Assessed Value* Cond. on Comp. Sales Noise Proxy (Kinked)

Notes: Sample restricted to those for which a comparable sales noise proxy, η_{it}^{CS}, can be constructed (1.9% of property-year observations in the Travis County sample). Travis County comparable sales noise proxy has mean -0.27% and standard deviation 7.69%. Linear control estimates RKD (analogous to Equation 2.2) including η_{it}^{CS} as a control. Kinked control estimates RKD (analogous to Equation 2.2) including both η_{it}^{CS} and $\eta_{it}^{CS} | \eta_{it}^{CS} > 0$ as separate controls, allowing for differential marginal effects for values of the noise proxy that are positive. All underlying regressions include year fixed effects. Coefficients are normalized to the value given a percent change in *Initial Assessed Value* between -1% and 0%. Standard errors are clustered at the neighborhood level.

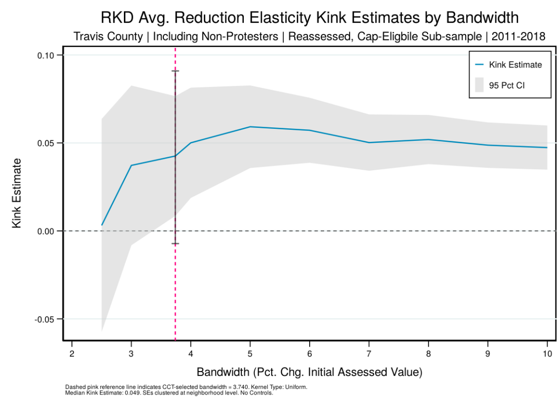
Figure A.13: Regression Kink Discontinuity Bandwidth Test: Difference in the Average Reductions Received (Unconditional on Protesting) with respect to Percent Change in *Initial Assessed Value.*



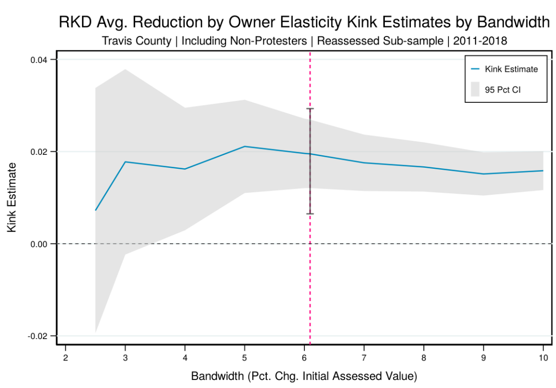
(A) Travis County



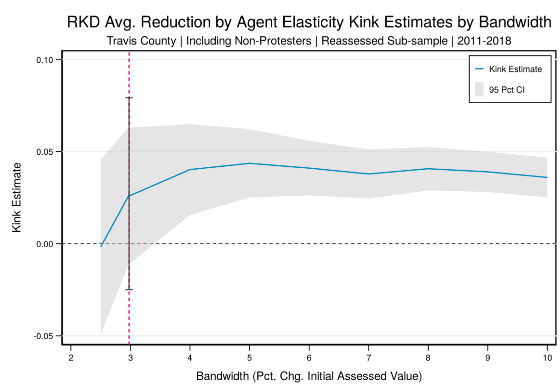
(B) (i) Travis County: Cap-Eligible Sub-Sample



(B) (ii) Travis County: Cap-Ineligible Sub-Sample



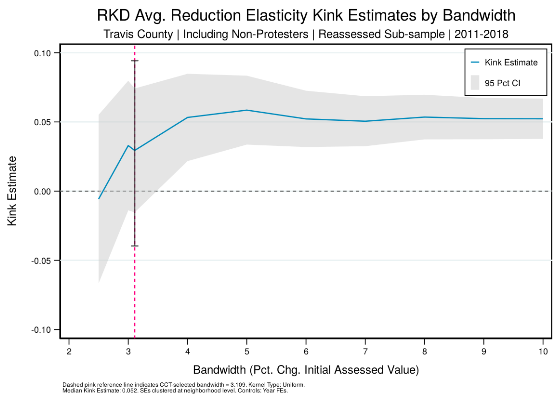
(C) (i) Travis County: Protests by Owner



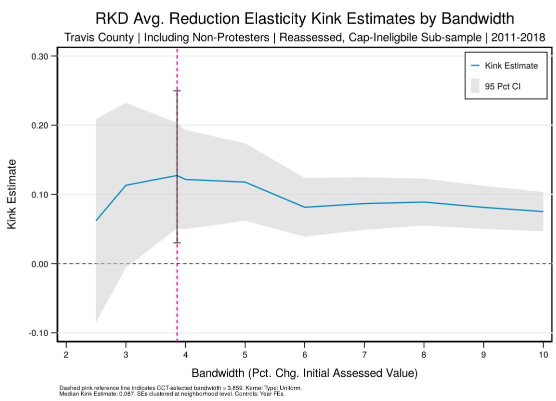
(C) (ii) Travis County: Protests by Representing Agents

Notes: The figures above show regression kink discontinuity (RKD) estimates of the *difference* in the elasticity of average reductions received (unconditional on protesting) above and below the reference point. Each plot is a bandwidth sensitivity test, showing the RKD estimates of separate regressions at symmetric bandwidths $k \in [2.5\%, 10\%]$ around the reference point. The CCT-selected bandwidth and (quadratic) robust confidence intervals are shown at the dashed-pink line (Calonico et al., 2014). No controls. Standard errors are clustered at neighborhood level; uniform kernel.

