When Do Property Taxes Matter? Tax Salience and Heterogeneous Policy Effects

Marina Gindelsky[†]
U.S. Bureau of Economic Analysis

Jeremy Moulton[§]
University of North Carolina – Chapel Hill

Kelly Wentland[‡]
George Mason University

Scott Wentland[*]
U.S. Bureau of Economic Analysis

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Abstract

Taxes create incentives; yet, the potency of these incentives may depend on the salience and households' perceptions of the tax itself. We investigate this issue in the context of property taxes, exploring how accurately households perceive their property tax liabilities and what factors determine misperception. Leveraging a unique national dataset, created by linking Zillow's ZTRAX data to internal data from the American Community Survey, we first compare survey responses for how much households *think* they pay in property taxes to how much they *actually* pay based on municipal administrative records from ZTRAX. While homeowners' tax perceptions are not substantially biased on average, we observe significant inaccuracy and systematic bias across different household(er) characteristics, institutional settings, and across states. Given that the vast majority of studies in the property tax capitalization literature use data concentrated in one state or locality, we also explore whether variation in tax misperceptions across states can help explain the heterogeneity in property tax effects on home prices. Results from a meta-analysis show that studies conducted in states with higher property tax misperceptions are significantly less likely to find property tax policy changes are fully capitalized into home prices.

JEL Classifications: H22, H71, J14, R23, R28

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[†]Office of the Chief Economist, 4600 Silver Hill Rd, Suitland, MD 20746; marina.gindelsky@bea.gov
§Department of Public Policy, Abernethy Hall, CB 3435, Chapel Hill, NC 27599; moulton@email.unc.edu
‡Department of Accounting, School of Business, 4400 University Drive, Fairfax, VA 22030; kwentlan@gmu.edu
[*]*Contact author*: Office of the Chief Economist, 4600 Silver Hill Rd, Suitland, MD 20746; scott.wentland@bea.gov

I. Introduction

Collected from over 91 million owner-occupied households in the U.S., property taxes are a crucial source of revenue for state and local governments, amounting to over $615 billion (in 2020).[1] Like other taxes, they also provide a mechanism for local policymakers to incentivize both economic and social objectives, including targeted exemptions and tax benefits for specific demographics (e.g., senior citizens or disabled veterans) or by socioeconomic status (e.g., low income/wealth households). Recent research is somewhat mixed, however, regarding whether and to what extent property tax policies effectively influence housing tenure and location decisions (e.g., Banzhaf et al. 2021; Kim and Dawkins 2021) or whether these policies work as intended (e.g., Bradley 2017; Moulton et al. 2018). In this paper, we dig deeper into why households' reactions to property tax policy might be so mixed. In particular, we first evaluate the possibility that property tax salience may differ from household to household and, thus, misperceptions about property taxes may vary in different contexts. Using a unique dataset, internal American Community Survey (ACS) microdata linked to administrative property-level tax assessor records from Zillow's ZTRAX database, we investigate whether, and to what extent, there are systematic differences between how much households *perceive* they pay in property taxes versus what they *actually* pay.[2] We then explore whether tax misperceptions can help reconcile the heterogeneous impact of property tax policies on home prices found in the literature.

[1] By comparison, U.S. federal tax revenue from corporate income taxes and federal individual income taxes was roughly $276 billion (NIPA Table 1.12) and $1.68 trillion (NIPA Table 3.4) in 2020. Property tax revenue is from NIPA Table 3.5. Homeownership is based on U.S. Census Bureau statistics for the typical rate of owner-occupied housing over 2016-2020. Source: https://apps.bea.gov/iTable/index_nipa.cfm

[2] One relevant definition of salience derives from psychology. The salience hypothesis as defined by the American Psychology Association's Dictionary of Psychology is, "a theory of *perception* according to which motivationally significant stimuli (objects, people, meanings, etc.) are perceived more readily than stimuli with little motivational importance" [*emphasis added*]. Source: https://dictionary.apa.org/salience-hypothesis. We return to its tie to economic motivation and our hypotheses in Section II below.

These questions are important to examine empirically because (1) the magnitude of property tax revenue is itself economically significant and is thus tied to a sizable literature examining determinants and responses from property tax policies,[3] and (2) there is a documented, but yet unsolved, puzzle in the literature – namely, that households are expected to have a better understanding of their property taxes, but the empirical evidence often conflicts with this prediction. Specifically, economics provides numerous theoretical reasons that households should understand and incorporate the implications of property taxes, which in part hinge on the tax's absolute size and its tie to a large purchase (Chetty, Looney, and Croft 2007).[4] Yet, the empirical literature is decidedly mixed on whether households actually understand these taxes very well or account for them rationally in their decision-making (Sirmans, Gatzlaff, and Macpherson 2008).

The flipside of this theory is that households will be less attentive to taxes that are smaller in magnitude, or normal 'everyday' purchases. Chetty et al. (2007) investigate sales tax salience and provide evidence that consumers are somewhat inattentive to taxes in this context. They explain that this response is understandable given that they examine small, frequent purchases: "more individuals pay attention to taxes when making large, one time choices (e.g. buying a house) than small, repeated purchases (e.g. food, clothing)" (Chetty et al. 2007, p. 34).[5] In contrast, Bradley (2017), for example, examines the response of home purchases to Michigan's

[3] Property taxes are also used as an input into user cost models of housing services (Gindelsky, Moulton, and Wentland (2019)) and in the national income and product accounts. While the BEA does not employ a user cost approach for measuring housing, it relies on the accuracy of the ACS for several statistics, including its new methodology for calculating housing services in GDP (Rassier et al. 2021).

[4] This logic is also consistent with models of labor income taxation that suggest high income households are more responsive to labor and capital income taxes given the effect is larger for these households (e.g., Feldstein 1995; Goolsbee 2000).

[5] This implies that the infrequency of a purchase (in addition to its size) correlates with greater attention and lower misperceptions with taxes, based on the expectation that the cognitive cost to calculate a tax is a fixed cost per transaction. However, it is also reasonable to expect that with different types of purchasing transactions and taxes that greater purchase frequency could lower tax misperception to the extent that frequency facilitates learnings that lowers these cognitive costs.

implementation of property tax assessment limits and finds that homebuyers were "woefully inattentive" to the tax implications of their home purchases, despite the theoretical prediction of a more attentive response.

Bradley (2017) fits within a broader, decades-long literature investigating how property taxes affect home prices, where buyers' and sellers' (mis)understanding of property taxes potentially plays an important role. That is, if property taxes are well-understood, and certain basic market conditions are met, then the taxes should be capitalized into the purchase price of a home. To illustrate, consider a stylized example where homebuyers are bidding on two identical homes (with identical structure characteristics, public services, and amenities – including location amenities), but one home happens to have substantially lower property taxes. If everyone expects the lower tax home to incur, say, $10,000 less taxes in net present value (NPV) terms over the life of the property, rational consumers would favor the tax-preferred asset, all else equal. As a result, they would be willing to bid a higher price – up to the point where their marginal benefit equals the marginal cost in a competitive market. Thus, in the short run, particularly when supply conditions are highly inelastic, we would expect an otherwise identical tax-preferred home to sell for more, where full capitalization is reached when the NPV of the expected tax benefit is included in the purchase price of the home (or, about $10,000 in the above example). In some circumstances, like if market conditions are imperfect, housing supply is relatively elastic, homebuyers are inattentive, or they simply do not understand the property tax implications, then the purchase price may partially (under) capitalize (<$10k in the example), overcapitalize (>$10k in the example), or not capitalize the differences at all ($0 difference in the example).[6]

[6] Besides household inattention or behavioral explanations, there may be other (rational) reasons for observing under/over-capitalization. For example, the beneficiaries of lower taxes may not expect to receive the full benefit over time in some submarkets, which could be the case for seniors valuing tax benefits far into the future when their life

While numerous studies find local instances of full capitalization, a review of decades of research on property tax capitalization by Sirmans et al. (2008) concluded that most studies did not find evidence of full capitalization.[7] The absence of uniform evidence for full capitalization naturally raises the following questions: 1) why is there so much variation in these findings, and 2) can variation in perceptions about property taxes help explain the heterogeneity in this literature? Given that the aforementioned studies are predominantly drawn from local, sub-national datasets, one factor that could explain the diverse impact of property tax policy is simply that these taxes are not uniformly salient across all households and settings; thus, systematic differences in misperceptions may be an important contributor to household responses.

We explore these questions empirically by using internal ACS microdata linked to administrative public tax records from Zillow's ZTRAX database. We first measure the difference between the (annual) amount of property taxes respondents report in the ACS survey compared to the corresponding tax amount actually assessed in the tax records. While a large portion of households report their property tax without much bias (as raw (signed) error is an underestimate of 1.4 percent of the actual tax assessed), the average absolute error is about 15 percent. Further, we find that misperception about property taxes varies systematically across household characteristics, institutional settings, and states.

When we investigate determinants of systematic differences in misperceptions, we find conditional correlations in the data consistent with the theoretical literature on inattention.

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expectancy is shorter than the average homebuyer. We return to this point in our meta-analysis below, as one of our state-level indexes controls for householder characteristics like age and other factors.

[7] Of the 28 studies they reviewed and summarized in Exhibit 1 of their paper, 9 studies found full capitalization, 7 found no significant capitalization, 2 found positive/overcapitalization, and 10 found partial capitalization. Several more studies on property tax capitalization have been published since this review, however. Gallagher et al. (2013), Livy (2018), Munro and Tolley (2018), Giertz et al. (2021) all found full capitalization depending on the discount rate chosen (or, at least they could not reject the hypothesis of full capitalization as stated by Giertz et al. 2021). If we include the latter 4 studies in the full capitalization group, then a total of 13 of the 32 studies find full capitalization.

Specifically, when households have greater motivation to devote attention to property taxes in terms of the size of the property tax base (home value) and property tax rate, we find these households tend to have lower levels of misperception or absolute error. Conversely, when property taxes are less important to the household, in particular when income (or an alternative tax base) is higher relative to home value, the household is less attentive to property taxes (in terms of absolute error). In addition, we also find that factors capturing different levels of information costs or gaps also correspond with household misperceptions about property taxes. Householders without a college degree, that are younger, or that have lower income tend to misperceive property taxes to a greater degree. Further, households who pay their tax indirectly via mortgage escrow (i.e., with less visibility) also have greater absolute error in their estimates than those who pay directly without a mortgage. There is also variation in the way the inattention (absolute error) related to different characteristics manifests in terms of (signed) raw error such that in some cases we do not find evidence of a corresponding influence on raw error. However, in other cases, we observe that the inattention corresponds with a difference in raw error as well, which would be consistent with reliance on a systematic form of inattention like a heuristic.

In our final set of analyses, we pivot from evaluating household determinants of misperception to examining state-specific variation in misperception, given that prior studies in the property tax capitalization literature often use local, subnational datasets. We find that there are substantial state-specific tax misperception differences, even after accounting for differences in property tax rates and other factors. Using these state-specific effects we create indices for tax misperceptions by state, which allow us to conduct a simplified meta-analysis for the property tax capitalization literature. Overall, we find a significant association between the level of tax misperception in a state and whether the study that used data from that state observed a full capitalization result. That is, if a state has higher tax misperceptions (in terms of absolute error), it substantially reduces the likelihood that a study set in that state found a full capitalization result, on average. In fact, a key result from this analysis is that a substantial amount of heterogeneity in the property tax capitalization literature can be explained by cross-state variation in tax misperceptions over the period we study.

These results contribute to multiple strands of literature and are relevant for policymakers and future research. First, results from the linked microdata help characterize the size and direction of property tax misperception across the U.S., which is an important set of findings to document in its own right. Unlike other studies of tax salience and misperceptions, we are able to examine and directly assess the perception versus reality of tax assessments on a household level across the U.S. as a whole. This is only possible with national data like ZTRAX linked to ACS data and underscores the utility of such data for research where heterogeneity across states or groups could be important. Accordingly, our analysis of the determinants of tax misperception with this unique administrative data reveals which characteristics are associated with inaccuracy (absolute error) and systematic over/underestimation (raw error).

Second, the results from our simplified meta-analysis shed new light on the property tax capitalization literature and the importance of systematic differences in tax misperceptions. The aforementioned literature largely relies on inferences about household reactions to property taxes from particular local, state, or regional datasets; and, in more recent literature (e.g., Moulton et al. 2018), the inferences are based on evidence from a particular group's (seniors, veterans, etc.) reaction to a state or local policy change. The results here caution researchers from generalizing too broadly about how rational, well-informed, or attentive households are about taxes based on local or subgroup data, as our findings show systematic differences, incentives, and context can be an important contributor to heterogeneous findings. Even if subsequent researchers use national data, systematic misperceptions across the subpopulations examined (e.g., by income level or age) may still confound variation in the results, depending on the study's research question. Thus, our results and state-level indices of property tax misperceptions provided in the Online Appendix may be useful for future research to exploit in additional analysis to scrutinize such concerns further.

Third, and more generally, our findings contribute to the literatures in public economics and tax accounting that examine explicit measures of misperceptions about taxes and their determinants. While this is the first U.S. study to examine the distribution and determinants of misperceptions about *property* taxes on a broad, representative sample, other studies have explored similar questions on misperceptions related to federal income taxes. This stream of research is often limited to much smaller, less representative samples (e.g., Enrick 1963, 1964; Fujii and Hawley 1988; Rupert and Fischer 1995; Ballard and Gupta 2018). Further, studies in this literature often must rely on calculated tax benchmark values based on characteristics of the household (e.g., whether respondents are high versus low income, own their home, are older, etc.) rather than tax assessor values when evaluating tax misperceptions (see Blaufus et al. 2022 for a detailed summary of the literature). Given the broad scope of our sample, our results underscoring the role of heterogeneity in household characteristics and geographic factors can shed new light on important issues for this literature to consider when making inferences with more limited data.

Finally, this analysis could be valuable for policymakers. For instance, if perceptions and salience about property taxes and capitalization differ across states/regions or certain demographics, distinctions by subpopulations will provide valuable information to policymakers interested in assessing whether these policies are more or less likely to impact homebuyer decisions in their local jurisdictions that vary along these dimensions.[8] Moreover, future research questions about property tax policies may again require researchers to focus on limited subpopulations within the U.S. (e.g., with a unique policy change in a particular state or pertaining to a particular demographic that departs from the typical U.S. landscape). Identifying how different features of the population alter tax misperceptions and capitalization rates would help with understanding how results from these narrower settings may (or may not) generalize more broadly.

II. Background and Related Literature on Tax Misperceptions

II.A. Property taxes and (inconsistent) responses to them

The property tax capitalization literature has a long history of grappling with substantial differences in findings across studies. Recall from the example in the introduction that a key assumption for measuring capitalization is that other factors besides taxes are equal across properties. Therefore, early studies tried to explain inconsistencies and heterogeneity in the results by focusing on model specification issues and the inherently difficult task of "holding all else equal" in a cross-sectional empirical design, where observable property and amenity characteristics were regressed on home prices using some variation of a hedonic regression model. Property tax rates are seldom raised and lowered in a vacuum, however, as changes in property tax policies often correspond to changes in a variety of other factors like public services, for example.[9] In the follow-up work to his seminal study on property tax capitalization, Oates (1973) made some

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[8] Regarding distributional concerns, how property taxes are capitalized also directly affects who bears the cost or reaps the benefit of a given tax policy change. For example, if changes to property taxes are fully capitalized, then the current homeowner bears/reaps the cost/benefits; yet, if there is no capitalization, then the future homeowner will bear/reap the cost/benefit. Partial capitalization implies that the buyer and seller share the impact of the policy change.

[9] Oates (1969) was the first to test the Tiebout mechanism with initial empirical work on capitalization of property taxes into home prices, finding partial capitalization. However, subsequent work like Pollakowski (1973) and others had criticized Oates (1969), citing specification issues and his lack of accounting for public services, for instance. Decades of research followed to modify the estimation strategy, include a richer set of controls, and exploit richer data in order to address issues like omitted variables bias and underidentification. See Sirmans et al. (2008) for a more detailed summary of this literature.

modifications to his initial empirical approach, which included accounting for public services, and his prior partial capitalization result ultimately reflected a full capitalization result. Thus, one of the explanations for heterogeneity of findings offered in the early literature seemed to be that better data allowed for more complete model specification (thus reducing omitted variables bias, as in Oates (1973)). Yet, this did not seem to resolve the issue entirely as subsequent work continued to produce mixed findings for decades (Sirmans et al. 2008).

Much of the property tax capitalization literature preceded what Angrist and Pischke (2010) call the "Credibility Revolution" in empirical economics, where the use of quasi-experimental research designs and the focus on identification of causal effects came to dominate applied microeconomic fields. But, even with improved identification strategies, the more recent literature on property taxes has continued to be mixed. For example, the previously mentioned Bradley (2017) study employs an instrumental variables approach to estimate the capitalization of temporary property tax savings stemming from Michigan's property tax system (Prop A), finding a behavioral result that homebuyers end up substantially overpaying for perceived property tax benefits.[10,11] On the other hand, Moulton et al. (2018) used a regression discontinuity in time (RDiT) design for Virginia and showed that policies expected to lower or exempt seniors' and disabled veterans' property taxes were fully capitalized into home prices, consistent with homeowners having a relatively sophisticated understanding of property taxes. Although Banzhaf et al. (2021) do not estimate home price capitalization, their evidence from Georgia using a quadruple difference-in-differences methodology suggests that seniors respond to property tax

[10] In fact, Bradley (2017, p.65) concludes that, "homebuyers are, on average, grossly mistaken about the implications of the Michigan property tax system and fail to obtain sufficient information to make financially sound decisions with regard to the tax consequences of homeownership, even with many thousands of dollars potentially at stake."

[11] Outside the U.S., recent studies drawing on data from Sweden (Elinder and Perrson 2017) and England (Koster and Pinchbeck 2022) also have varying results on capitalization. The former finds more mixed evidence, with significant capitalization in the high-end market but no overall impact, while the latter "gives little reason to suggest that households misoptimize by materially undervaluing very long-term financial flows in this high-stakes context."

incentives in predictable ways consistent with their understanding of incentives. They found age-based tax exemptions increased housing consumption and altered location and housing tenure decisions in ways that imply property taxes are an important, salient input to their decision-making.