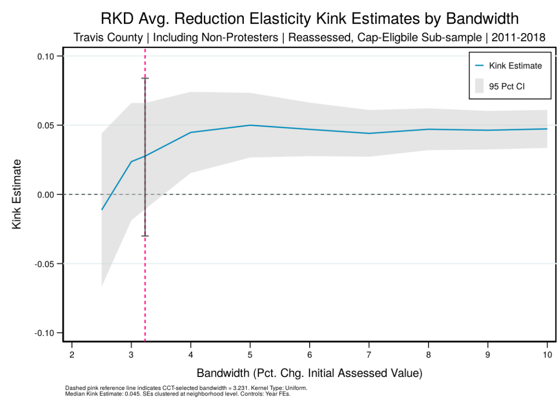
Figure A.14: Regression Kink Discontinuity Bandwidth Test: Difference in the Average Reductions Received (Unconditional on Protesting) with respect to Percent Change in *Initial Assessed Value* [Robustness Check: Including Year Fixed Effects].



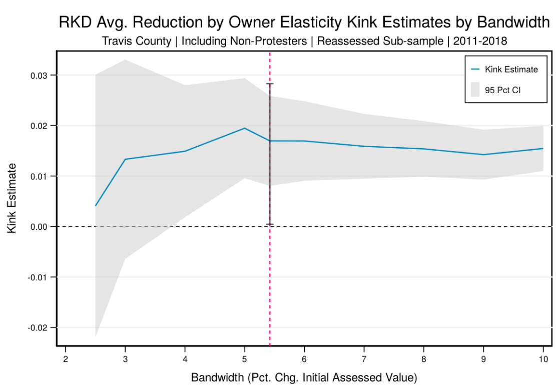
(A) Travis County



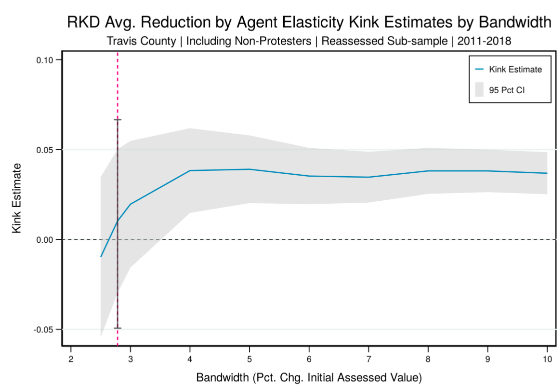
(B) (i) Travis County: Cap-Eligible Sub-Sample



(B) (ii) Travis County: Cap-Ineligible Sub-Sample



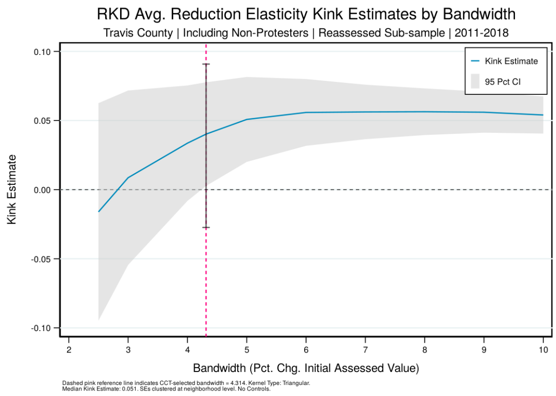
(C) (i) Travis County: Protests by Owner



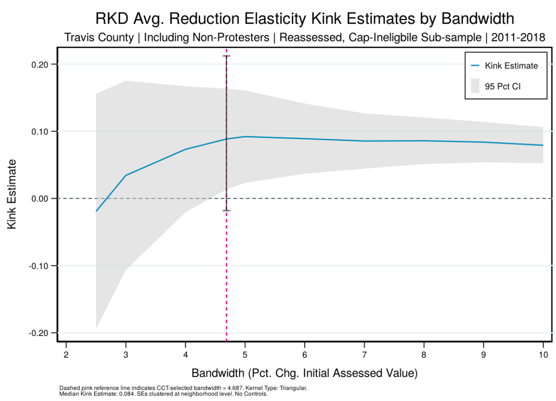
(C) (ii) Travis County: Protests by Representing Agents

Notes: Robustness figure analogous to Appendix Figure A.13, but including year fixed effects in RKD estimates. The figures above show regression kink discontinuity (RKD) estimates of the *difference* in the elasticity of average reductions received (unconditional on protesting) above and below the reference point. Each plot is a bandwidth sensitivity test, showing the RKD estimates of separate regressions at symmetric bandwidths $k \in [2.5\%, 10\%]$ around the reference point. The CCT-selected bandwidth and (quadratic) robust confidence intervals are shown at the dashed-pink line (Calonico et al., 2014). Standard errors are clustered at neighborhood level; uniform kernel.