Understanding whether households are attentive to (and respond rationally to) property taxes is foundational for setting optimal policy. A common assumption in public finance and models for optimal taxation is that agents are expected to respond optimally to changes in taxes without incorporation of a role for misperception or complexity in tax policies (e.g., Ramsey 1927, Mirrlees 1971). In contrast, a series of books and articles in the political economy literature generally argues that the visibility of a tax can be important because it can lead to misperceptions about tax costs (a characteristic termed "fiscal illusion"). These misperceptions can impact not only individual consumer behavior but also government policy response to this behavior (e.g., McCulloch 1845; Mill 1848; Buchanan 1967; Buchanan and Wagner 1977; Finkelstein 2009).[12,13]

A concurrent working paper explores the role of property tax misperceptions and their implications for "fiscal illusion," albeit with a different scope than our study.[14] Cabral and Hoxby (2012) examine whether the method of payment (via indirect tax through tax escrow accounts versus direct payment) affects governmental decisions (in terms of tax rates and limits). Their main finding is that indirect payments of property tax via tax escrows correspond to increases in property tax rates, suggesting that governments expand in scale (measured as collected revenues) when

[12] See Finkelstein (2009) for a detailed discussion of this literature and conceptual framework that incorporates an imperfect awareness of their actual tax liability into consumer decisions and the government response to this behavior.
[13] Additionally, research in behavioral economics provides evidence that agents fail to fully incorporate other (non-tax) factors (e.g., shipping costs, hospital and college rankings, earnings news) when making decisions (see a review of this literature in DellaVigna 2009). Recent work by Bengali (2022) explores whether home prices in California capitalize direct levies and homeowners' association (HOA) dues, finding partial capitalization.
[14] There is also a literature that runs parallel to this study, measuring homeowner misperception of home *values* that uses linked data. Instead of property taxes, this literature measures the difference between what homeowners perceive their homes to be worth and what they are actually worth (as determined by recent sales, professional appraisals, or other estimated values). Early empirical examples include Kain and Quigley (1972) and Goodman and Ittner (1992). For more recent examples, see Kiel and Zabel (1999) and Benítez-Silva, Eren, Heiland, and Jiménez-Martín (2015).

taxes are less salient. As part of this analysis, they first validate that the indirect method of payment with tax escrows corresponds to the construct of interest (i.e., lower salience) by showing it contributes to greater inaccuracy (but not bias) for a sample of Ohio homeowners. In their main analysis of less than 1,000 observations, they focus on understanding political economy outcomes and provide an important contribution to the literature in terms of consequences of property tax misperceptions. However, we substantially expand on the scope of their analysis of property tax misperceptions by using a large-scale national data set (the linked ZTRAX and ACS data from Census) to examine the distribution of misperceptions and a long list of determinants for these misperceptions, including the influence of payment via tax escrows, while also accounting for a rich set of features about the specific homes and households examined. Further, our findings can support future research interested in consequences of fiscal illusion by examining an alternative, important consequence of property tax misperceptions: their influence on home prices (via capitalization of property tax policies) and the heterogeneous impact of these policies across states.[15]

II.B. Theory and hypothesis development

If tax misperceptions are random noise, or the errors are distributed classically, then the story here might be quite simple: people make random mistakes. However, if these errors are not entirely random, the economics and psychology literatures may provide lenses through which we view errors and salience. In particular, Taubinsky and Rees-Jones (2018) stress the importance of investigating heterogeneity in tax salience beyond just considering the average consumer misperception focused upon in much of prior literature. They emphasize that documenting heterogeneity is critical because it can create a market consequence that “is conceptually distinct

[15] Recent research on property tax capitalization and related issues also include: Propheter (2019), Lee (2019), and Kim and Dawkins (2021).

from the effect of a homogenous mistake" (i.e., a similar misperception across consumers) (p. 2,469). If misperception is homogenous across consumers, it still preserves the allocation of products based on those who value them most. In contrast, heterogeneity in misperception can instead create an allocation failure such that products (or properties in the housing market context) are no longer purchased by the highest consumer's value for the product. Taubinsky and Rees-Jones (2018) consider heterogeneity in the context of tax salience with sales tax for small consumer purchases, such as cleaning supplies. However, they explain that the consequences of misallocation are especially glaring when supply is inelastic relative to demand, a circumstance that may be particularly relevant in the housing market, at least in the short run. At the same time, they propose that partial inattention to taxes may be less problematic for efficiency costs with misallocation for infrequent, large purchases. Yet, they argue efficiency costs could still exist with these types of purchases when some consumers ignore the tax fully.

There are at least two forms of heterogeneity related to taxpayers that are relevant in the property tax setting. The first type is whether tax misperception varies as the motivation for attention (or the importance of accuracy for utility) increases. Along these lines, Taubinsky and Rees-Jones (2018) examine variation in the tax base (product price) and tax rate (the sales tax rate) and predict that consumers give greater attention (or misreact less) to sales taxes as these characteristics increase. This effect is also sometimes referenced as a "debiasing" channel effect whereby greater motivation to attend taxes mitigates misperception (Reck 2016). In the context of property taxes, this reasoning suggests that when the tax base (assessed home values) and tax rates (property tax rates) are higher that households will more accurately perceive and respond to their property tax burdens. Alternatively, home purchases may be so consequential that homeowners more generally have accurate perceptions about their property taxes (in line with the prediction in

Chetty et al. (2009)) and this response is homogenous across homeowners. In this case, we should not observe that higher assessed home values correspond with less tax misperception as even homeowners with lower assessed values fully attend to property taxes. We state the related hypothesis below in the alternative form:

> **H1**: Homeowners with greater financial motivation for attention to property taxes misestimate their property taxes less.

The second relevant type of heterogeneity is whether tax misperception varies with other potential costs or knowledge gaps.[16] This follows from the idea of bounded rationality whereby the taxpayer either has information available for understanding her taxes but faces a cost (e.g., effort) when making estimates or is lacking information about the role of the tax for a decision (Handel and Schwartzstein 2018; Maćkowiak, Matějka, and Wiederholt 2023). Studies in this literature often predict that misperception will be lower for those expected to have expertise or more knowledge in comparison to less knowledgeable consumers to assess whether bounded rationality can explain the misperception. Household-specific factors like education, income, and age (as a proxy for experience) may correlate with market savvy and relevant expertise. Factors like a household's mortgage type, and whether it includes the property taxes in escrow, may represent a cost or barrier to expertise in one's own property taxes, as those who pay the property tax directly likely accrue greater experience and thus salience with this particular tax by manually making the payment each period themselves. We reference the corresponding hypothesis below in the alternative form:

> **H2**: Homeowners with lower information costs for evaluating property taxes will misestimate their property taxes less.

[16] For brevity (and readability), in the remainder of the paper, we reference this as information costs, although we acknowledge that there are a number of terms used in the literature to describe a similar construct.

Finally, we should emphasize a couple caveats. First, this literature is by no means the only lens through which to view our results. Again, we offer these hypotheses as a way of framing the empirical results below, acknowledging that there may be alternative explanations for these findings. Second, the purpose of this paper is not to pin down these predictions with strong causal claims; instead, these hypotheses guide our interpretations of the results as *consistent with* but not *confirming* these hypotheses in a definitive, causal sense. The household-level results motivate further analysis, including the meta-analysis, which is a point we return to in Section VI.

III. Sample and Summary Statistics

The dataset we use for this paper derives from matched internal American Community Survey (ACS) microdata and Zillow Transaction and Assessment Dataset (ZTRAX) data. Specifically, we began with internal household-level 5-year ACS appended microdata files from 2013-2017, which were then matched to ZTRAX assessment data (spanning 2014-2016) on an address-level by Census Bureau staff.[17] The ACS is a large annual household survey, conducted 12 months per year by the Census Bureau, which contains many questions on housing, in addition to demographic and labor market questions. It is one of the most widely used datasets in applied microeconomic research, sampling approximately 3.5 million American households per year. When household weights are applied, the sample is representative of the U.S. population.[18] Although data is reported for each individual by the household head, this paper uses the household-

[17] The ZTRAX records were assigned a Master Address File Identifier (MAFID) at an address-level, using the same process as ACS and other Census records that algorithmically assigns each raw address with this identifier. We then linked the datasets by this identifier, as opposed to our own address-level linking (avoiding the ad hoc problem of matching, for example, 123 First Street vs. 123 1st St). MAFIDs are used internally at the Census Bureau to link other household data across datasets. While imperfect matches can be made, we take additional steps in culling the data to discard bad matches (described below).

[18] Although the American Housing Survey (AHS) also has many detailed questions on housing, it is a much smaller sample and lacks some of the demographic information available in the ACS. Therefore, the ACS is a better choice for this exercise.

level sample (i.e., each observation is a household, not an individual) as our unit of observation. The adjoining dataset's observation unit is at the property-level.

ZTRAX data is housing microdata provided by Zillow in two groupings for each state: assessment data and transaction data. The assessment data includes many of the parcel characteristics typically shown on Zillow's website, which are drawn from public tax assessor records at local municipalities.[19] For this analysis, we only kept data pertaining to residential homes with property characteristics such as assessed value, square footage, lot size, bedrooms, and bathrooms. The ZTRAX transaction data containing information about a home's sale price and other transactional information was not used for this analysis. This avoids one issue with the ZTRAX transaction data, which is that some states do not publicly report sale prices; however, all 50 states report information like property tax amounts in the assessment data.

Once the ACS and ZTRAX data have been matched by address (i.e., the main piece of administrative information common to both datasets), observations are then culled to ensure the appropriate fit for this research question. We limited the sample to owner-occupied single-family residences (both ACS and Zillow),[20] and those observations where the tax year of the Zillow data is no more than one year greater than the ACS survey year to help ensure the timing of the response corresponds closely with the timing of the property tax bill.[21] When we compared the limited

[19] The transaction data includes information pertaining to home sales that would be disclosed to a local tax assessor's office at the time of the sale, but was not used for this analysis.

[20] Other matching issues may arise with non-single family residences, as they are more likely to have unit numbers within the address, for example. While Census's MAFID assignment algorithm can generally handle this for their own data, we chose to omit these from the matched sample to rule out any potential issues associated with matching these types of properties and focus on single family residences (the largest group of housing units in the U.S.).

[21] The vast majority of tax assessor records in the ZTRAX vintage data come from 2014-2016. In terms of coverage, the property tax amount is populated for about 84 percent of all single family residences in the data nationally (with variation by state). The assessor data does not have the timing of when the property tax bill is mailed. Additionally, the ACS respondents answer the survey 12 months out of the year and the survey question regarding property taxes does not ask for a specific tax year corresponding with the tax year. Given that property tax values often change over time, requiring that the ZTRAX tax year is no more than one year greater than the ACS survey year helps to limit issues associated with measurement error by narrowing down the data to cleaner matches, which is why our final

summary statistics of the variables common to both ACS and ZTRAX data, we found that they were quite similar in terms of home characteristics.[22] To reduce the possibility of matching-error, observations are dropped if the ACS and Zillow fields for county are not the same, which is one indication of matching the wrong address. After the initial culling to improve the linkage was done, the dataset comprised 889,000 matched observations (which were used in our initial regression analysis below).

In refining the sample to be more "Zillow consistent" (i.e., ensuring the property match has a reasonable correspondence to ZTRAX property characteristics to ensure a correct match and a clean sample following similar approaches to Nolte et al. 2021 and others using ZTRAX), observations are dropped if (1) the difference in the number of bedrooms reported is more than 2, (2) the absolute value of the difference between the reported tax in the ACS and Zillow is more than 1 (or 100%), or (3) the difference in the reported year built is greater than 10 prior to 2002 (ACS year built is in coarse buckets) or greater than 5 after 2002 (finer buckets). To mitigate the influence of outliers or less relevant observations in the ACS, we drop observations if they meet any of the following conditions: (1) the householder is younger than 20, (2) household income is less than $1,000, (3) home value is less than $10,000, (4) respondents have been in the home less than 1 year,[23] or (5) the taxes or home value in the ACS are imputed by Census. The resulting

dataset is much narrower than either the ACS full sample or the Zillow transactions data set that goes back much further than the assessor data.

[22] There are limited variables available for comparison: year built (in buckets in the ACS), number of rooms, number of bathrooms, and acreage (in bins). Both samples have an average of 6 rooms and 3 bedrooms and a very similar distribution of home age.

[23] It is important that the responding household has resided at the address for at least a year so that they have had time to receive a property tax bill. For example, while recent purchasers might be a very relevant group, if a household purchases a home in December and is surveyed the following month in January, they may not have received either last year's property tax bill or the current year's. As we are unable to observe when the household receives a bill, we must have this restriction. Moreover, some portion of the property taxes may (or may not) be included in the closing costs negotiated to be paid by the buyers, or the sellers. Our results, however, are not particularly sensitive to this restriction.

dataset yields about 431,000 observations that are both consistent with the above criteria and have non-imputed values in all variables.[24] This is the sample used for our descriptive statistics and the default tax misperception specifications for the regressions discussed in the next subsection. The full list of variables we use in our analysis and their descriptions are in Table 1.

Table 2 provides a set of descriptive statistics for the linked ACS-ZTRAX dataset that we use for most of our analysis. The median home in the matched sample is a 3-bedroom single-family home built in 1990, valued by the homeowner at $263,000. The median yearly property tax amount paid was reported on the ACS as $3,000, while the median value in ZTRAX was $3,210 in the preferred matched sample. Overall, ACS respondents slightly underestimate their true property tax value on average. The raw (signed) error distribution is centered close to 0 for the overall sample (raw error: -1.4% mean and -0.7% median). However, in terms of absolute error, which unlike raw error does not allow for offsets of underestimates and overestimates, the misperception is larger at 15.4%. In contrast, earlier work by Goodman and Ittner (1992) using linked data (from the American Housing Survey) to examine home value misperceptions found homeowners tended to *over*estimate the value of their homes by about 6%, with a mean absolute error of about 14%. Thus, while on average households have a less biased sense of their tax liability than their home value compared to prior estimates in the literature, there is still substantial inaccuracy (absolute error) and a significant degree of skewness and pronounced kurtosis in the sample, motivating additional statistics by subsamples.[25]

[24] One of the main restricting factors for this data is aligning the ZTRAX tax assessor year with the survey year of the ACS or to at least ensure it falls within a year of the tax assessor year. The ACS question for property taxes asks: "What are the annual real estate taxes on THIS property?" but does not mention a particular tax year. Further, the ZTRAX tax assessor data does not have information on the timing of which particular months of the year tax is remitted for evaluating actual payment timing relative to the survey.

[25] In the Online Appendix, Figures A1-A6, we report kernel densities to illustrate the distribution of errors for various subpopulations, often showing the data follows a double exponential or Laplace distribution centered near zero.

IV. Determinants of Property Tax Misperceptions: Research Design and Results

The summary statistics in the prior section reveal significant absolute error and a small degree of bias, but say little about the determinants of tax misperceptions across various subgroups and settings. To explore these determinants more systematically, we employ a simple multivariate regression specification to investigate the hypotheses above (subsection A) and present the related results (subsection B).

IV.A. Research design

Using a pooled cross-sectional dataset of matched ACS-ZTRAX data, we estimate the following fixed-effects regression specifications for the determinants of (1) the absolute value of a household's property tax error and (2) their raw error, respectively (both scaled by the ZTRAX tax assessor value to allow the coefficient interpretations to be in percentage terms):

(1) $$Absolute\ Error = \alpha_0 + \sum \varphi_i\ Motivation_i + \sum \delta_i\ Information\ Cost_i + \sum \beta_i\ Other\ Property\ Characteristics_i + \sum \gamma_i\ Other\ Household\ Characteristics_i + \propto + \varepsilon$$

(2) $$Raw\ Error = \alpha_0 + \sum \varphi_i\ Motivation_i + \sum \delta_i\ Information\ Cost_i + \sum \beta_i\ Other\ Property\ Characteristics_i + \sum \gamma_i\ Other\ Household\ Characteristics_i + \propto + \varepsilon$$

where our dependent variables are measured as the perceived property tax reported by the householder in the ACS minus the assessed property tax captured in ZTRAX scaled by the assessed property tax where equation (1) uses *Absolute Error* and equation (2) signed *Raw Error*. The key research question here is the difference between the assessed taxes and the homeowner's knowledge or perception of those taxes, regardless of whether the homeowner feels the taxes have been assessed fairly.[26] This approach is common in both the income tax misperception literature (see Blaufus et al. 2022 for a summary) and home value misperceptions literature (e.g., Goodman

[26] In cases where a homeowner feels the property tax has been incorrectly assessed, they may contact the assessor to dispute the bill. However, in these cases, the homeowner will be very aware of the tax level and we expect to see little/no discrepancy between response and administrative value.

and Ittner 1992). Because the underlying source data for the ZTRAX measure of assessed property taxes is drawn from local municipalities' administrative data, we believe this is reasonably accurate, barring any measurement error due to coding/recording issues and the culling of observations which contain obvious typos.[27] The absolute error captures the relative inaccuracy of householder perceptions whereas the signed error captures biases in perception.[28] Similar to Taubinsky and Rees-Jones (2018), when making predictions below, we do not make assumptions about the form of inattention, which can manifest from bounded rationality, incorrect beliefs, heuristics, or a combination of these responses.[29]

Our variables are defined in more detail in Table 1, and we use categorical transformations of some of the variables mentioned above for ease of interpretation and cleaner (more compact) presentation of the results. Our standard errors are clustered by county in our default specification, given that property tax rates are often set at the county level; but, for robustness we estimate

[27] We acknowledge at the outset that there may also be imperfections with the ZTRAX data or the administrative records it draws from, too. As a check, we randomly selected 60 ZTRAX property observations in our sample from across 50 states, then searched local tax assessor websites for the related property tax amount. We were able to find property tax information for 55 of the 60 property observations using local tax assessor websites (typically a department of revenue, taxation, or treasury website). For a handful of properties, some properties may no longer exist or the local assessor may not have an easy was to locate the records by address (as opposed to parcel ID). Further, given that some local assessor websites only make the most recent year(s) available (e.g., 2021 or 2022 as of the search date), and most our values come from 2014-2016, we focus our matching checks on those where the local tax assessor data period overlapped within a year of our ZTRAX vintage's data period. Of the 42 remaining observations in the match, we find that 88 percent (37) have an exact match, while the remaining observations generally have only a small difference, which suggest ZTRAX property tax values provide reasonably accurate coverage of actual property taxes assessed.

[28] It also possible that measurement error may arise from differences in how the survey respondent views the question. For example, the ACS survey question asks: "What are the annual real estate taxes on THIS property?" but does not mention whether it is asking for the tax amount in gross versus net (i.e., net of any particular property tax discounts applied to a particular locality or household), nor does it explicitly ask for which tax year (i.e., current or last year).

[29] Survey respondents for the ACS may either report the tax amount based on memory, recent experience paying it, or simply look it up, like from a recent mortgage statement, property tax bill that they received in the mail, or on the local assessor's website. Hence, another interpretation of the measured error is, at least in part, related to conscientiousness for filling out a survey accurately and completely. In the age of easy internet searches and smart phones, knowing something versus knowing how (or being willing to take the time to) find the information readily via Google, for example, blurs the practical distinction. This caveat may be relevant for any tax salience study after the widespread promulgation of smart phones.

alternative clustering approaches in our results below.[30] Following from our hypotheses in II.B, our primary variables of interest are grouped by predictions relevant to H1 and H2, respectively. In terms of motivation (H1), we investigate differences in tax base (assessed home values) in line with Taubinsky and Rees-Jones (2018), but also consider household income as a proportion of the home value as indication of the relative size or importance of the property tax relative to other sources of income (and tax). A higher assessed home value likely increases the importance of the tax to the household and, as a result, serves as greater motivation to be attentive to property taxes ($\varphi_i < 0$ for medium and high value homes relative to the omitted category of low values homes). However, if the household's income is a larger proportion of the home's value, this reduces the property tax's relative importance to the household and reduces the motivation for attention to property taxes, all else equal ($\varphi_i > 0$ for increases in the ratio of household income to home value).