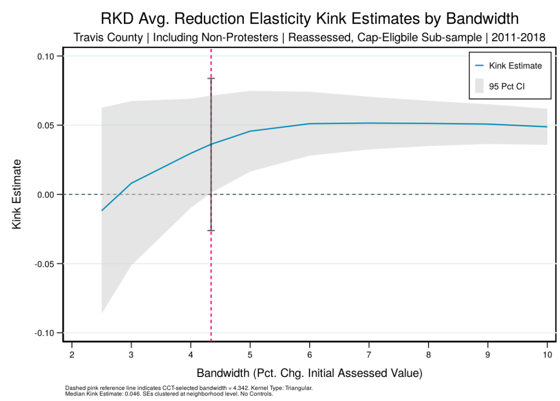
Figure A.15: Regression Kink Discontinuity Bandwidth Test: Difference in the Average Reductions Received (Unconditional on Protesting) with respect to Percent Change in *Initial Assessed Value* [Robustness Check: Triangular Kernel].



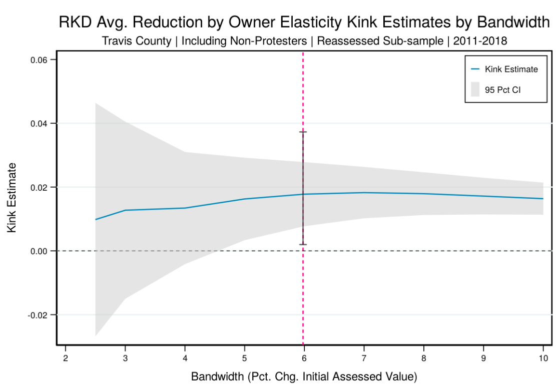
(A) Travis County



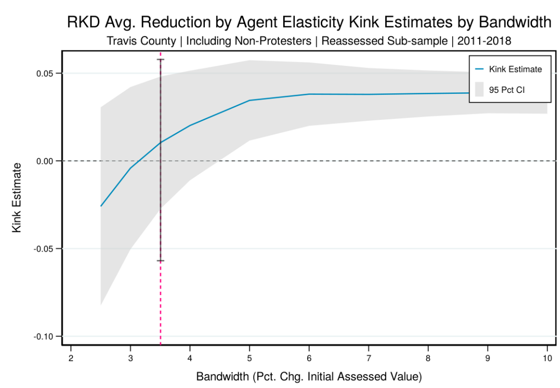
(B) (i) Travis County: Cap-Eligible Sub-Sample



(B) (ii) Travis County: Cap-Ineligible Sub-Sample



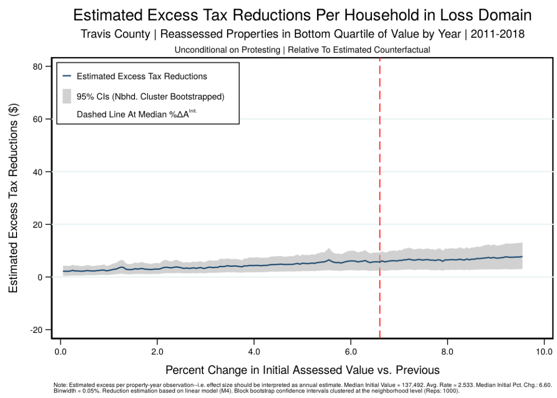
(C) (i) Travis County: Protests by Owner



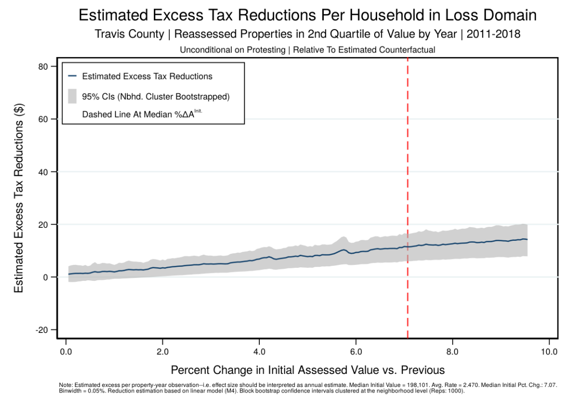
(C) (ii) Travis County: Protests by Representing Agents

Notes: Robustness figure analogous to Appendix Figure A.13, but using a triangular kernel. The figures above show regression kink discontinuity (RKD) estimates of the *difference* in the elasticity of average reductions received (unconditional on protesting) above and below the reference point. Each plot is a bandwidth sensitivity test, showing the RKD estimates of separate regressions at symmetric bandwidths $k \in [2.5\%, 10\%]$ around the reference point. The CCT-selected bandwidth and (quadratic) robust confidence intervals are shown at the dashed-pink line (Calonico et al., 2014). Standard errors are clustered at neighborhood level.