Another motivation Taubinsky and Rees-Jones (2018) investigate is whether higher tax rates (sales tax rates in their study) serve as motivation to better attend taxes. While certainly a relevant and important motivation, statutory property tax rates vary extensively at the locality level and there are often significant departures between the effective tax rate to households and the statutory property tax rates (unlike sales tax). To our knowledge, there is no universal database of statutory property tax rates coupled with local exemptions across tax jurisdiction in the US to determine each household's tax rate. Instead, what we have available is the information in the ACS (e.g., tax paid/home values), which is often used in the literature and popular press to report local effective property tax rates. The numerator itself is a key part of our dependent variable, and we do not include it as one of our proxies for H1 in our primary analysis. Instead, in the results section

[30] Property taxes are also set at lower levels than the county, especially as they are often tied to school funding, but variation in rates may also span across various other districts like fire districts, police districts, irrigation districts, etc. For this reason, we also consider sub-county fixed effects like tract fixed effects (see Table 3) and alternatives like block groups in untabulated tests.

IV.D. we return to the role of property tax rates, relying on a coarse proxy (state level median effective property tax rate based on the ACS). We use this to examine our baseline analysis in sample cuts across states with low, medium, and high levels of median property tax rates, and we use it for additional analysis in the Online Appendix.[31]

Considering information costs (H2), we examine different levels of education, age, and income as different aspects of household level information costs for evaluating property taxes. Prior research finds that those with higher educational attainment are more financially literate (Lusardi 2008), where these households may face lower costs to process expected tax burdens or have less gaps in their knowledge about financial attributes like property taxes. Aside from education, experience (age) affords additional experience with budgeting and exposure to peer networks that can enhance financial investment decisions (Kaustia and Knüpfer 2012). Higher income, after accounting for education or age, may capture another aspect of ability (Griliches and Mason 1972) or exposure to financially literate peers, where greater ability may lower the cost of estimating property taxes for the household. Thus, we expect that more educated households, older households, and households with greater income to have a lower degree of misperception about property taxes (i.e., we expect $\delta_i < 0$ for householders with at least a bachelor's degree (college), seniors (60+), and those with medium and higher income will face lower information costs in terms of assessing property taxes in comparison to their respective omitted household categories). Finally, in line with Cabral and Hoxby (2012), we also examine whether the property taxes are paid indirectly through a mortgage (i.e., is less visible) influences property tax misperception.

[31] Further, in Online Appendix II Panel A (column 5), we find that, consistent with the prediction from theory, the median state effective property tax rate has the expected relationship with absolute error – a negative coefficient significant at the 1 percent level. Additionally, the results in Panels A and B (column 5 in both) show that results for the other motivation and information cost variables are very similar when including the median state (effective) property tax rate variable.

Cabral and Hoxby (2012) argue that payment of taxes in an indirect, less visible way via mortgage escrow should increase inattention to property taxes (i.e., we expect $\delta_i > 0$ relative to the omitted category of households without a mortgage and pay these taxes directly).

We account for a host of other characteristics that may contribute to property taxes assessed and misperception. *Other Property Characteristics* include a year built category and number of bedrooms; *Other Household Characteristics* include household size, tenure (years in the household), marital status, race, and an indicator for whether the household uses a mortgage payment that does not include the property tax in escrow; $\propto$ are state by survey year fixed effects, which we use as our default specification (we explore county and census tract fixed effects in alternative specifications).[32]

Finally, we should note that our predictions above focus on how motivations (H1) and information costs (H2) influence absolute error with property tax perceptions (eq. (1)), but do not have consistent directional results with raw error (eq. (2)) to test H1 and H2. Hence, in the proceeding analysis, we include results with raw error to supplement our analysis because we expect these will be of interest to policymakers and future research that want to understand how the direction of error with inattention may apply to a particular setting of interest. For example, signed error observed with raw error may be helpful in evaluating differences in household reactions to a specific local tax policy proposal. Additionally, understanding the direction of the error with inattention may be helpful for future research with regional datasets that have a higher

[32] For instance, we consider the sensitivity of the results to county and Census tract fixed effects in later columns of Table 3 to account for role of variation in the level of local government services and the cost of those services (among other local factors), which could reasonably contribute to perceptions about property taxes in line with the discussion of the Tiebout (1956) hypothesis in Sirmans et al. (2008). Further, in untabulated results, we considered the sensitivity of the results to leaving out individual states one at a time from our analysis in Table 3. The results were very similar.

representation of particular household types in terms of whether interpretations with this research are likely to carry over to the broader national average.

IV.B. Results for H1 and H2

We present results for tests of H1 (motivation for attention) and H2 (information costs) in Table 3 columns (1)-(5) and the corresponding results with raw error in column (6). In the column to the right of the variable names, we provide sign predictions based on the hypothesis development in the prior two sections. In all five columns of Table 3 corresponding with eq. (1), we observe results that support the predictions above in terms of H1 and H2, as all coefficients of interest are of the predicted sign and are statistically significant at the one percent level. Columns (1)-(5) all provide estimates of eq. (1) but differ based on the particular dimensions of fixed effects and clustering used, as indicated in the rows at the bottom of the table. The consistency across columns indicates these results are not sensitive to the type of fixed effects and clustering; the coefficient estimate magnitudes are within one percentage point of each other across columns. Given the consistency of the results, we use the specification which has both the cleanest matched sample and cleanest presentation of the results in column (5) with state-by-year fixed effects and standard errors clustered by county as our default specification.[33] For example, we lose observations in the tract specification due to some tracts with singleton observations dropping out.

As we noted in the prior subsection, one reason we collapsed some variables into coarser buckets was for ease of interpretation and presentation of the results. For completeness, in Online Appendix I Table A1 columns (1) and (2), we report a more expanded set of the categorical classifications of interest (home values, education, age, and income) first for a broader sample with

[33] In Online Appendix II Panels A and B, we add groups of the independent variables iteratively in a state and year fixed effects specification. In the last specification of that table (column (5)), we incorporate additional controls from the ZTRAX dataset that account for more detailed home characteristics and the state median effective property tax rate (as estimated using the ACS). We discuss this table further in the results section below.

fewer sample restrictions and then for our primary sample, respectively. The results with the expanded categories for both samples (columns) support our findings and inferences with tests of H1 and H2 in Table 3, which suggest that these results are not alternatively driven by restrictions required for our final sample or the dimension of category classification used in our main analysis. In some cases, we observe larger effect sizes, such as a 5 percentage point reduction in absolute error for households in the top quintile of home value (relative to the bottom quintile).

IV.C. Additional Results for Policymakers and Future Research

Table 3 also reports the results for our default specification, but for (signed) raw error as the dependent variable in column (6). One takeaway from examining the raw error is that there are differences in how the inattention in columns (1)-(5) with absolute error manifests across characteristics with raw error. For example, inattention that relates to having higher income as a proportion of home value is more in line with a noisy form of inattention where we are unable to reject the null that higher income as a proportion to home value does not alter raw error. In this case, the elevated absolute error is approximately symmetric over zero. On the other hand, while households with higher tax bases (home value) have more accuracy in terms of absolute error, they tend to be biased slightly lower in raw error (i.e., negative coefficient estimates on the medium and high home value in column 6, significant at the one percent level). In terms of information costs, the higher inattention associated with less education, lower income, and younger ages corresponds with higher raw error. In particular, in column (6), there are negative coefficient estimates on “At least college,” “Medium Income,” and “High Income,” and there is a positive coefficient estimate on each of the younger age categories, all of which are significant at the one percent level. Finally, paying taxes indirectly via a mortgage correlates to lower raw error (the negative, significant coefficient in the last column), signifying that these households underestimate their taxes, on average. While statistically significant, the magnitudes of these household characteristics in Table 3 are relatively modest individually; but, these effects can stack, which can add up (e.g., an educated, high-income, high home value household that pays property taxes directly would have an economically meaningfully lower error than the opposite household type).

In addition to results related to the motivation and information cost variables of interest, estimates with "Other Household Characteristics" may also be of interest to policymakers and future researchers who want to understand or investigate how adjustments to property taxes might influence subsets of the national population or be reflected in data with disproportionate representation of certain household types (e.g., targeted tax relief policies or alternative tax disclosure or education campaign policies). For instance, there are significant differences by race in terms of absolute error and raw error relative to the omitted (benchmark) group race (White), as well as differences by marital status and household size. To provide further detail for policymakers and future research, in Online Appendix I Tables A2-A4 and Figures A1-A6, we provide a sequence of tables and kernel density graphs for these results along different breakouts (e.g., running estimates separately for different racial groups, age groups, and by mortgage category as well as univariate comparisons for certain household characteristics) in case understanding the interaction or subpopulation stacking of different household characteristics is useful for future research.

IV.D. Additional Analysis Considering the Role of Property Tax Rates

We noted in the research design section above (IV.A) that tax rates serve as another important motivation for attention. While we do not incorporate it in our formal predictions for H1 (motivations) above in our primary analysis, in Online Appendix II Panels A and B column (5), we re-estimate Table 3 columns (5) and (6), respectively, with the addition of a property's effective tax rate (taxes paid/home value) and controls for additional property characteristics. As we would predict based on the findings in Tabinsky and Rees-Jones (2018), we find a negative, significant association between an individual household's property tax rate and absolute error, in line with the higher tax rate providing motivation for greater attention. At the same time, we continue to find that results and inferences with our characteristics of interest in tests of H1 and H2 are very similar in the analysis when we include this property tax rate variable and further property characteristics from ZTRAX as controls. Overall, the results in Online Appendix II reinforce the results in Taubinsky and Rees-Jones (2018) sales tax rate motivation setting in the case of property taxes (i.e., suggest they provide an important motivation for attention to property taxes).

To provide additional detail on how property tax rates interact with our other characteristics of interest in H1 and H2, in Table 4, we re-estimate our default absolute error and raw error specifications (columns (5) and (6) from Table 3) in Panels A and B, respectively, using a coarser proxy for the tax environment based on the state median effective property tax rate. What we find in Panel A is that in high property tax rate states (column (4)) that some of the characteristics like income as a ratio of home value, age, and the indirect payment of tax with a mortgage do not appear to alter attention to property taxes or have a more muted impact. Intuitively, this makes sense, as in the highest property tax rate states where motivation to be attentive to property taxes is already high, taxpayers may more (homogenously) attend to property taxes, leaving less room for other factors to alter remaining inattention. By contrast, in Table 4 Panel A, we continue to find similar results for all H1 and H2 characteristics in both low and medium property tax rate states as there is more scope for alternative factors to differentiate the more substantial inattention in these settings. That said, in terms of (signed) raw error results for Table 4 Panel B, many more of the characteristics of interest from H1 and H2 do not correspond with raw error in high property tax rate states. In other words, the remaining characteristics that alter inattention (absolute error) in high property tax rate states appear to correspond more with noisy error as opposed to a directional (signed) error relative to low and medium property tax rate states.[34]

V. Results – Determinants of Property Tax Misperceptions: Geographic Heterogeneity

The results in Tables 3 and 4 suggest a host of property, household, and geographic characteristics (e.g., state median effective property tax rate) contribute to differences in attention and misperceptions about property taxes. Yet, recall that in section II.A that prior studies often focused on analysis in a single state or region find different (mixed) results regarding whether property taxes are capitalized into home prices. This geographic heterogeneity in the literature motivates further investigation into whether 1) there is significant geographic-specific heterogeneity in tax misperceptions, and 2) whether this heterogeneity can account for the differences across property tax capitalization studies. Hence, in this section we pivot from evaluating household-specific factors for H1 and H2 to broader heterogeneity in tax misperceptions across state lines. Then, in section VI, we develop state-level indices for property tax misperceptions to assess what role this geographic heterogeneity in property tax misperceptions plays in the mixed findings with the property tax capitalization literature.

To do this, we first focus on state fixed effects separately (not interacted by year, in this case) rather than individual demographic characteristics, which account for time-invariant state-specific factors relevant to property tax misperceptions or property tax policy more generally (e.g., state policies, norms, assessment quality, infrastructure, etc.).[35] We include the full results in

[34] Another potential mechanism related to error may be that high tax states invest more in property valuation, which may in turn impact the variability of assessments. We leave further analysis to future research.

[35] For example, California famously has a state law (constitutional amendment), Proposition 13, that restricts property tax rate and assessment increases. Many other states have state-level rules regarding exemptions for veterans, seniors, and other groups (Moulton et al. 2018), which affect the property taxes environment and thus may have an impact on its salience.

Online Appendix II, but discuss the takeaways from the table and corresponding results here. In the table, we begin in column (1) by only including controls for property characteristics from the ACS data (in particular, the number of bedrooms, year-built categories, and home value categories). This allows the state fixed effect to capture a broader scope of geographic variation before conditioning on particular demographic and household compositional differences across states. Across columns, we then iteratively add different groups of observables to evaluate how conditioning on this compositional heterogeneity of households alters the state fixed effect coefficients.[36]

Overall, we find state-specific heterogeneity is a significant, economically important determinant of property tax misperceptions. From these results, it is clear that states like Arizona, Michigan, and many others have substantial differences in both absolute error and raw error (relative to Alabama – the omitted state, which is close to average error in the initial specification), while quite a few other states have substantial differences for raw error, but not absolute error. For example, in Online Appendix II, we find that Californians underestimate their property tax liability by 6 to 11 percentage points more than Alabama householders (Panel B) and have a lower absolute error relative to those in Alabama depending on the observables accounted for (Panel A). In many cases, once we control for the property tax rate (in column (5)), there is a substantial change to the error, indicating that for many states the property tax rate and the other observables we incorporate in that column are powerful determinants of salience and attentiveness. At the same time, the fact that we still observe many states with significant coefficient estimates in the last column (that

[36] Alabama (a low property tax state) is the omitted category and reference group, although in the last specification (as we introduce more control variables from ZTRAX: lot size, square footage, number of bathrooms, number of stories) a couple states drop out of our analysis due to limited observations (i.e., Louisiana and South Dakota). Though the reference group is somewhat arbitrary, Alabama's misperception is near the mean and ranks among the middle of the pack (27) in our initial index, QAI. The ranking in Online Appendix III is not altered by this choice, however.

conditions on the largest set of observables) suggests that there is still scope for future research to evaluate additional factors that contribute to geographic variation in property tax misperceptions.[37]

VI. Property Tax Misperceptions and the Capitalization Literature: A Meta-analysis

In the final set of analyses in this paper, we answer the question of whether there is a statistically meaningful relationship between tax misperception across states and key findings in the property tax capitalization studies, which has been a literature with frequent reliance on single state settings for estimating capitalization. The prior section documented considerable state-level variation in property tax misperception, as measured by the fixed effects in the regression models in Online Appendix II. But, what is not yet clear, despite the plausible prediction that misperceptions could matter, is whether this variation is meaningful enough or consistent enough to explain the substantial heterogeneity in the findings in the literature discussed above.[38] Thus, we explore this question empirically in a simplified meta-analysis of this literature.

VI.A. State-level property tax misperception indices

We begin with the state-fixed effects specifications discussed above and reported in Online Appendix II Panel A. We create the first tax misperception index, labeled a "Quality Adjusted Misperception Index" (QAI), with an approach analogous to hedonic models that construct "quality adjusted" home price indices but with tax misperceptions as the outcome of interest. We derive this from the state fixed effects in column (1) from Online Appendix II, which capture state differences in tax misperception after accounting for the size, age, and value of properties in those

[37] As an example of another factor that could be interesting to consider, Ballard and Gupta (2018) find that taxpayer beliefs about the fairness or effective use of tax dollars influences misperceptions about federal income taxes. Given that Cabral and Hoxby (2012, p. 1) suggest property taxes are disliked more than any other tax but that people "simultaneously report that property tax revenue is better spent than any other tax revenue," Thus, it seems reasonable that variation in attitudes towards these taxes could be an interesting alternative factor for future research to investigate.

[38] For example, perhaps state-level variation in misperceptions is driven by differences in data quality or some other systematic measurement error. Or, perhaps misperceptions change rapidly over time, and a simple static measure of cross-sectional differences may not be informative for understanding results from decades of literature. In either case,

states. To standardize the coefficients for an easily interpretable index, we make a simple transformation to standardize the state fixed effects to be mean-zero with a standard deviation of one across all states in each specification (shown in Online Appendix III).[39]

We then create a second misperception index based on the state fixed effect coefficients from the final column (column (5)) of Panel A (with the most conditions accounted for). Because the specification in column (5) of Panel A also contains all of the demographic and household characteristics from our analysis (and even additional characteristics from ZTRAX and the household's property tax rate), we label this second index the "Household Adjusted Misperception Index" (HAI); it is standardized in the same way as the other index. This simplifies the interpretation of both indexes to be a value in units of a standard deviation from the average state's quality adjusted (and household adjusted) tax misperception. Higher values of both indices correspond to a higher average inaccuracy or misperception about property taxes in a particular state, albeit with somewhat different interpretations regarding the nature of the misperception. The QAI encompasses factors outside the basic property quality controls. Hence, the interpretation with the QAI is a broader measure of property tax misperceptions, as the cross-state variation will be driven both by the compositional differences of the omitted observables and unobservables that shape tax misperceptions.[40] Conversely, the HAI will vary based only on unobservables, as it

[39] This is simply the QAI = $(X_s - \mu)/\sigma$, where X is the state fixed effect for state *s* in column (1) specification in Online Appendix II, μ is the mean state fixed effect, and σ is the standard deviation across all states.

[40] Plausible unobservables of interest may include individual/household characteristics (e.g., political ideology, cultural norms/attitudes, conscientiousness, cognitive ability) and broader factors like the institutional settings of the tax environment (e.g., local tax codes regarding exemptions, heterogeneity of the local tax assessor quality, opacity of the property tax statement, or state-specific tax policies). For example, the complexity and quality of local assessments may contribute to differences in property tax variance, for example, which itself may generate uncertainty among the public about property taxes. See, for example, Mehta and Giertz (1996), Kim et al. (2020), and Avenancio-León and Howard (2022), for further discussion on variability of assessor quality and its consequences.

controls for differences across household observables, additional property characteristics, and the property tax rate.[41]

We present the variation in the index across the contiguous 48 states in two maps in Figure 5 (Panels A and B). The figure categorizes the states by quartiles of each index, respectively. While it is clear from the state fixed effects in our Online Appendix II that there is distinct state-level variation in property tax misperception, mapping the index quartiles better illustrates regional comparisons and patterns (to the extent any exist). For comparison then, in Panel C, we highlight the state locations of 31 studies that have used state-specific data in the property tax capitalization literature since 1969, where studies in *italics* font had a non-full capitalization result as their primary finding. Comparing across maps, we can see that among these states used in this literature there is considerable heterogeneity in tax misperception, as states like New Jersey, Utah, and Illinois have relatively low misperception, while Michigan, New York, and Pennsylvania have relatively high misperception. Taken together, there is enough smoke here, so-to-speak, to indicate caution that misperception varies by geography and that it also varies across states from which individual studies draw their data. In the next section, we move beyond anecdotal generalizations and perform a test for whether there is a measurable statistical relationship in this pattern, using a simplified meta-analysis for this literature.

VI.B. Meta-data – 31 published studies on property taxes and home values

To construct meta data on this literature, we first draw on the extensive review by Sirmans et al. (2008), which reports basic information about 28 capitalization papers in their Exhibit 1,

[41] One concern about the initial, broad measure is that perhaps the primary driver of this variation is simply the tax rate or the demographic factors. For example, households in high-tax states might have a very strong knowledge of their property taxes and those in low-tax states have a very weak knowledge of their taxes (thus explaining most of the variation in perceptions). Online Appendix II shows that while the tax rate is an important factor, there is little evidence it is the only, or even primary, driver. While the observables are important, the considerable overlap in the rank order of the index quartiles suggests that the unobservables are likely the key drivers of the state-level misperceptions indices. We leave further exploration of this to future research.

including the overall finding (no/partial/full capitalization) and the state in which each study was conducted. We use 25 of their 28 studies in our meta-analysis (dropping one from England, one from Canada, and one using data from multiple states). While they have multiple categories for the capitalization finding (full capitalization, partial, none, overcapitalization), a common theme among non-full categories is that they depart from the neoclassical prediction of rational, fully informed agents, while full capitalization is usually associated with a rational, informed, and attentive characterization. Thus, we choose the binary categorization (full capitalization vs. non-full capitalization) for our analysis, both for ease of interpretation and the fact that it simplifies the analysis by standardizing the result from the study to focus on a bottom-line, qualitative finding.[42] This binary categorization approach also allows us to add more recent studies of property tax capitalization (e.g., Bradley 2017 and Moulton et al. 2018) that do not focus on the *rate* change, but still estimate the degree of capitalization of a particular property tax policy. Finally, we incorporate four more recent studies that fall after the Sirmans et al. (2008) review, which include Gallagher et al. (2013), Livy (2018), Munro and Tolley (2018), and Giertz et al. (2021), totaling 31 studies on property tax capitalization since Oates (1969).

VI.C. Method and results of a simplified meta-analysis

Of these studies, 13 report a full capitalization finding, while 18 report a non-full capitalization finding. Descriptively, Figure 6 (Panels A and B) shows the kernel density of both indices for studies with either full capitalization (solid line) or non-full capitalization (dashed line).

[42] While it is typical to select a common coefficient or statistical test shared by all studies in a meta-analysis, there is always a challenge with choosing a standardized, comparable finding. Other meta-analysis studies like Turnbull and Zheng (2021), which aim to explain variation in studies of school quality capitalization in home prices, focus on t-statistics from its target literature, while others use coefficients of a shared variable across studies. Like Turnbull and Zheng (2021), we also account for year in the meta-analysis. In particular, they use year groupings/partitions to account for a variety of factors that vary across time with studies, including data quality issues. For example, they note that older studies tend to use coarser, more aggregated data, while studies in more recent decades are more likely to “take disaggregate approaches” (p.1,140 of their article), among other differences.

The distributions provide initial evidence that there are more instances of full capitalization in states with low to medium property tax misperception. Studies with less than full capitalization run the gamut of the distribution of both indices but have higher instances on the medium to high end of the misperceptions index.

We then regress the full capitalization binary outcome on the QAI and then the HAI in a simplified meta-analysis. We account for the year the study was conducted (*Year*) as our only other independent variable, given that these studies span decades.[43] The results are tabulated in Table 5 Panel A, displaying the coefficients for each index in a linear probability model (columns (1) and (2)), logit model (columns (3) and (4)), and with OLS (columns (5) and (6)) where in the last two columns the residuals are produced from a univariate regression of full capitalization and year. The latter residualized regression produces similar results, but the interpretation of the R^2 becomes the incremental variation of the outcome not already accounted for by time (as opposed to the R^2 in the first four columns that represents the variation in the outcome explained by all independent variables including time). Finally, Panel B of Table 5 repeats the analysis from the first two columns but splits the sample into pre-/post-1975 (roughly half the sample) and post-1990.

The results from the meta-analysis are striking. In Panel A of Table 5, all models show a statistically significant relationship between both property tax misperception indices and the full capitalization outcome. Specifically, a one standard deviation increase in a state's property tax misperception means that a study drawing data from that state will be 15-20 percentage points less likely to find a full capitalization result, on average. The results are similar across different methodological approaches (columns), albeit a bit higher, if we estimate this relationship with a

[43] In untabulated analysis, we also include categorical variables for the method (OLS vs. 2SLS vs. MLE/RE), but given the shifting norms of using these methods in analyses over decades, it should not be surprising that these descriptors did not have much explanatory power (nor do they really change our results). To save degrees of freedom, we thus excluded it from the tabulated regression.

logit model (as we display the marginal effects in the table for ease of interpretation across columns). Further, the R^2 from the last two columns in Panel A suggests that property tax misperception alone explains a substantial portion of the variation in this key finding in the literature, roughly 13% and 17% when using the QAI and HAI, respectively.

One limitation of our data is that we can only measure tax misperception/error for a narrow period of time, where the bulk of our linked observations come from the middle of the last decade (2014-2016). Yet, we are trying to explain variation in study outcomes from decades ago with this measure. This implicitly assumes that these geographical misperceptions are slow to change, which may nonetheless be contributing to measurement error. As expected, when we split the sample approximately down the middle, separately estimating the meta-regression for pre-1975 and post-1975, the likely measurement error of the early era of studies appears to swamp the statistical significance (shown in columns (1) and (2)). However, columns (3) through (6) in Panel B show a highly significant and economically meaningful relationship in the post-1975 and post-1990 studies. In fact, despite the small sample of only 10 observations post-1990, the coefficients on the QAI and HAI correspond to a 46 and 72 percentage point reduction in the likelihood of the study finding a full capitalization result, respectively. Further, in the post-1990 observations, the indices explain about 73% and 78% of the variation in the findings, respectively.[44] Of course, there are many other factors that could contribute to variation in findings across this literature (e.g., housing supply elasticities, competitiveness of these markets, local data quality, etc.). Yet, despite the small sample and few controls, the results from this simplified meta-analysis provide meaningful evidence that state-specific property tax misperceptions can explain a substantial

[44] In untabulated tests, when we residualize the last two columns of Panel B as we had in Panel A, we observe and R^2 of 0.38 and 0.55, respectively.

amount of the heterogeneous impact of property taxes on home prices reported in the published literature.[45]

Finally, we consider a couple additional confounders in the meta-analysis. First, we consider whether the variation in capitalization results in the literature is, in part, driven by other tax considerations, like the deductibility of property taxes from state income taxes or state property tax relief through income tax credits.[46] Second, we consider whether financial literacy requirements in high school curriculums can explain the variation in capitalization results across states.[47] Overall, in Online Appendix IV, we find that neither factor seriously confounds the main findings. Specifically, when we omit studies from Texas (the only state among the 31 studies that does not have an income tax, which therefore has no added complexity for calculating capitalization from a state income tax standpoint), we find the results in the first two columns are basically the same as our prior findings. Alternatively, when we then include an indicator for whether a state has income tax credits for property tax relief, the coefficient estimates on QAI and HAI for columns (3) through (6) are similar to their corresponding columns in Table 5.

Accounting for a state's financial literacy requirement in high school (final four columns of Online Appendix IV), we also find similar results, but with some notable caveats. We observe that a state with a higher proportion of high school students with a financial literacy requirement

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[45] Future research may examine a couple different propositions that are consistent with our data, but without a time-series of tax misperceptions (or the ability to examine this within household over time) we cannot confirm them. First, we expect that the state-level tax misperceptions index likely changes slowly over time (or at least remains relevant for capitalization many years around the time of its measurement, albeit not forever). Second, state-level tax misperceptions measured *after* a home purchase are likely to be correlated with relevant misperceptions *before/during* the home purchase. We cannot confirm either of these predictions; so, while these may follow logically from the results we do have, we cannot affirm these claims unless we have more data.

[46] We code binary indicators for whether states offer property tax relief credits through state income tax systems from the Tax Policy Center (2005) study: https://www.urban.org/sites/default/files/publication/51451/1000852-Property-Tax-Credits-Offered-Through-State-Income-Tax-Systems.PDF

[47] State financial literacy requirements are drawn from Urban (2020), which documents which states have a standalone requirement or an embedded course requirement for financial literacy. We code the higher value from the standalone map versus embedded map for each state, signifying the percentage of students required to have either financial literacy option. Source: https://papers.carlyurban.com/FinEdUSHighSchools.pdf

is linked to a higher likelihood that a study will find full capitalization in that state. However, this is only statistically significant for property tax capitalization studies since 1990 and for only one of our indices (QAI). This is intuitive, given that financial literacy requirements are a relatively recent phenomenon in most states, so *ex ante* we do not expect this to have much explanatory power for studies conducted more than 30 years ago. Moreover, recall that one difference between the interpretation of specifications with QAI (where financial literacy is significant) and HAI (where it is not) is the inclusion of household characteristics as controls when we constructed the latter. By controlling for household characteristics, the state-level variation in HAI will largely come from factors outside of those characteristics, so a financial literacy control is unlikely to change the coefficient on HAI. This is what we find. Variation in QAI, on the other hand, will represent a broader mixture of factors, including education and income, where it makes sense that financial literacy is statistically significant and the coefficient on QAI becomes more pronounced (i.e., moves closer to the coefficient of HAI) when this is added as a control. Coupled with the results related to H2 (the role of information costs), this is consistent with education and financial literacy being an important (albeit, not the sole) source of both household-level and state-level heterogeneity in tax misperceptions.

VII. Conclusion

Overall, the findings from our analysis show that 1) significant systematic differences in error or misperceptions about property taxes exist in the U.S., and 2) differences in property tax misperception across states help explain substantial heterogeneity in the literature on the question of whether home prices fully capitalize changes in property tax policy. In the analysis above, we first document that errors in a householder’s estimation of their own property taxes vary systematically by a number of factors using a unique linked dataset, which matches internal

American Community Survey data with administrative tax records from Zillow's ZTRAX database. These factors include household and institutional characteristics, where prior literature expects inattention to property taxes to vary based on 1) motivation (e.g., tax base and rate and the relative importance of the property tax base in comparison to income) and 2) information costs or gaps when evaluating property taxes (such as education (college), age, income, and whether the property tax is paid directly vs. indirectly through a mortgage escrow). Further, we observe substantial heterogeneity across states in addition to the factors outlined above. In a meta-analysis, we exploit this geographic variation to develop two state-level property tax misperception indices, which we use to explain variation in results of a sizable literature on property tax capitalization. Not only is there a statistically significant relationship between state-level tax misperception indices and the likelihood a study finds full capitalization of property taxes, but the extent of variation it explains in this literature is economically meaningful. For more recent studies, a simple model containing state-level measures of property tax misperception explains nearly 80 percent of the variation in the main outcome of these capitalization studies.

Taken together, by showing that property tax misperceptions are not uniform across all household types, states, and institutional settings, these results help explain a puzzle posed in the introduction. That is, one reason for such heterogeneous findings in the property tax capitalization literature is that underlying misperceptions about taxes may also differ along the dimensions we document in this study, given that prior literature primarily uses state-specific data. The evidence from our meta-analysis supports this explanation, suggesting that misperception about property taxes is an important factor for why households across different states respond differently to changes in property tax policy. Future research can draw on these results to investigate this possibility in greater depth along with other factors that contribute to this heterogeneity in order to better understand household response to property taxes and their accompanying incentives.

Finally, it is worth reemphasizing a key lesson from our findings that researchers using local datasets, which draw from a single state or locale, should consider exercising caution in generalizing about policy responses to property taxes (and, perhaps other taxes more generally). Both observable and unobservable factors vary considerably over a large and diverse country like the U.S.; but, studies using detailed, national data and a careful research design can overcome many of these confounders. Indeed, one benefit of quantifying tax misperceptions by state is that future research using national or multi-state data may use a tax misperceptions index as a means to investigate the policy mechanism or heterogeneous effects of a given policy response. For example, one might expect a more attentive (high-salience) response to a property tax-related policy change in low-misperception states, which could be distinct from the effect in high-misperception states where a noisy and/or biased response may be more likely. We leave further study of heterogeneous policy effects, the role of tax misperceptions, and additional applications to future research.

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Table 1
Variable Descriptions

Dependent Variables	
Variable	**Description**
Raw Error	$(Tax_{ACS}-Tax_{Zillow})/Tax_{Zillow.}$ where Tax_{ACS} is based on the perceived property tax reported by the householder in the ACS and Tax_{Zillow} is the assessed property tax captured with Zillow. We exclude observations with values below (above) -1 (1).
Absolute Error	The absolute value of the Raw Error variable.
Explanatory Variables (ACS)	
Variable	**Description**
Race	Race (ethnicity) of householder, as reported in ACS, coded into mutually exclusive categories (Dummy variables, Yes=1) White only Black (primary racial response) Asian (primary racial response) Hispanic (regardless of race) Other Race (all other racial responses)
Age	Age of the household head, as reported in ACS, and then collapsed into buckets as below (Dummy variables, Yes=1) Age <=30 (or 20-30) Age 31-40 Age 41-50 Age 51-60 Age 61+ In most regressions, age categories are further collapsed to (1) Age <=30, (2) Age 31-60, and (3) Age 61+.
Education	Years of education of the householder, as reported in ACS, and then collapsed into buckets as below (Dummy variables, Yes=1) No College (educational attainment is at most high school) Some College (educational attainment is high school and <4 years of college) College Degree (educational attainment is a bachelor's degree) (*college)* Graduate Degree (educational attainment is more than a bachelor's degree) (*graduate*) In most regressions, educational categories are further collapsed to (1) No college degree and (2) At least a college degree.
Married	Dummy variable: Yes=1 if household head is married, as reported in ACS
Household Size	Number of household members, as reported in ACS. (*hhsize*)
Years in House	Years since the householder moved into the home, as reported in ACS.
Year Built	Year the home was built, as reported in the ACS, and then collapsed into the categories below (Dummy variables, Yes=1) <=1970 1971-1990 1991-2010 2011+
Bedrooms	Number of bedrooms, as reported in ACS.

Table 1 – Continued

Income	Inflation-adjusted household income, as reported in ACS. Then, households are ranked (within state and survey year) and quintiles are constructed and used as below (Dummy variables, Yes=1) Low income (quintile 1). Medium income (quintiles 2, 3, and 4). High income (quintile 5).
Home Value	Inflation-adjusted home value, as reported in ACS. Then, households are ranked (within state and survey year) and quintiles are constructed and used as below (Dummy variables, Yes=1) Low value (quintile 1). Medium value (quintiles 2, 3, and 4). High value (quintile 5).
Income/ Home Val	Inflation-adjusted household income, as reported in ACS / inflation-adjusted home value, as reported in ACS.
Mortgage (or Tax Payment)	Mortgage status of each household, as reported in ACS (Dummy variables, Yes=1) Mortgage with Tax (*Mortgage with Tax)* Mortgage without Tax (*Mortgage No Tax)* Pay Taxes Separately (either no mortgage, or else mortgage does not include tax)
Median State Tax	Median tax rate of each state, was calculated as the property tax as a share of the home value as reported in ACS (using ACS years 2015 and 2016). Then states are ranked, and quartiles are constructed and used as below (Dummy variables, Yes=1) Low tax (quartiles 1 and 2): Range 0 to <1% Medium tax (quartile 3 and part of quartile 4): Range 1% to <2% High tax (remaining part of quartile 4): Range 2%-3%
Explanatory Variables (Zillow)	
Variable	**Description**
Lot Size	Natural log of property lot size (in acres), as reported in ZTRAX
Square Footage	Natural log of home square footage, as reported in ZTRAX
Bathrooms	Number of bathrooms, as reported in ZTRAX
Number of Stories	Number of stories of the home, as reported in ZTRAX

Table 2
Summary Statistics

Panel A Descriptive Statistics (N = 431,000)

	Mean	**Median**	**Std. Dev.**	**Min**	**Max**
Raw Error	-0.0140	-0.00705	0.249	-1.0000	1.00000
Absolute Error	0.1540	0.0712	0.196	0.0000	1.0000
Home Value	353,000	263,000	404,000	10,900	9,760,000
Income	128,000	101,000	126,000	1,000	3,100,000
Age	51.1	51.0	13.30	20.00	102.0
Years in House	9.92	9.00	5.88	2.00	43.10
Year Built	1990	1990	20.30	1930	2020
Bedrooms	3.440	3.000	0.833	0.000	6.000
Household Size	2.84	2.00	1.44	1.00	16.20
Married	0.714	1.000	0.452	0.000	1.000
Tax_{ACS}	4,140	3,000	3,650	1.00	22,500
Tax_{Zillow}	4,350	3,210	5,680	4.18	631,000

Panel B Representation by Category (N = 431,000)

Mortgage Categories	**% of the Sample in the Category**
No Mortgage	19.90
Mortgage Without Tax Escrow	19.90
Mortgage With Tax Escrow	60.10
Age Categories	**% of the Sample in the Category**
<=30	4.39
31-40	19.30
41-50	26.90
51-60	25.20
61+	24.30
Race Categories	**% of the Sample in the Category**
White	74.40
Black	6.18
Asian	6.84
Hispanic	8.35
Other Race	4.21

Table 2 presents summary statistics for the sample of households in our analysis examining determinants of property tax misperception. Panel A reports the distribution of values for our misperception (error) variables, a series of determinants we examine, and the components of our misperception variables (ACS perceived tax and Zillow actual tax assessed). Panel B outlines the distribution of households in three categories we use in later stratifications of misperception values. Values are rounded in accordance with Census disclosure requirements. Because values are rounded, the %s in Panel B per category do not sum to exactly 100%.

Table 3
OLS Regressions of Property Tax Misperceptions on the Household Characteristics

Dep Var				**Absolute Error – eq. (1)**			**Raw Error – eq. (2)**
	Abs Err Pred	(1)	(2)	(3)	(4)	(5)	(6)
Motivation							
Med Home Val	−	-0.023***	-0.023***	-0.021***	-0.014***	-0.023***	-0.010***
High Home Val	−	-0.033***	-0.033***	-0.029***	-0.022***	-0.033***	-0.017***
Income/ Home Val	+	0.016***	0.016***	0.014***	0.012***	0.016***	0.001
Info Cost							
At least college	−	-0.007***	-0.007***	-0.007***	-0.005***	-0.007***	-0.004***
Age <=30	+	0.022***	0.022***	0.024***	0.024***	0.022***	-0.016***
Age 31-60	+	0.012***	0.012***	0.013***	0.013***	0.012***	-0.006***
Medium	−	-0.012***	-0.012***	-0.012***	-0.011***	-0.012***	0.001
High Income	−	-0.015***	-0.015***	-0.015***	-0.013***	-0.015***	0.000
Mrtg With Tax	+	0.022***	0.022***	0.023***	0.022***	0.022***	-0.014***
Controls:							
Other Property Characteristics							
Built 1971-1990		-0.004	-0.004**	-0.005**	-0.001	-0.004**	-0.004**
Built 1991-2000		-0.008***	-0.009***	-0.01***	-0.006***	-0.009***	-0.015***
Built 2011+		0.004	0.003	0.000	0.001	0.003	-0.022***
Bedrooms		0.001	0.001	0.000	-0.001	0.001	-0.004***
Other Household							
Household		0.003***	0.003***	0.003***	0.003***	0.003***	0.000
Years in House		-0.001***	-0.001***	0.000***	0.000***	-0.001***	0.001***
Married		-0.004***	-0.004***	-0.004***	-0.003***	-0.004***	-0.005***
Black		0.040***	0.038***	0.033***	0.023***	0.038***	0.004
Asian		-0.010	-0.012**	-0.013***	-0.012***	-0.012***	0.022***
Hispanic		0.011***	0.011***	0.012***	0.006***	0.011***	0.007**
Other Race		0.023***	0.023***	0.021***	0.017***	0.023***	0.001
Mrtg No Tax		-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	0.008***
Constant		0.161***	0.162***	0.161***	0.154***	0.162***	0.023***
Survey Year FE		√		√	√		
State FE		√					
County FE				√			
State x Year FE			√			√	√
Census Tract FE					√		
Adj. R-squared		0.0455	0.0522	0.0796	0.1290	0.0522	0.0343
N		431,000	431,000	431,000	426,000	431,000	431,000
SE Clustered by		State	State-by-	County	County	County	County

Table 3 report estimates of eq. (1) in columns (1)-(5) and eq. (2) in column (6) with our default fixed effects and clustering from column (5). Columns (1)-(5) vary by the dimension of fixed effects and clustering applied. Standard errors are clustered by county and omitted for brevity. Coefficients and N (obs) are rounded according to Census disclosure guidelines. We define the variables in Table 1. The symbols ***, **, and * denote statistical significance at the 1%, 5% and 10% levels (two-tailed), respectively.