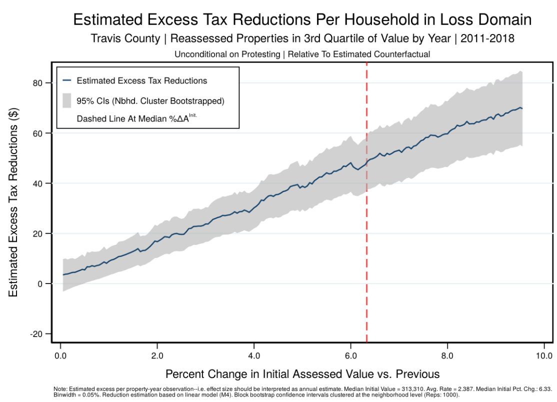
Figure A.16: Estimates of Annual Excess Tax Reductions per Household in the Loss Domain (including Non-Protesters) by Quartile of Property Value. Travis County *Re-assessed Sub-Sample*.



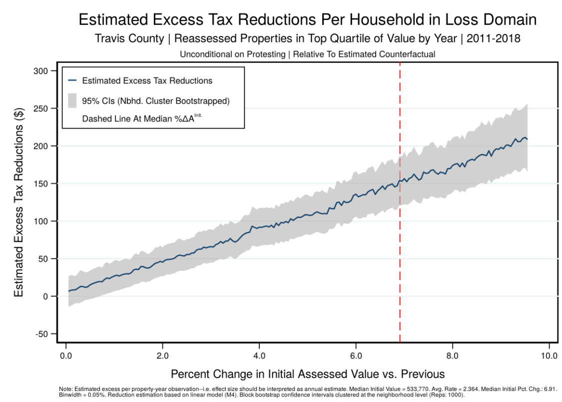
(A) Bottom Quartile



(B) 2nd Quartile



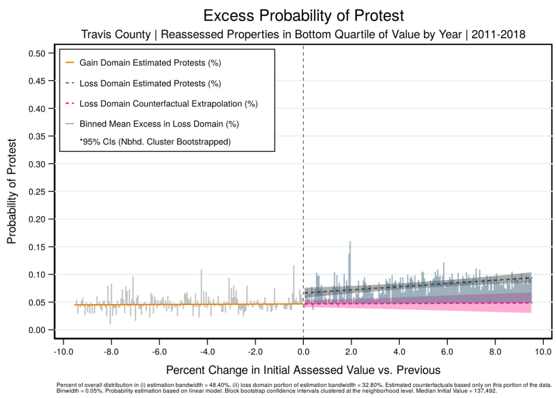
(C) 3rd Quartile



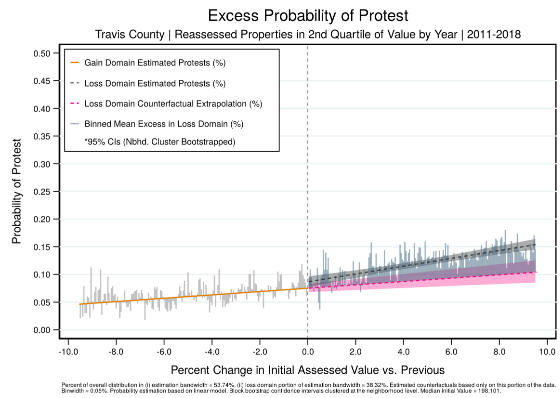
(D) Top Quartile

Notes: See Figure 2.11 footnotes and Table 2.6. Appendix Figures A.17, A.18 and Figure A.16 replicate the same analysis as Figure 2.11, separately by quartile of *Initial Assessed Value* (quartile defined within year).

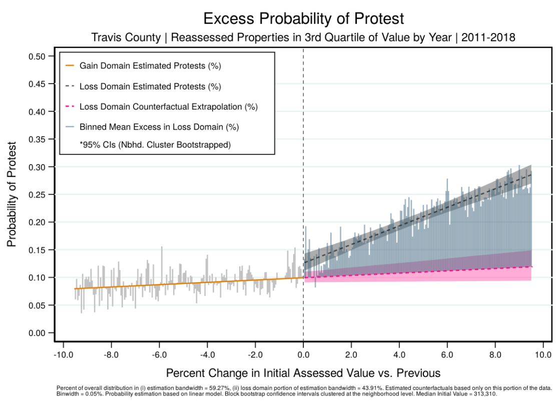
Figure A.17: Estimates of Excess Protests in the Loss Domain vs. Estimated Counterfactual by Quartile of Property Value. Travis County *Re-assessed Sub-Sample*.