Table 4
OLS Regressions of Eq. (1) and (2) Stratified by Median State Effective Property Tax Rates

Panel A: Dependent Variable Absolute Error – Eq. (1)

		All	Low Tax Rate	Medium Tax Rate	High Tax Rate
	Abs Err Pred	(1)	(2)	(3)	(4)
Motivation					
Medium Home Val	−	-0.023***	-0.023***	-0.018***	-0.026***
High Home Val	−	-0.033***	-0.034***	-0.033***	-0.022***
Income/Home Val	+	0.016***	0.017***	0.019***	0.004
Info Cost					
At least college	−	-0.007***	-0.008***	-0.007***	-0.005***
Age <=30	+	0.022***	0.029***	0.016***	0.003
Age 31-60	+	0.012***	0.016***	0.008**	0.003
Medium Income	−	-0.012***	-0.009***	-0.015***	-0.019***
High Income	−	-0.015***	-0.012***	-0.019***	-0.018***
Mrtg With Tax	+	0.022***	0.026***	0.023***	0.004
Controls:					
Other Property Characteristics					
Built 1971-1990		-0.004**	-0.005**	-0.001	-0.012**
Built 1991-2000		-0.009***	-0.008***	-0.010***	-0.009*
Built 2011+		0.003	-0.005	0.015	0.018*
Bedrooms		0.001	0.001	0.000	0.002
Other Household Characteristics					
Household Size		0.003***	0.003***	0.004***	0.003***
Years in House		-0.001***	-0.001***	-0.000	-0.000
Married		-0.004***	-0.004**	-0.004*	-0.006*
Black		0.038***	0.032***	0.045***	0.055***
Asian		-0.012***	-0.020***	0.003	-0.005
Hispanic		0.011***	0.011***	0.009	0.014**
Other Race		0.023***	0.021***	0.026***	0.025***
Mrtg No Tax		-0.013***	-0.015***	-0.011***	-0.011***
Constant		0.162***	0.168***	0.161***	0.139***
State x Year FE		√	√	√	√
Adj. R-squared		0.0522	0.0428	0.0462	0.0869
N		431,000	237,000	144,000	51,000
SE Clustered by		County	County	County	County

Table 4 – Continued

Panel B: Dependent Variable Raw Error – Eq. (2)	All	Low Tax Rate	Medium Tax Rate	High Tax Rate
	(1)	(2)	(3)	(4)
Motivation				
Medium Home Val	-0.010***	-0.013***	-0.010**	0.013**
High Home Val	-0.017***	-0.025***	-0.004	-0.004
Income/Home Val	0.001	-0.001	0.002	0.009**
Info Cost				
At least college	-0.004***	-0.005***	-0.004	-0.001
Age <=30	-0.016***	-0.016***	-0.021***	0.005
Age 31-60	-0.006***	-0.005**	-0.009***	0.002
Medium Income	0.001	0.003	-0.001	-0.001
High Income	0.000	0.001	0.002	-0.008**
Mrtg With Tax	-0.014***	-0.015***	-0.017***	-0.002
Controls:				
Other Property Characteristics				
Built 1971-1990	-0.004**	-0.004	-0.003	-0.009*
Built 1991-2000	-0.015***	-0.016***	-0.012***	-0.018***
Built 2011+	-0.022***	-0.033***	0.002	-0.053***
Bedrooms	-0.004***	-0.002*	-0.004***	-0.013***
Other Household Characteristics				
Household Size	0.000	-0.001	0.001	0.001
Years in House	0.001***	0.001***	0.001*	0.001***
Married	-0.005***	-0.007***	-0.002	-0.006**
Black	0.004	0.000	0.010	0.009
Asian	0.022***	0.022***	0.027**	0.009**
Hispanic	0.007*	0.001	0.017*	0.014**
Other Race	0.001	-0.006	0.015	0.009
Mrtg No Tax	0.008***	0.010***	0.005**	0.003
Constant	0.023***	0.019***	0.021***	0.043***
State x Year FE	√	√	√	√
Adj. R-squared	0.0343	0.0307	0.0391	0.0465
N	431,000	237,000	144,000	51,000
SE Clustered by	County	County	County	County

Table 4 Panels A and B report estimates of eq. (1) and (2), respectively, stratified by median state effective property tax rates. Col. (1) contains households in states for all property tax rate levels whereas Col. (2)-(4) differ based on subsamples of states with alternative levels of effective property tax rates. Standard errors are clustered by county and omitted for brevity. Coefficients and N (obs) are rounded according to Census disclosure guidelines. Because N is rounded, the sum of N across Col. (2)-(4) will not equal N in Col. (1). We define the variables in Table 1. The symbols ***, **, and * denote statistical significance at the 1%, 5% and 10% levels (two-tailed), respectively.

Table 5
Simplified Meta-Analysis of the Property Tax Capitalization Literature

Panel A – Alternative Estimation Approaches

Approach:	*Linear Probability Model*		*Logit*		*OLS*	
	Full Capitalization	Full Capitalization	Full Capitalization	Full Capitalization	Residual	Residual
	(1)	(2)	(3)	(4)	(5)	(6)
QAI	-0.155**		-0.163***		-0.135**	
	(0.057)		(0.062)		(0.065)	
HAI		-0.203***		-0.301***		-0.185***
		(0.063)		(0.098)		(0.067)
Year	0.017***	0.0164***	0.0154***	0.0173***		
	(0.003)	(0.003)	(0.002)	(0.002)		
Constant	-0.0116	0.0405			-0.0613	-0.0230
	(0.088)	(0.010)			(0.075)	(0.072)
R-squared	0.331	0.364	0.284	0.356	0.125	0.169
N	31	31	31	31	31	31

Panel B – Alternative Periods – Using a Linear Probability Model

Period:	*< 1975*		*>= 1975*		*>= 1990*	
	(1)	(2)	(3)	(4)	(5)	(6)
QAI	-0.119		-0.372***		-0.462**	
	(0.088)		(0.091)		(0.190)	
HAI		-0.131		-0.389***		-0.717**
		(0.095)		(0.090)		(0.215)
Year	0.015	0.011	0.006	0.006	0.039***	0.033***
	(0.025)	(0.024)	(0.007)	(0.006)	(0.010)	(0.009)
Constant	-0.004	0.0704	0.401	0.493*	-1.190**	-0.799**
	(0.184)	(0.172)	(0.285)	(0.240)	(0.402)	(0.328)
R-squared	0.109	0.087	0.372	0.456	0.732	0.785
N	15	15	16	16	10	10

Table 5 presents estimates from a simplified meta-analysis where observations represent findings from prior literature on whether property taxes are fully capitalized into home prices. We separately regress a binary variable, whether or not property taxes are fully capitalized in home prices in a given study, on two alternative, state-level indices that are increasing to the extent that householders in that state misperceive property taxes. The Quality Adjusted Misperception Index (QAI) adjusts out misperception explained by variation in the quality of the property (house), and the Household Adjusted Misperception Index (HAI) adjusts for not only property quality characteristics but also the influence of household characteristics on property tax misperception. Panel A evaluates whether increases in misperception in the state of the original study corresponds with the likelihood the study observes a full capitalization of property taxes. Columns differ based on the estimation approach used. Panel B re-estimates the first two columns from Panel A across different periods. We use robust standard errors, and standard errors are reported in parentheses. The symbols ***, **, and * denote statistical significance at the 1%, 5% and 10% levels (two-tailed), respectively.

Figure 1: State Level Misperception Indices Across the U.S. and the Location of States with Property Tax Capitalization Studies
Panel A Quality Adjusted Misperception Index (QAI)

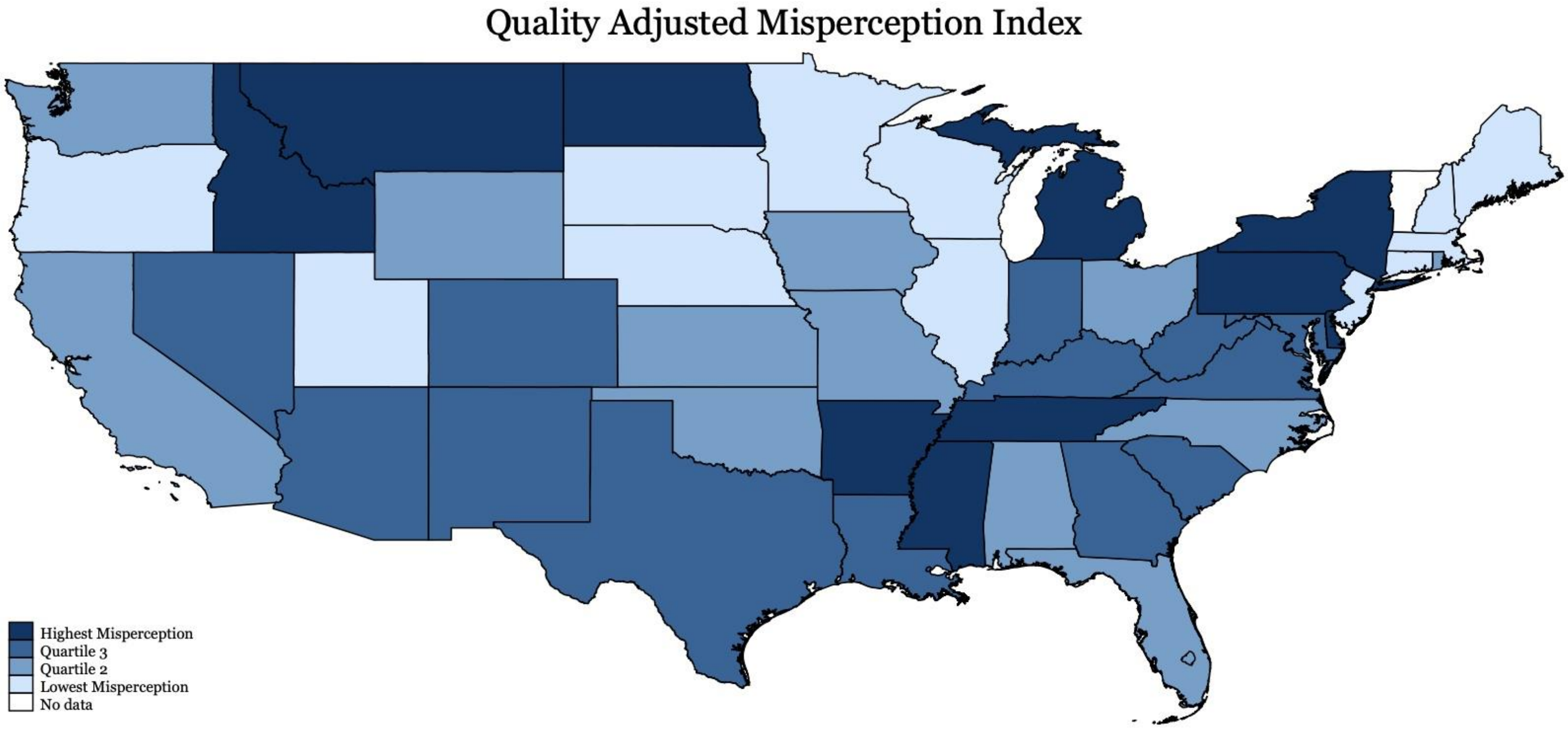


Figure 1 – Continued
Panel B Household Adjusted Misperception Index (HAI)

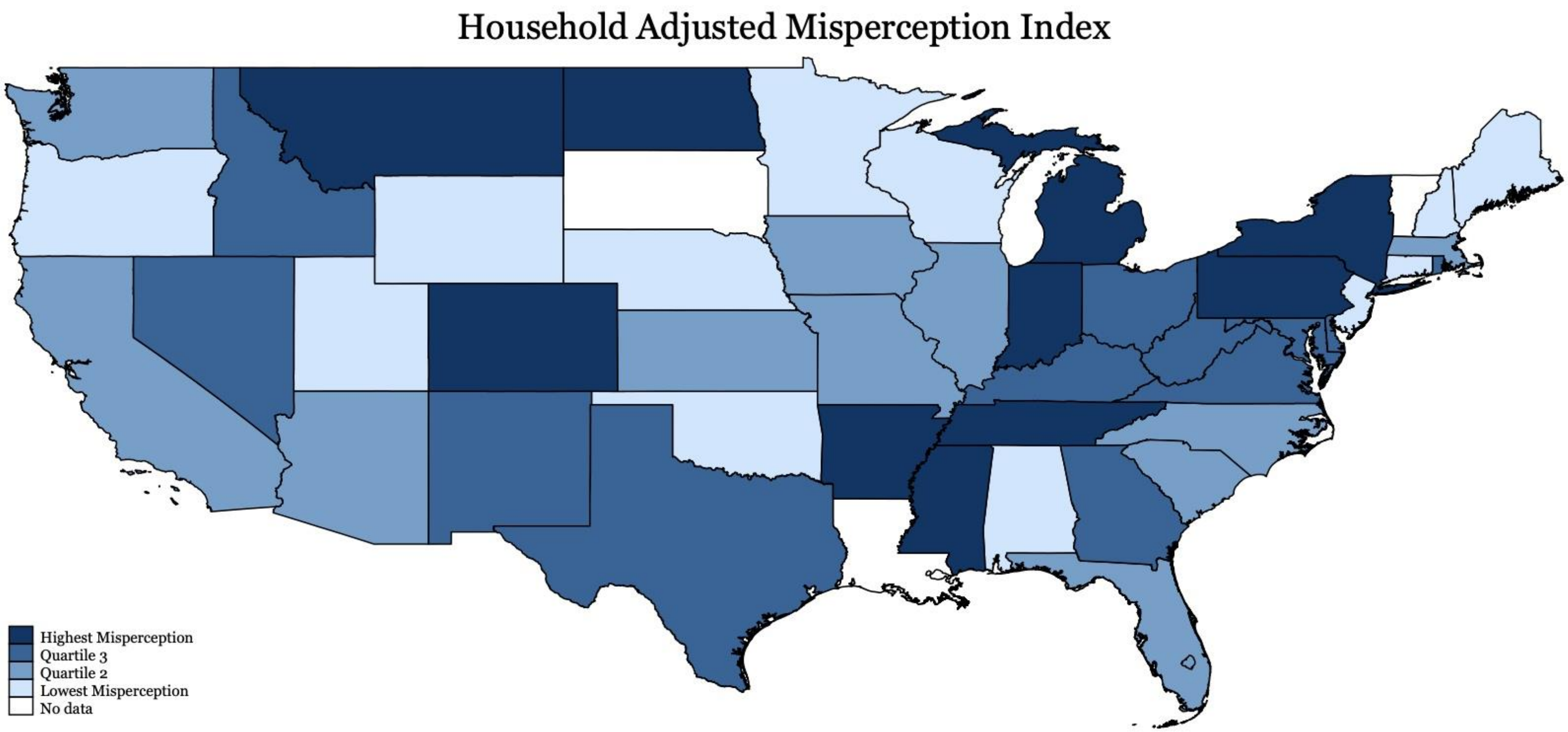


Figure 1 – Continued
Panel C - States Used in Property Tax Capitalization Studies

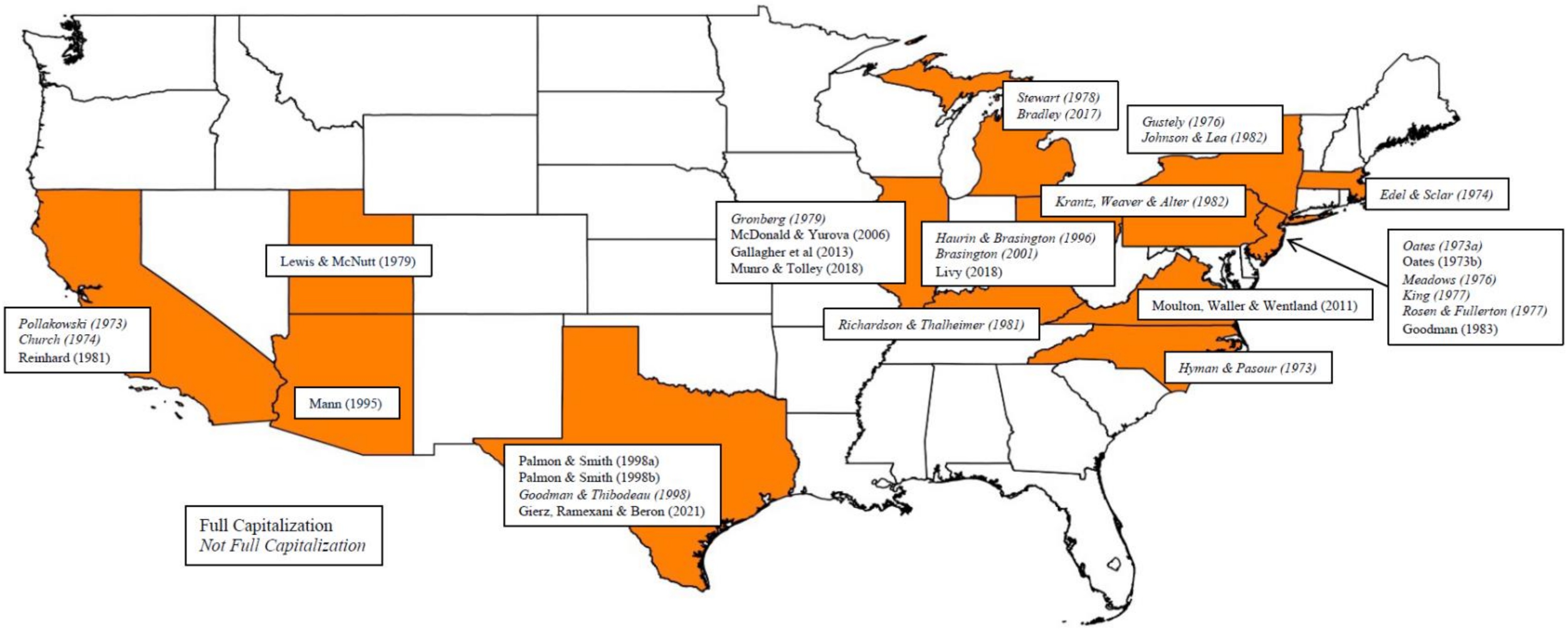
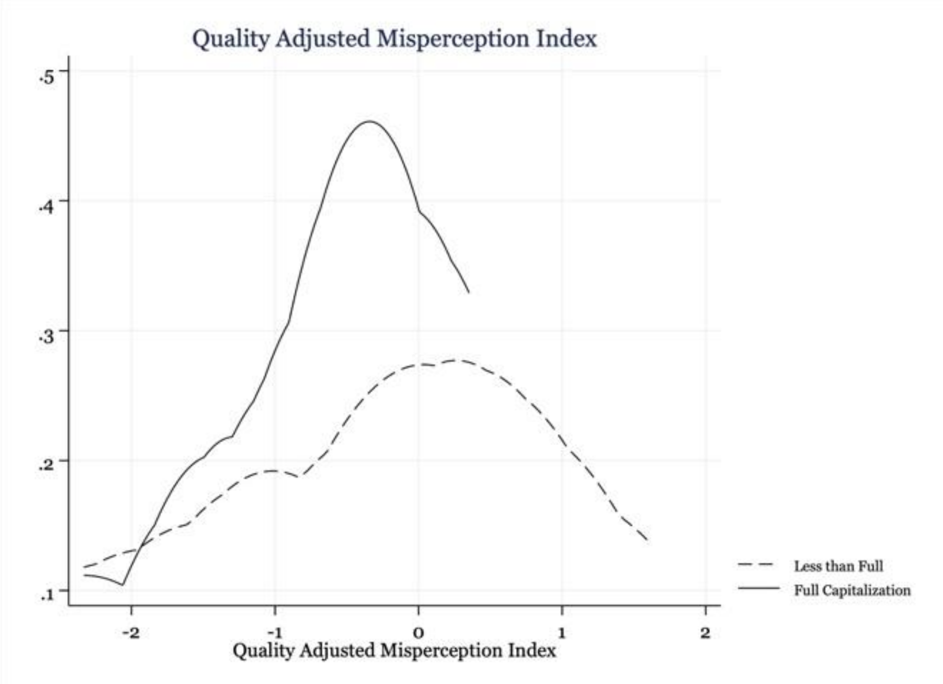


Figure 1 Panels A and B provide a visual representation of the state level misperception indices across the U.S., ranging from low levels of misperception (light blue) to higher levels of misperception (dark blue). Panel C instead provides a visualization of the states represented in the prior literature that examines whether property taxes are capitalized into home prices (in orange), which corresponds with our simplified meta-analysis. Studies finding full capitalization are included in default script, while those finding anything but full included in *italics*.