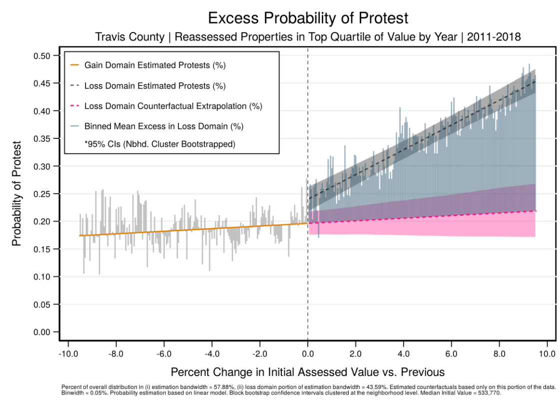
(A) Bottom Quartile



(B) 2nd Quartile



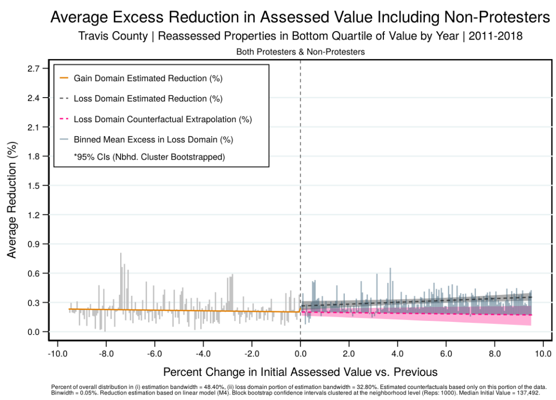
(C) 3rd Quartile



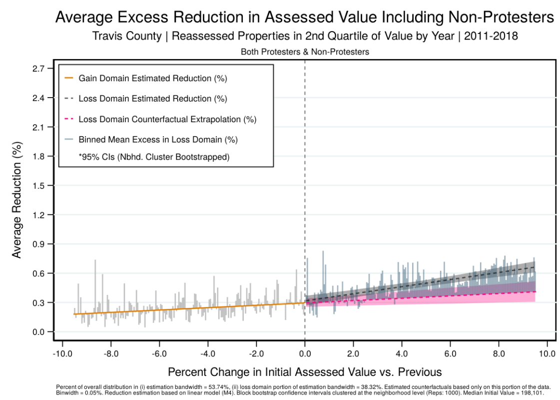
(D) Top Quartile

Notes: See Figure 2.11 footnotes and Table 2.6. Appendix Figures A.17, A.18 and A.16 replicate the same analysis as Figure 2.11, separately by quartile of *Initial Assessed Value* (quartile defined within year).

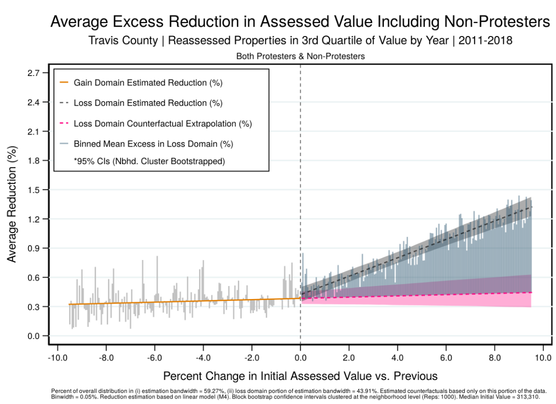
Figure A.18: Estimates of Excess Assessed Value Reductions in the Loss Domain vs. Estimated Counterfactual by Quartile of Property Value. Travis County *Re-assessed Sub-Sample*.



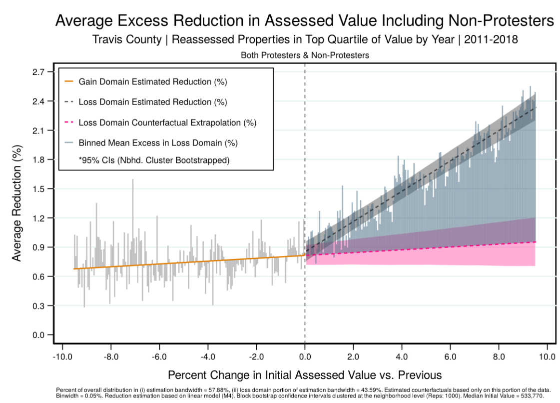
(A) Bottom Quartile



(B) 2nd Quartile



(C) 3rd Quartile



(D) Top Quartile

Notes: See Figure 2.11 footnotes and Table 2.6. Analogous to the analysis as Figure 2.11, separately by quartile of *Initial Assessed Value* (quartile defined within year). All estimates based on underlying micro-data; the figures show binned average effects.

A.2 Appendix Tables

Table A.1: Travis County RKD diagnostic checks for covariate balance near zero percent change in *Initial Assessed Value*.

					CCT (Quadratic) Robust CI		
Observable Covariate	Test	Est.	SE	p-value	BC CI LB	BC CI UB	BC p-value
Square Feet	Jump	-90.49	84.25	0.28	-454.13	-29.37	0.03
HVAC Sq. Ft.	Jump	-71.77	82.03	0.38	-427.01	3.40	0.05
Bathrooms	Jump	-0.10	0.07	0.13	-0.36	-0.06	0.01
Year Built (1st)	Jump	-4.69	2.30	0.04	-11.92	-0.81	0.02
Grade	Jump	-0.01	0.02	0.63	-0.06	0.02	0.31
Square Feet	Kink	-5169.44	3769.19	0.17	-38621.70	14374.28	0.37
HVAC Sq. Ft.	Kink	-6073.83	3821.00	0.11	-37296.67	16493.31	0.45
Bathrooms	Kink	-4.15	2.79	0.14	-29.21	7.45	0.24
Year Built (1st)	Kink	-198.47	104.17	0.06	-915.38	543.35	0.62
Grade	Kink	2.09	1.03	0.04	-6.15	3.19	0.53

Notes: This table shows the results of RD and RKD placebo regressions estimated using the CCT-selected bandwidth from the main estimate of the kink in the probability of protesting around zero percent change in *Initial Assessed Value* from Appendix Figure A.3(A) (bandwidth = 0.03371 log points). Table shows both the conventional SE and conventional p-value, as well as CCT-suggested (quadratic) robust confidence intervals. No controls included in placebo regression estimates. Standard errors are clustered at neighborhood level; uniform kernel.

Table A.2: RKD and RD estimates of the Probability of Protesting by Percent Change in *Initial Assessed Value* in the Travis County sample, corresponding to Appendix Figure A.3(A).

	Bandwidth (Log Points)			
	0.0337†	0.05	0.07	0.0953
α^{Gain}	0.120	0.115	0.114	0.111
	(0.006)	(0.005)	(0.004)	(0.004)
α^{Loss}	0.127	0.127	0.135	0.146
	(0.008)	(0.007)	(0.006)	(0.006)
β^{Gain}	0.952	0.595	0.579	0.440
	(0.257)	(0.154)	(0.098	(0.070)
β^{Loss}	1.841	1.805	1.432	1.064
	(0.407)	(0.217)	(0.149)	(0.117)
Jump, $\alpha^{Loss} - \alpha^{Gain}$	0.007	0.013	0.021	0.035
	(0.008)	(0.007)	(0.007)	(0.006)
Kink, $\beta^{Loss} - \beta^{Gain}$	0.890	1.210	0.853	0.624
	(0.507)	(0.268)	(0.178)	(0.139)
N	451,803	544,331	681,249	873,583

†CCT-selected bandwidth

Notes: This table shows the full set of parameter estimates from four of the regressions of underlying Appendix Figure A.3(A), specified by Equation 2.2. No controls included; sample limited to reassessed properties. Conventional SEs clustered at the neighborhood level shown in parentheses; uniform kernel. Note that the log point bandwidth 0.0953 corresponds to a 10% increase.

Table A.3: Probability of bunching at *Previous Assessed Value* among Harris County *Opinion-Stated Protesters* for which *Initial Assessed Value* increased (i.e. limited to those with an initial increase). Binary dependent variable indicates *Final Assessed Value* equals *Previous Assessed Value*.

	Prob. of Final Buncher			
	(1)	(2)	(3)	(4)
(a) Opinion = Previous	0.134	0.101	0.130	0.098
	(0.003)	(0.004)	(0.003)	(0.003)
(b) Owner Protested	0.003	-0.002	-0.002	-0.009
	(0.001)	(0.002)	(0.001)	(0.002)
(c) Opinion = Final			0.093	0.095
			(0.002)	(0.004)
(a) & (b)	0.017	0.021	0.014	0.020
	(0.003)	(0.005)	(0.003)	(0.004)
(b) & (c)			0.037	0.051
			(0.003)	(0.005)
Cons.	0.060	0.118	0.043	0.092
	(0.002)	(0.005)	(0.002)	(0.005)
$\ddot{A}_{it}^{Init}$ 4th-Deg. Poly.	X	X	X	X
Year FEs		X		X
Property-Owner Pair FEs		X		X
Adj. R^2	0.054	0.088	0.088	0.123

Obs. = 670,624. SEs clustered at neighborhood level.

Notes: This table shows linear probability estimates relating bunching in the distribution of *Final Assessed Value* to bunching in the distribution of *Opinion of Value*.

A.3 Appendix Notes

Sample Construction

Each county sample was constructed using the following criteria. I limit the sample to single-family residential properties (State Class A1) with: (i) one building onsite (excluding detached structures like a garage or shed), (ii) less than ten acres, (iii) no more than eight bathrooms, (iv) No more than 10,000 square feet. Additionally, I drop property-year observations if: (v) there is a new owner in the current tax year, (vi) there is new construction or remodeling in the current or previous year, (vii) there are less than 20 properties in the neighborhood or there average less than 30 properties in the neighborhood during the sample period, (viii) the absolute value of (a) percent change in *Initial Assessed Value* is greater than 50%, (b) percent change in *Final Assessed Value* versus prior is greater than 50%, or (c) percent reduction after protesting exceeds 50%, (ix) a protest was filed, but received after the deadline, and (x) a very small number of other properties that are outliers for other idiosyncratic reasons. In Harris County, 14% of A1 property-year observations are excluded from the main sample, with the vast majority of those exclusions (83%) resulting from either (v) or (vi).

I define the reassessed sub-sample as properties that either had no change in *Initial Assessed Value* or that belonged to a neighborhood where 80% or more of the properties had no change in value. Additionally, in the Travis County sample I exclude 2.6% of observations from the reassessed sample whose only change in assessment most likely came from a partial reassessment and not a full reassessment (stemming only from very small changes in depreciation of improvements).