Figure 2: Distribution (Kernal Density) of State Level Indices by Capitalization Level
Panel A: Quality Adjusted Misperception Index (QAI) (State Level Index)



Panel B: Household Adjusted Misperception Index (HAI) (State Level Index)

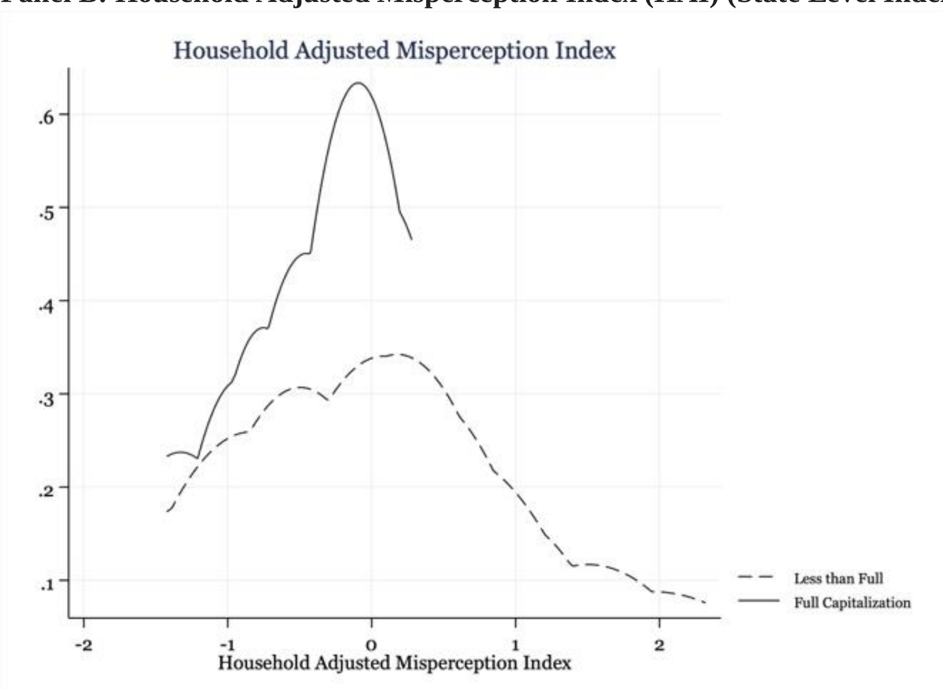


Figure 2 Panels A and B report the distribution (kernel density) of the state level Quality Adjusted Misperception Index (QAI) and Household Adjusted Misperception Index (HAI), respectively, for states in our simplified meta-analysis. Each panel reported the distribution separately for states with studies that find a full capitalization of property taxes vs. states with studies that observe less than full capitalization of property taxes. X-axis values further from (closer to) zero represent a higher (lower) value of the misperception measure.

Online Appendix I – Additional Tables and Figures

Table A1 (Table 3 – Expanded Sample and Category Classification for col. (1))
OLS Regressions of Property Tax Misperceptions (Absolute Error) on the Household Characteristics – Eq. (1)

	Expanded col. (1)		**Copy of Columns (1)-(5) from Table 3**				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Motivation							
Home Val Q2	-0.023***	-0.017***					
Home Val Q3	-0.035***	-0.030***					
Home Val Q4	-0.046***	-0.041***					
Home Val Q5	-0.051***	-0.048***					
Medium Home Val			-0.023***	-0.023***	-0.021***	-0.014***	-0.023***
High Home Val			-0.033***	-0.033***	-0.029***	-0.022***	-0.033***
Income/Home Val			0.016***	0.016***	0.014***	0.012***	0.016***
Info Cost							
At least college			-0.007***	-0.007***	-0.007***	-0.005***	-0.007***
Some college	-0.002	0.000					
College	-0.009***	-0.007***					
Graduate	-0.004**	-0.003*					
Age <=30	0.025***	0.021***					
Age 31-40	0.016***	0.014***					
Age 41-50	0.015***	0.014***					
Age 51-60	0.010***	0.011***					
Age <=30			0.022***	0.022***	0.024***	0.024***	0.022***
Age 31-60			0.012***	0.012***	0.013***	0.013***	0.012***
Income Q2	-0.007***	-0.006***					
Income Q3	-0.007***	-0.007***					
Income Q4	-0.005**	-0.007***					
Income Q5	0.000	-0.001					
Medium Income			-0.012***	-0.012***	-0.012***	-0.011***	-0.012***
High Income			-0.015***	-0.015***	-0.015***	-0.013***	-0.015***
Mrtg With Tax	0.014***	0.021***	0.022***	0.022***	0.023***	0.022***	0.022***
Controls:							
Other Property Characteristics							
Built 1971-1990	-0.009***	-0.004	-0.004	-0.004**	-0.005**	-0.001	-0.004**
Built 1991-2000	-0.011***	-0.007***	-0.008***	-0.009***	-0.010***	-0.006***	-0.009***
Built 2011+	0.008**	0.006	0.004	0.003	0.000	0.001	0.003
Bedrooms	0.000	0.002***	0.001	0.001	0.000	-0.001	0.001

Table A1 (Table 3 – Expanded Sample and Category Classification for col. (1)) – Continued

	Expanded col. (1)		Copy of Columns (1)-(5) from Table 3				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Other Household Characteristics							
Household Size	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***	0.003***
Years in House	0.000***	0.000***	-0.001***	-0.001***	0.000***	0.000***	-0.001***
Married	-0.003***	-0.002	-0.004***	-0.004***	-0.004***	-0.003***	-0.004***
Black	0.038***	0.038***	0.040***	0.038***	0.033***	0.023***	0.038***
Asian	-0.007	-0.010	-0.010	-0.012**	-0.013***	-0.012***	-0.012***
Hispanic	0.012***	0.009***	0.011***	0.011***	0.012***	0.006***	0.011***
Other Race	0.033***	0.021***	0.023***	0.023***	0.021***	0.017***	0.023***
Mrtg No Tax	-0.016***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***	-0.013***
Constant	0.186***	0.163***	0.161***	0.162***	0.161***	0.154***	0.162***
Survey Year	√	√	√		√	√	
State FE	√	√	√				
County FE					√		
State x Year FE				√			√
Census Tract						√	
Adj. R-squared	0.0471	0.0465	0.0455	0.0522	0.0796	0.1290	0.0522
N	889,000	431,000	431,000	431,000	431,000	426,000	431,000
SE Clustered by	State	State	State	State-by-Yr	County	County	County

Table A1 columns (1) and (2) report estimates of eq. (1) expanding different category classifications first with the full sample (few restrictions) and then again with our final sample. Col. (3)-(7) copy the results from column (1)-(5) in Table 3 for ease of reference. Standard errors are clustered by county and omitted for brevity. Coefficients and N (obs) are rounded according to Census disclosure guidelines. We define the variables in Table 1. The symbols ***, **, and * denote statistical significance at the 1%, 5% and 10% levels (two-tailed), respectively.

Table A2
OLS Regressions of Eq. (1) and (2) Stratified by Mortgage Category

	All	**No Mortgage**	**Mortgage w/o Tax Escrow**	**Mortgage with Tax Escrow**
	(1)	(2)	(3)	(4)
Panel A: Dependent Variable Absolute Error – Eq. (1)				
Built 1971-1990	-0.004**	-0.009***	-0.002	-0.004**
Built 1991-2000	-0.009***	-0.011***	-0.008***	-0.010***
Built 2011+	0.003	0.000	0.010	0.000
Age <=30	0.022***	0.046***	0.024***	0.017***
Age 31-60	0.012***	0.02***	0.004**	0.010***
Black	0.038***	0.042***	0.051***	0.034***
Asian	-0.012***	-0.005	-0.009**	-0.015***
Hispanic	0.011***	0.012**	0.013**	0.009***
At least college	-0.007***	-0.007***	-0.007***	-0.007***
Medium Income	-0.012***	-0.006***	-0.012***	-0.017***
High Income	-0.015***	-0.002	-0.012***	-0.022***
Medium Home Val	-0.023***	-0.022***	-0.024***	-0.020***
High Home Val	-0.033***	-0.030***	-0.031***	-0.033***
Income/Home Val	0.016***	0.008***	0.016***	0.019***
Mrtg No Tax	-0.013***			
Mrtg With Tax	0.022***			
Other Controls	√	√	√	√
Panel B: Dependent Variable Raw Error – Eq. (2)				
Built 1971-1990	-0.004**	-0.007**	-0.003	-0.003
Built 1991-2000	-0.015***	-0.014***	-0.013***	-0.014***
Built 2011+	-0.022***	-0.031**	-0.014	-0.022***
Age <=30	-0.016***	-0.011	-0.009	-0.017***
Age 31-60	-0.006***	-0.007***	-0.004**	-0.006***
Black	0.004	-0.001	0.011	0.003
Asian	0.022***	0.023***	0.024***	0.017***
Hispanic	0.007**	0.013**	0.007	0.005
At least college	-0.004***	-0.004**	0.000	-0.006***
Medium Income	0.001	0.000	0.007**	0.001
High Income	0.000	-0.003	0.003	0.002
Medium Home Val	-0.010***	-0.011***	-0.007	-0.012***
High Home Val	-0.017***	-0.022***	-0.013**	-0.017***
Income/Home Val	0.001	0.001	0.002	0.000
Mrtg No Tax	0.008***			
Mrtg With Tax	-0.014***			
Other Controls	√	√	√	√
N	431,000	91,000	88,500	252,000

Table A2 Panels A and B report estimates of eq. (1) and (2), respectively, stratified by mortgage category. Col. (1) contains all households with all mortgage categories whereas Col. (2)-(4) differ based on households with different mortgage categories. Other Controls includes: Bedrooms, Married, Years in House, and Other Race. State-by-year fixed effects are used with all estimates. Standard errors are clustered by county and omitted for brevity. Coefficients and N (obs) are rounded according to Census disclosure guidelines. Because N is rounded, the sum of N across Col. (2)-(4) will not equal N in Col. (1). We define the variables in Table 1. The symbols ***, **, and * denote statistical significance at the 1%, 5% and 10% levels (two-tailed), respectively.

Table A3
OLS Regressions of Eq. (1) and (2) Stratified by Householder Age Category

	All	**Age <=30**	**Age 31-60**	**Age 61+**
	(1)	(2)	(3)	(4)
Panel A: Dependent Variable Absolute Error – Eq. (1)				
Built 1971-1990	-0.004**	-0.005	-0.003	-0.006**
Built 1991-2000	-0.009***	-0.004	-0.007***	-0.012***
Built 2011+	0.003	0.012	0.004	-0.006
Age <=30	0.022***			
Age 31-60	0.012***			
Black	0.038***	0.048***	0.036***	0.043***
Asian	-0.012***	-0.014	-0.017***	0.005
Hispanic	0.011***	0.006	0.009***	0.015***
At least college	-0.007***	0.026**	0.020***	0.026***
Medium Income	-0.012***	-0.021***	-0.007***	-0.004***
High Income	-0.015***	-0.016	-0.017***	-0.010***
Medium Home Val	-0.023***	-0.005	-0.024***	-0.021***
High Home Val	-0.033***	-0.018**	-0.035***	-0.029***
Income/Home Val	0.016***	0.009	0.017***	0.013***
Mrtg No Tax	-0.013***	-0.024***	-0.020***	-0.004**
Mrtg With Tax	0.022***	-0.001	0.016***	0.032***
Other Controls	√	√	√	√
Panel B: Dependent Variable Raw Error – Eq. (2)				
Built 1971-1990	-0.004**	-0.003	-0.005**	-0.001
Built 1991-2000	-0.015***	-0.014**	-0.014***	-0.014***
Built 2011+	-0.022***	-0.016	-0.021***	-0.028***
Age <=30	-0.016***			
Age 31-60	-0.006***			
Black	0.004	-0.059***	0.007**	-0.002
Asian	0.022***	0.034**	0.022***	0.017**
Hispanic	0.007**	0.025***	0.007	-0.003
At least college	-0.004***	-0.014	0.001	0.011
Medium Income	0.001	0.003	-0.003**	-0.008***
High Income	0.000	-0.006	0.004	-0.008**
Medium Home Val	-0.010***	-0.012	-0.011***	-0.007**
High Home Val	-0.017***	0.008	-0.017***	-0.017***
Income/Home Val	0.001	0.017	0.001	-0.001
Mrtg No Tax	0.008***	0.002	0.009***	0.005**
Mrtg With Tax	-0.014***	-0.023***	-0.012***	-0.017***
Other Controls	√	√	√	√
N	431,000	18,500	299,000	113,000

Table A3 Panels A and B report estimates of eq. (1) and (2), respectively, stratified by householder age category. Col. (1) contains householders with all age categories whereas Col. (2)-(4) differ based on householders with different age categories. Other Controls includes: Bedrooms, Married, Years in House, and Other Race. State-by-year fixed effects are used with all estimates. Standard errors are clustered by county and omitted for brevity. Coefficients and N (obs) are rounded according to Census disclosure guidelines. Because N is rounded, the sum of N across Col. (2)-(4) will not equal N in Col. (1). We define the variables in Table 1. The symbols ***, **, and * denote statistical significance at the 1%, 5% and 10% levels (two-tailed), respectively.

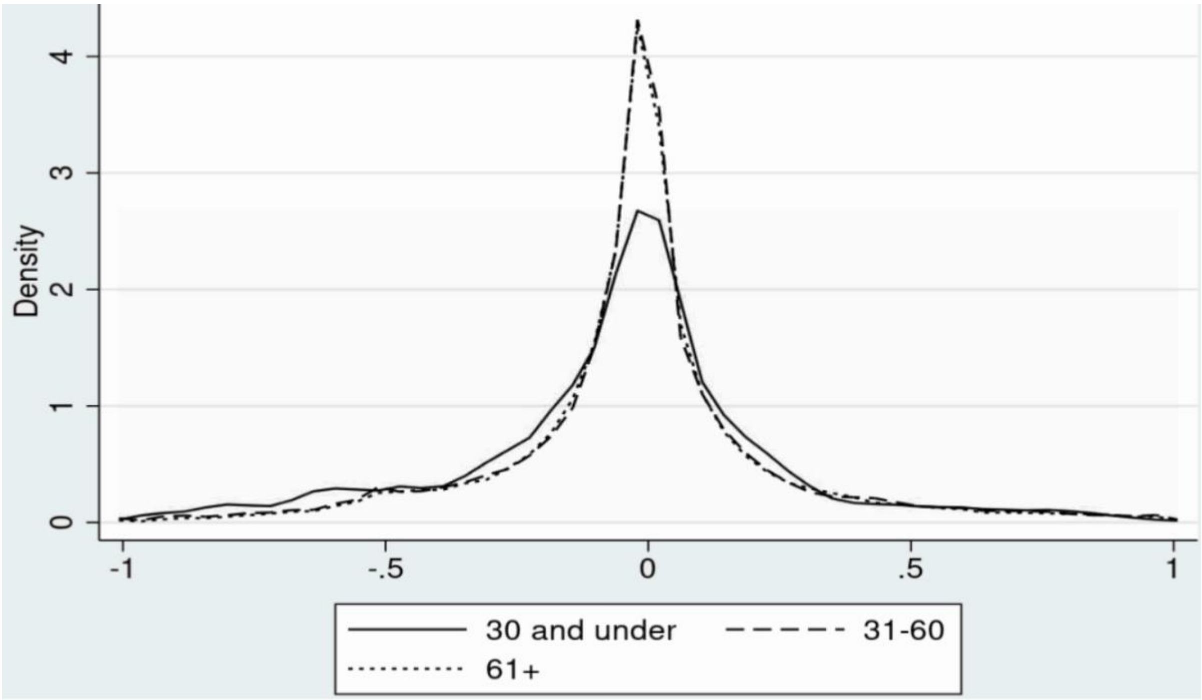
Table A4
OLS Regressions of Eq. (1) and (2) Stratified by Householder Race

	All	**White**	**Black**	**Asian**	**Hispanic**
	(1)	(2)	(3)	(4)	(5)
Panel A: Dependent Variable Absolute Error – Eq. (1)					
Built 1971-1990	-0.004**	-0.005***	-0.007	-0.004	0.002
Built 1991-2000	-0.009***	-0.010***	-0.008	0.001	-0.004
Built 2011+	0.003	0.000	0.014	0.013	0.005
Age <=30	0.022***	0.022***	0.023	0.018	0.018**
Age 31-60	0.012***	0.014***	0.005	-0.003	0.010**
Black	0.038***				
Asian	-0.012***				
Hispanic	0.011***				
At least college	-0.007***	-0.007***	-0.004	-0.003	-0.017***
Medium Income	-0.012***	-0.015***	0.001	-0.005	-0.012**
High Income	-0.015***	-0.016***	-0.015**	-0.009	-0.018**
Medium Home Val	-0.023***	-0.021***	-0.020***	-0.036***	-0.020***
High Home Val	-0.033***	-0.031***	-0.047***	-0.042***	-0.038***
Income/Home Val	0.016***	0.016***	0.009**	0.016***	0.015**
Mrtg No Tax	-0.013***	-0.013***	-0.004	-0.017***	-0.014***
Mrtg With Tax	0.022***	0.023***	0.017***	0.019***	0.024***
Other Controls	√	√	√	√	√
Panel B: Dependent Variable Raw Error – Eq. (2)					
Built 1971-1990	-0.004**	-0.004**	-0.009	-0.014***	0.004
Built 1991-2000	-0.015***	-0.012***	-0.031***	-0.018***	-0.012**
Built 2011+	-0.022***	-0.022***	-0.031**	-0.014	-0.012
Age <=30	-0.016***	-0.016***	-0.074***	0.000	0.014
Age 31-60	-0.006***	-0.006***	-0.002	-0.005	0.004
Black	0.004				
Asian	0.022***				
Hispanic	0.007**				
At least college	-0.004***	-0.006***	0.017***	0.000	-0.008**
Medium Income	0.001	-0.001	0.021**	0.013**	-0.005
High Income	0.000	-0.003	0.033***	0.016**	0.003
Medium Home Val	-0.010***	-0.009***	-0.012	0.002	-0.016**
High Home Val	-0.017***	-0.015***	-0.028**	0.003	-0.033***
Income/Home Val	0.001	0.003	-0.015**	-0.004	0.003
Mrtg No Tax	0.008***	0.006***	0.015	0.007**	0.009
Mrtg With Tax	-0.014***	-0.014***	-0.007	-0.023***	-0.013**
Other Controls	√	√	√	√	√
N	431,000	335,000	21,000	28,500	30,500

Table A4 Panels A and B report estimates of eq. (1) and (2), respectively, stratified by householder race. Col. (1) contains householders of all race categories whereas Col. (2)-(4) differ based on householder race. Other Controls includes: Bedrooms, Married, Years in House, and, just in col. (1), Other Race. State-by-year fixed effects are used with all estimates. Standard errors are clustered by county and omitted for brevity. Coefficients and N (obs) are rounded following Census disclosure guidelines. Because N is rounded, the sum of N across Col. (2)-(4) will not equal N in Col. (1). We define the variables in Table 1. The symbols ***, **, and * denote statistical significance at the 1%, 5% and 10% levels (two-tailed), respectively.