I define the cap-ineligible sub-sample as properties whose owners owned the property for at least two years, never had a cap-assessed value, and never claimed a homestead exemption (which provides the benefit of a cap-assessed value, should it be applicable); I define the cap-eligible sub-sample as properties whose owners owned the property for at least two years, and claimed a homestead exemption in at least one year. As such, I do not classify some properties as definitively cap-eligible or cap-ineligible, excluding them from both sub-samples.

For purposes of this study, I treat a protest as valid if it was received on time and did not result in an increase in assessed value. Increases are a very rare result occurring in less than 0.12% of appeals in both samples. I treat opinions as valid if they are not greater than the *Initial Assessed Value*, which, like increased value revisions, are extremely rare, occurring in less than 0.36% of opinion-stated protests in both samples. Additionally, I drop (i) opinions recorded as zero which stem from record-keeping procedures, (ii) opinions recorded as the *Initial Assessed Value* which can indicate that the protester is not challenging the assessed value, and (iii) implausibly low opinions (e.g. suggesting a value less than $25,000 in the Travis sample).

For the uniform and equal noise proxy analysis, I define a comparable property as any other property in a subject property's neighborhood whose improvements satisfy the following conditions: (i) has the same building grade as the subject property's improvements, (ii) has square footage within 15% of the subject property's improvements, (iii) was built within 5 years of the subject property's improvements. I then calculate the price per square foot of improvements for each comparable property, and then use the median price per square foot of comparable properties, provided that at least five comparable properties can be identified. Subsequently, I apply this "uniform and equal comparable price per square foot" to the actual square footage of the subject property, adding back the value of the land to attain a *Uniform And Equal Implied Value*. The uniform and equal noise estimate is defined as $\eta_{it}^{UE} = \log(\textit{Initial Assessed Value}/\textit{Uniform And Equal Implied Value})$.

The comparable sales noise proxy is calculated in a similar fashion. Using the same parameters to define a comparable property, I identify sale prices from transactions of comparable properties in a subject property's neighborhood that occurred in the nine months prior to the (January 1st) *Initial Assessed Value*. When identifying sales prices, I only use prices from warranty deeds and special warranty deeds (which are the two most common deed types, representing 90% of sale prices) as they are most likely to reflect arms-length transactions at fair market value. For the comparable sales noise proxy, I cannot separate the value of land. Instead, I calculate a sales ratio for each comparable property defined as $CSR = \log(\textit{Sale Price (Preceding Months)}/\textit{Previous Final Assessed Value})$. This statistic provides an estimate of how to update assessments in a neighborhood appropriately. As before, I then assign the subject property the median comparable sales ratio, provided that sale prices for five comparable properties can be identified. The comparable sales noise estimate is then defined as one's percent change in *Initial Assessed Value* less the median CSR. As such, for both noise proxies, higher values indicate that a property owner may be more likely to be entitled to a reduction if they protest.

Covariate Imbalance in Harris Sample

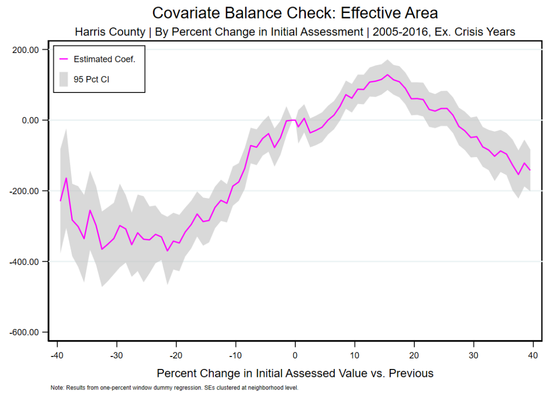
Appendix Figure A.19 summarizes the potential covariate imbalance in the Harris County sample. Appendix Figure A.20 points to evidence that there do not appear to be systematic valuation inconsistencies, conditional on being reassessed. Panel (A) shows that I predict (improvement) assessment valuations very precisely based on observable characteristics. Panel (B) shows the average residual difference (in assessed value dollars) between my predicted assessment and the actual assessment by percent change in *Initial Assessed Value* (conditional on reassessment). This suggests that while there maybe be differences in observable characteristics near the threshold of interest, controlling for those differences (by, for example, using property-owner pair fixed effects) should alleviate concerns that reassessed properties might be valued differently on either side of the reference point.

Wage-Related Administrative Cost Per Protest

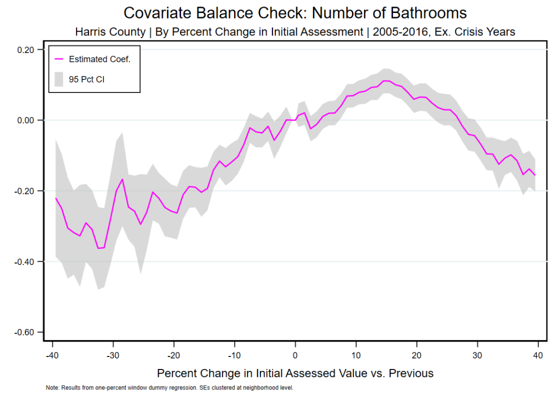
To estimate the wage-related cost per protest in Travis County, I first determine the average hourly wage of assessors and ARB panel arbiters. Using annual salary information from TCAD's published annual budget, I calculate an average hourly wage equal to $28.46 for assessors, weighting appropriately by pay grade (job titles Assessor I-IV). Using *per diem* ARB arbiter pay statistics published by the Texas Comptroller, I estimate an average hourly wage equal to $22.50 for ARB arbiters. Empirically, 29% of protests advance to an ARB hearing. A panel of three arbiters will be present and the allotted time slots are 15 minutes. As such, estimating the labor cost associated with ARB panelists is relatively straightforward.

Determining the average handling time that each protest requires of an assessor is murkier, and undoubtedly varies from case to case. Some protests are likely resolved with very little work on the part of an assessor. Others will require only an informal meeting, only a formal

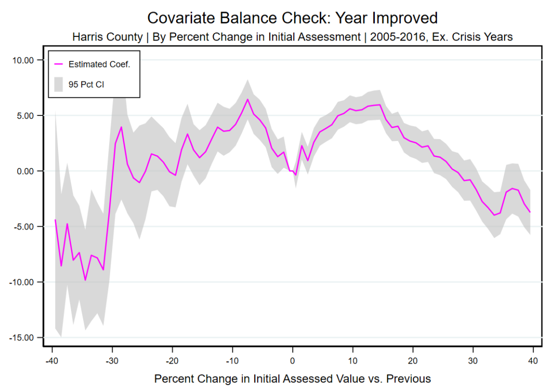
Figure A.19: Harris County RKD diagnostic checks for covariate balance near zero percent change in *Initial Assessed Value*.



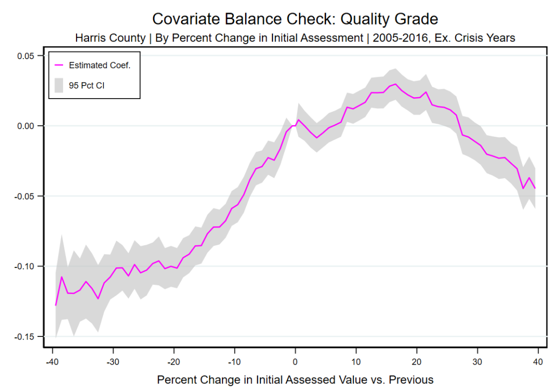
(A) Covariate Balance: Effective Area



(B) Covariate Balance: Number of Bathrooms



(C) Covariate Balance: Year Improved

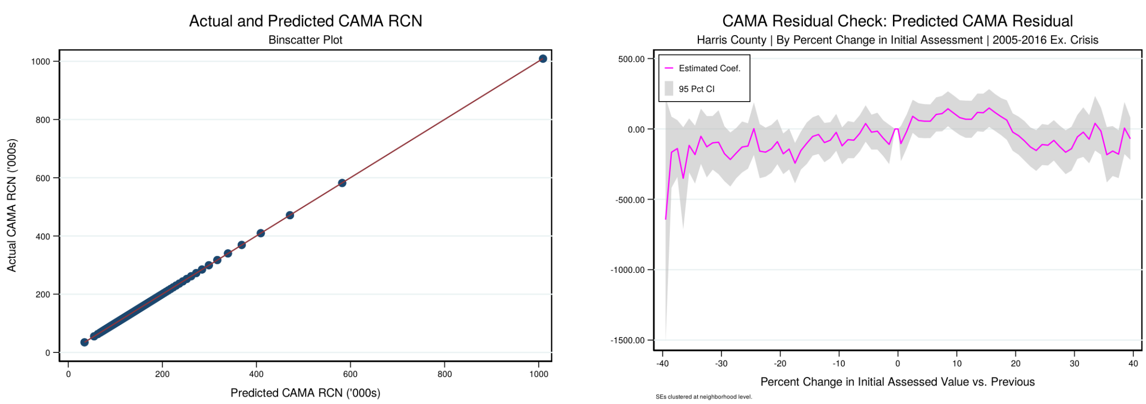


(D) Covariate Balance: Grade (Numeric Conversion)

hearing, or both an informal meeting and a formal hearing, each requiring an assessor's time. While imperfect, I assume an average assessor handling time of 20 minutes per case, which reflects an average assessor handling time close to that of an ARB case, plus additional time for minimal preparation.

Together, this results in an estimated administrative cost-per-protest equal to $28.46/3 + (0.29)(3 \times (22.50/4)) = \$14.38$, which almost surely understates the true administrative cost-per-protest, which also involves non-labor expenses. While by no means a perfect estimate, this provides a useful metric to calibrate an administrative burden associated with the additional protests induced by loss aversion.

Figure A.20: Harris County CAMA predictions and residuals.



(A) CAMA Value & Predicted CAMA Value

(B) CAMA Residual Conditional on Reassessment