Figure A1: Distribution (Kernal Density) of Property Tax Misperception by Householder Age

Panel A: Raw Error



Panel B: Absolute Error

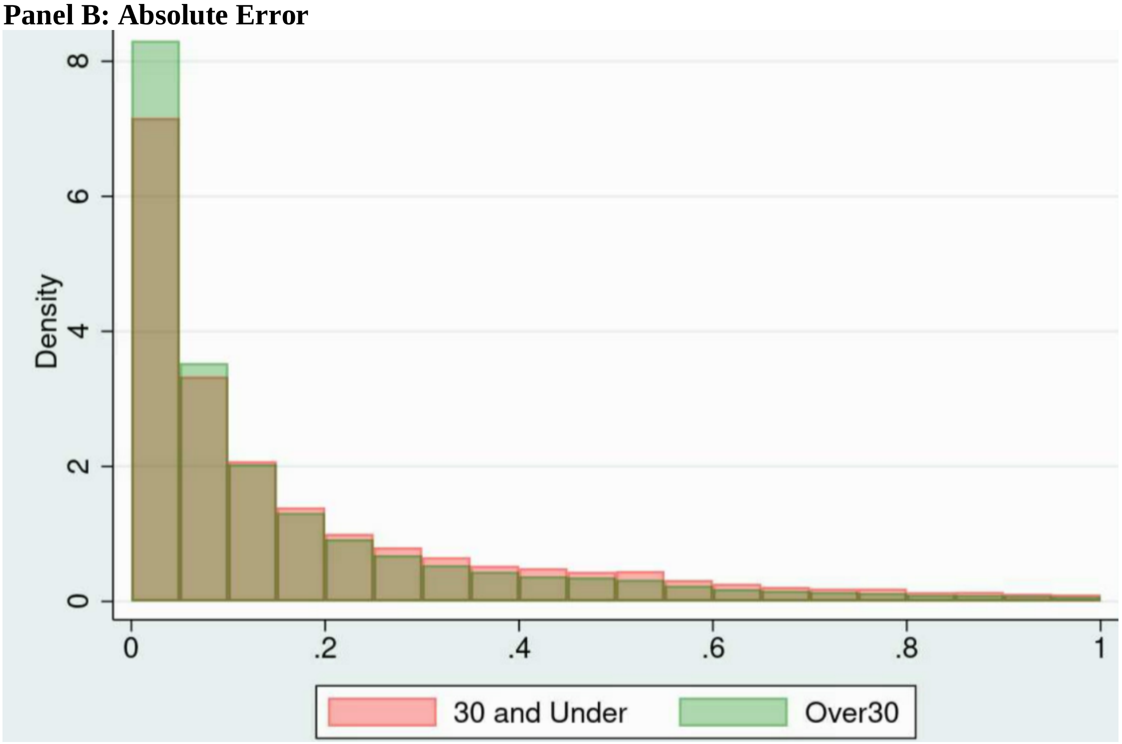
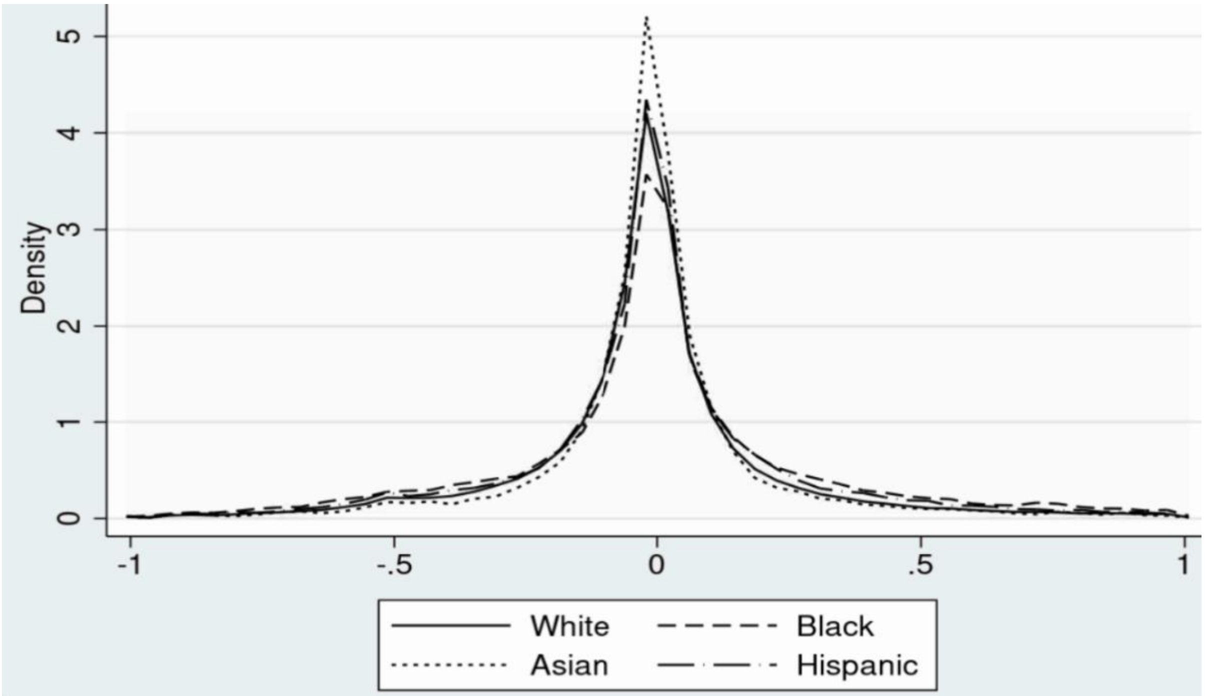


Figure A1 Panels A and B report the distribution (kernel density) of property tax misperception based on raw error and absolute error, respectively, by householder age. X-axis values further from (closer to) zero represent a higher (lower) value of the misperception measure.

Figure A2: Distribution (Kernal Density) of Property Tax Misperception by Householder Race
Panel A: Raw Error



Panel B: Absolute Error (Black vs. White)

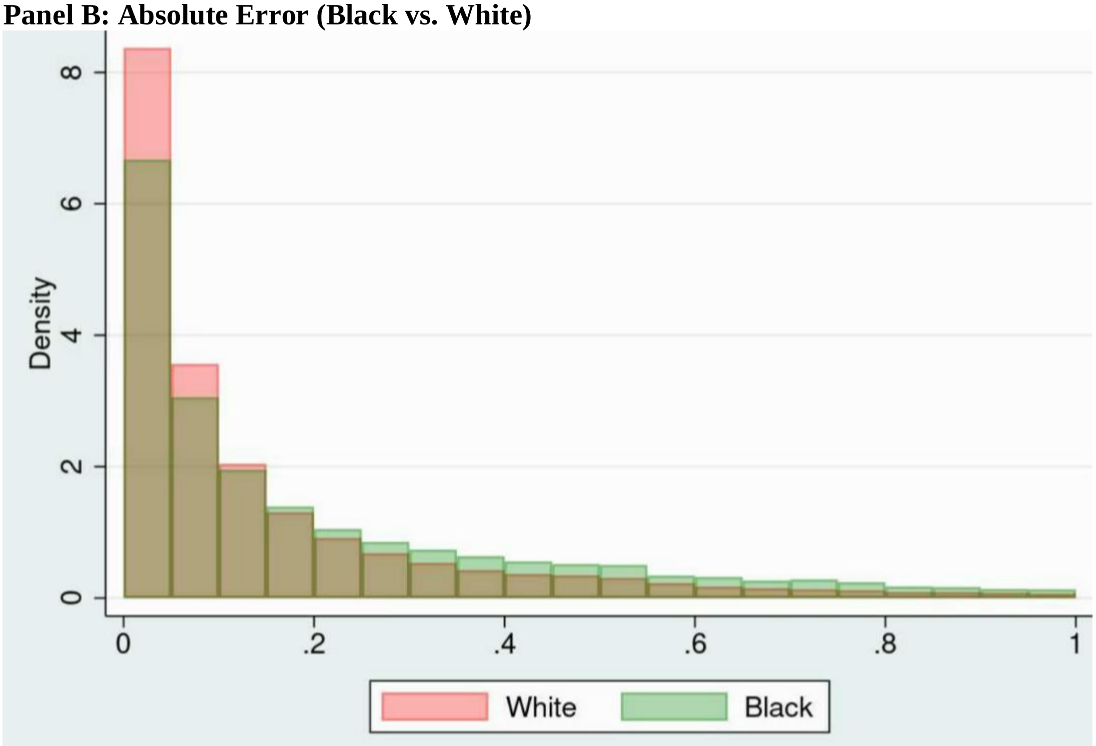
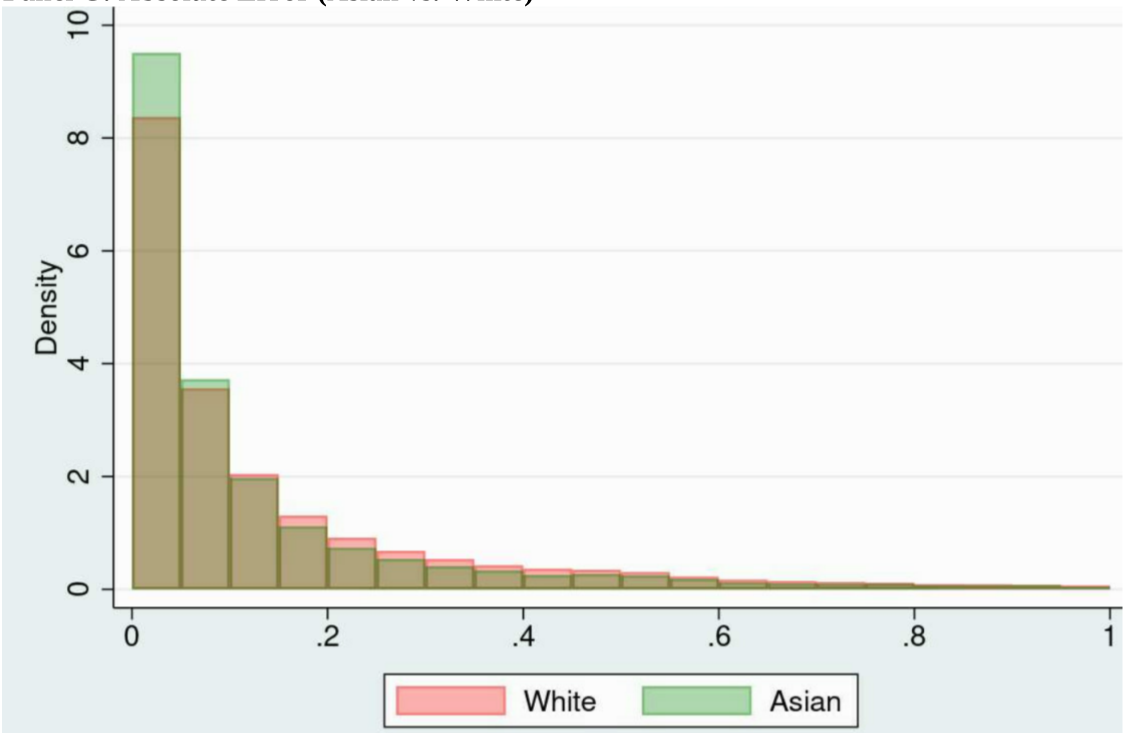


Figure A2 – Continued
Panel C: Absolute Error (Asian vs. White)



Panel D: Absolute Error (Hispanic vs. White)

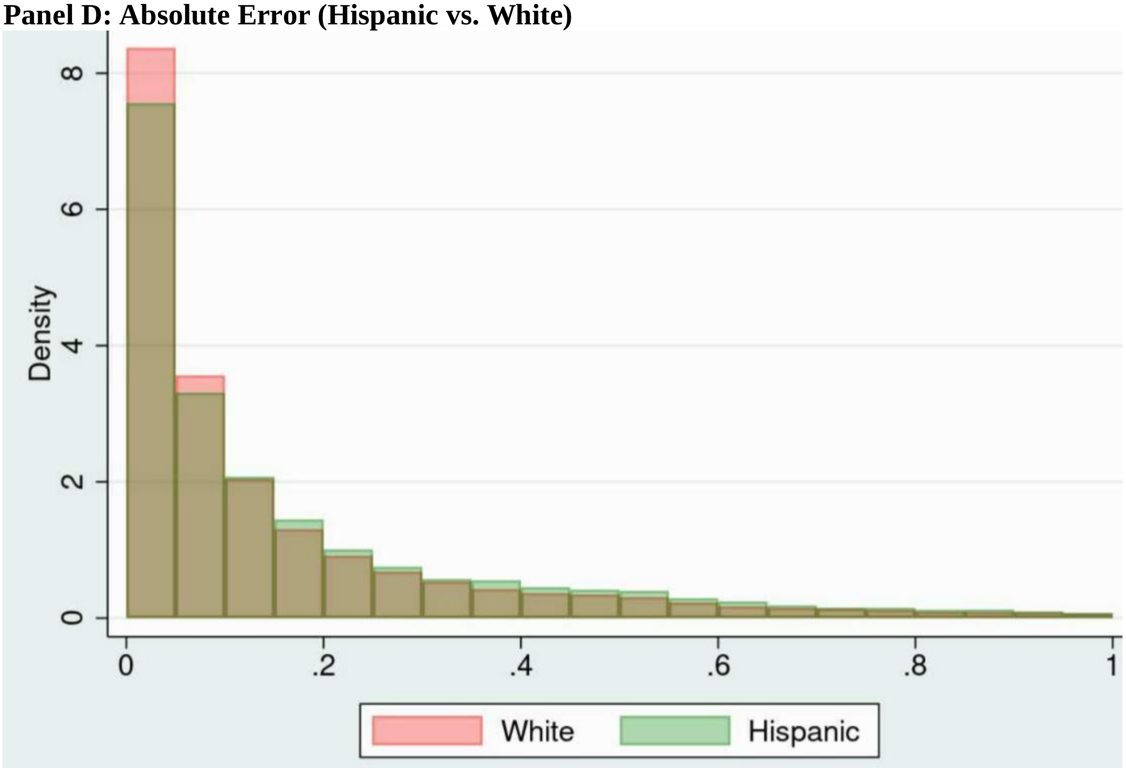
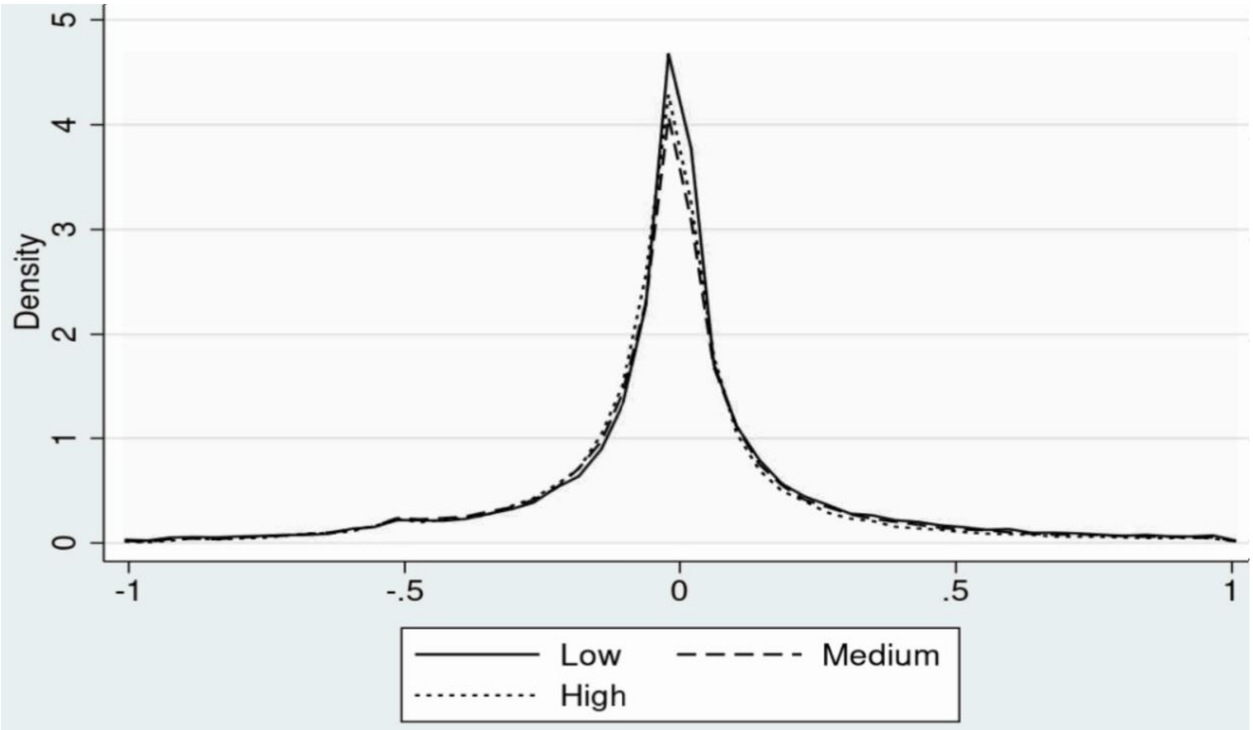


Figure A2 Panel A (Panels B-D) report(s) the distribution (kernel density) of property tax misperception based on raw error (absolute error) by householder race. X-axis values further from (closer to) zero represent a higher (lower) value of the misperception measure.

Figure A3: Distribution (Kernal Density) of Property Tax Misperception by Household Income
Panel A: Raw Error



Panel B: Absolute Error

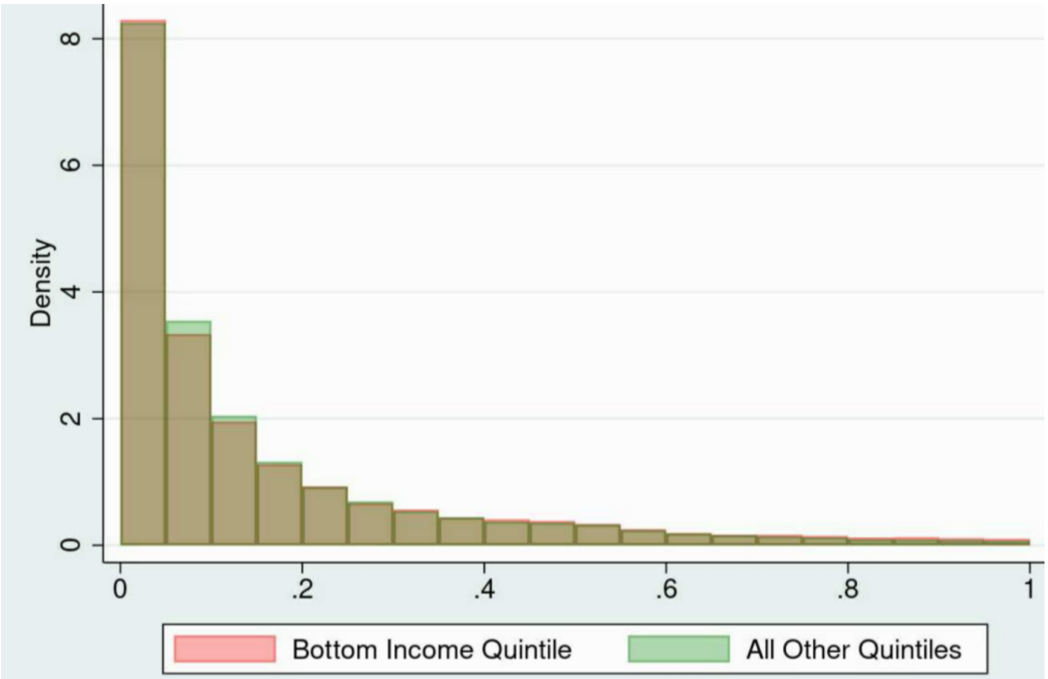
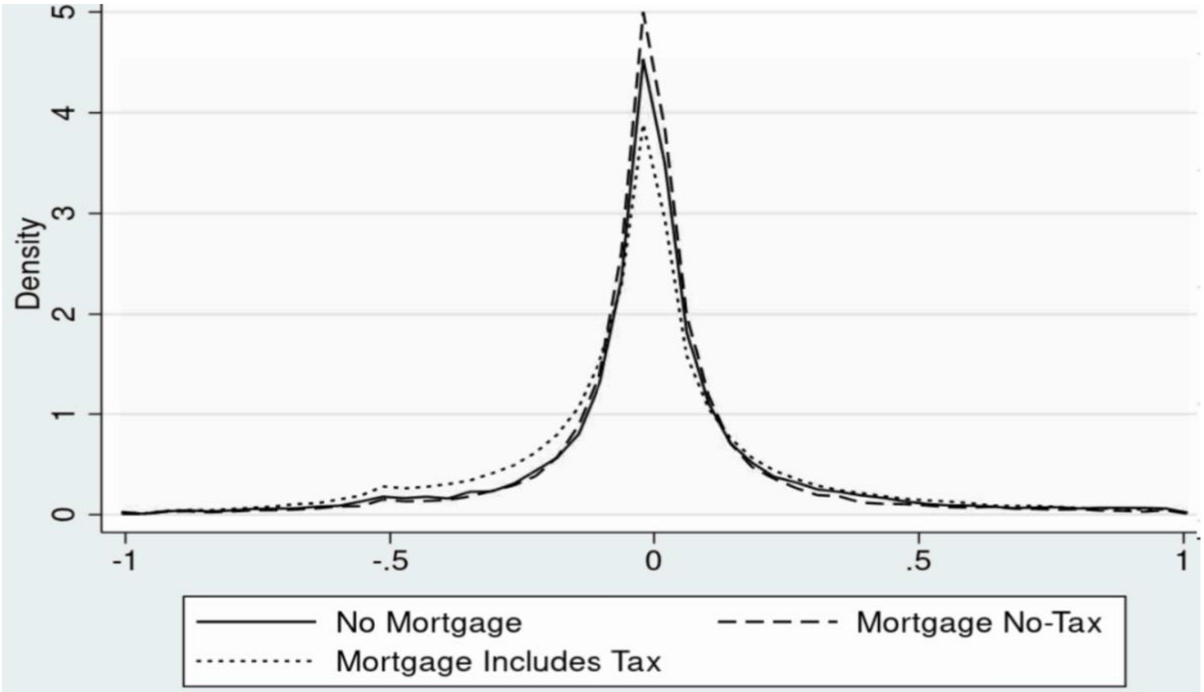


Figure A3 (Panels A and B) reports the distribution (kernel density) of property tax misperception based on raw error and absolute error, respectively, by household income. X-axis values further from (closer to) zero represent a higher (lower) value of the misperception measure.

Figure A4: Distribution (Kernal Density) of Property Tax Misperception by Mortgage Category
Panel A: Raw Error



Panel B: Raw Error (By How Taxes Are Paid)

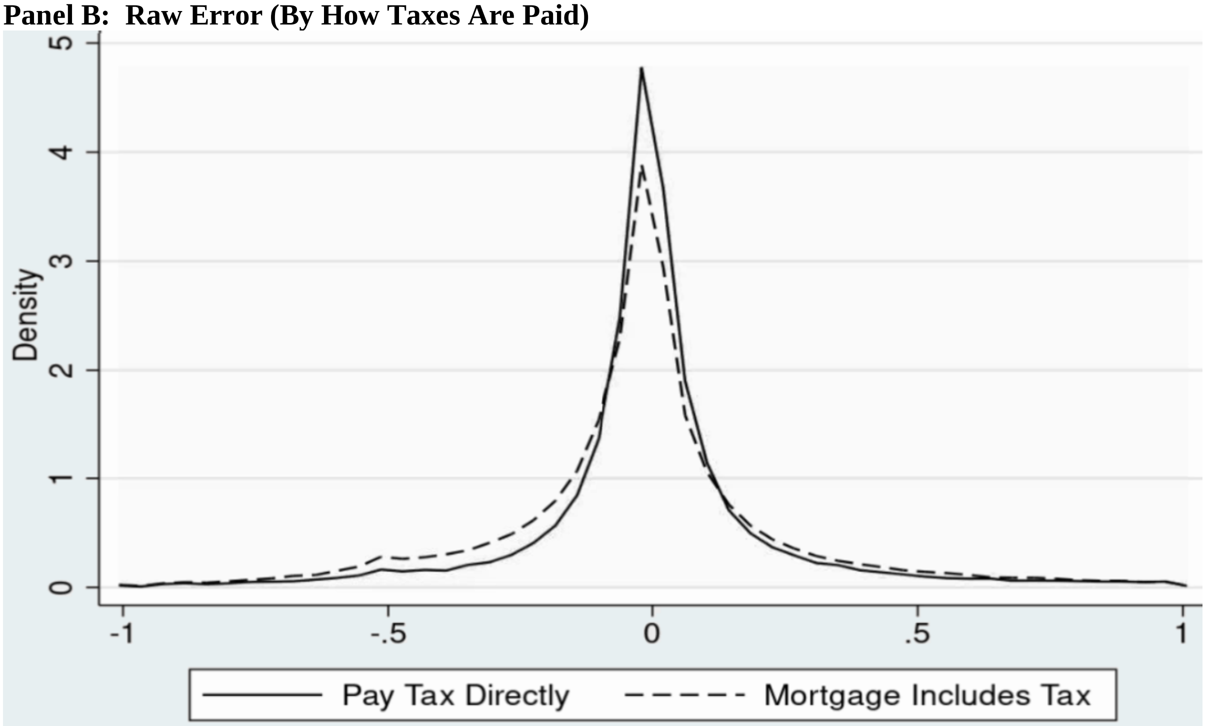


Figure A4 – Continued
Panel C: Absolute Error (By How Taxes Are Paid)

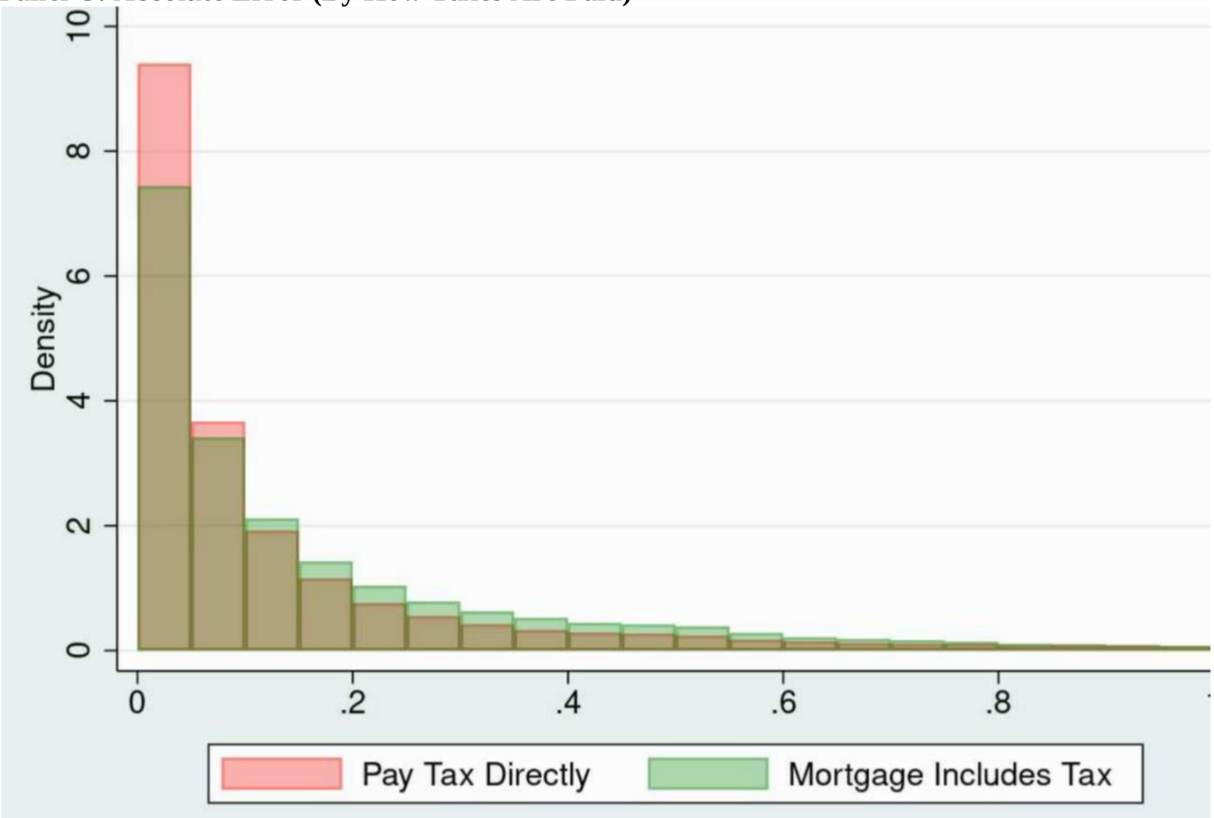
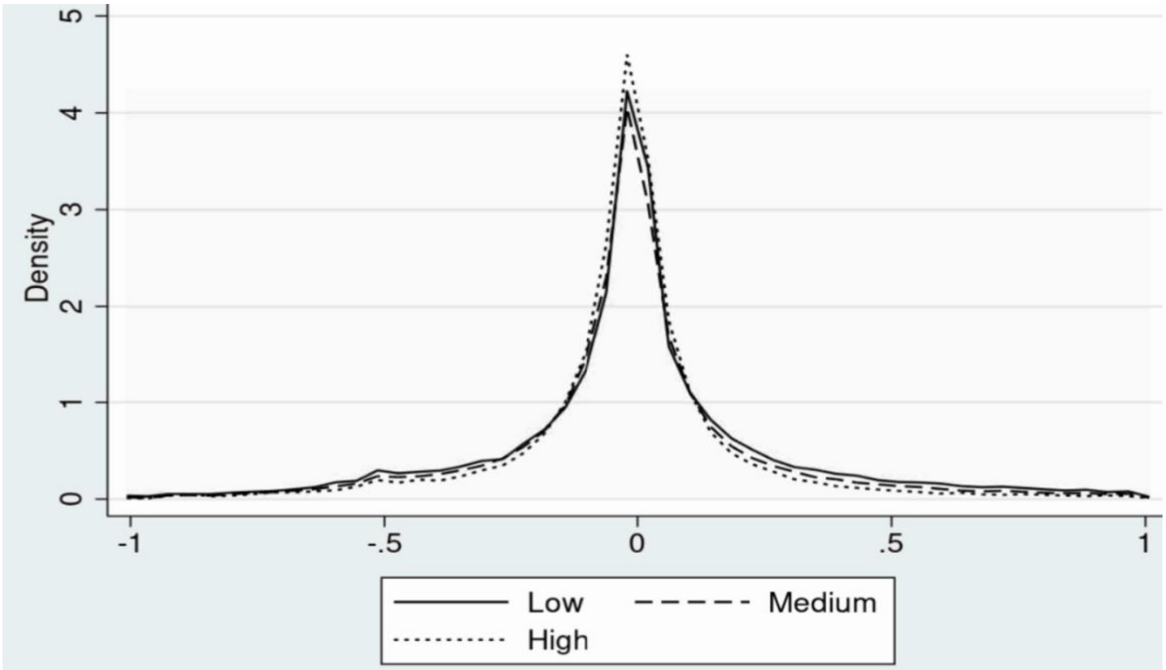


Figure A4 Panels A and B (Panel C) report the distribution (kernel density) of property tax misperception based on raw error (absolute error) across mortgage categories, which correspond with whether the tax is paid directly or indirectly. X-axis values further from (closer to) zero represent a higher (lower) value of the misperception measure.

Figure A5: Distribution (Kernal Density) of Property Tax Misperception by Home Value

Panel A: Raw Error



Panel B: Absolute Error

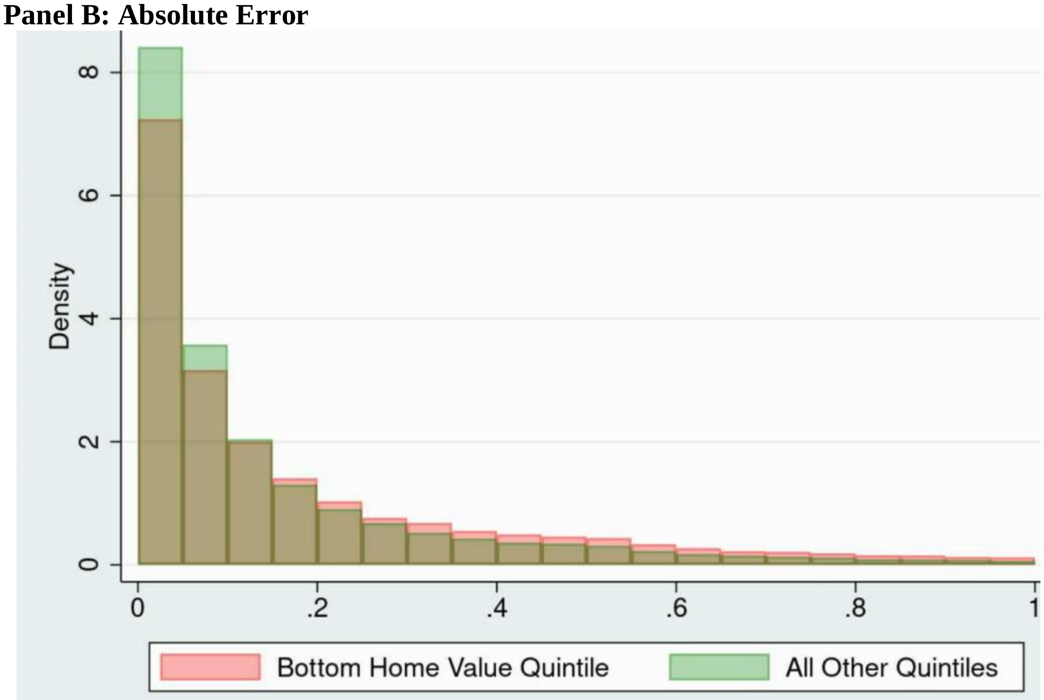
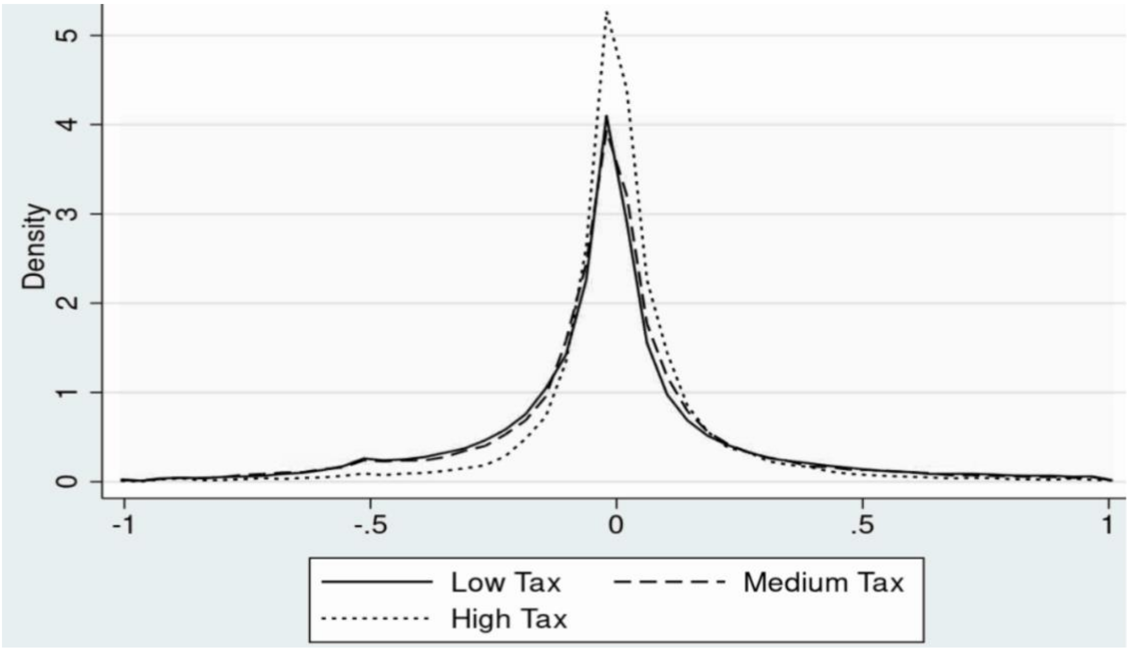


Figure A5 Panels A and B report the distribution (kernel density) of property tax misperception based on raw error and absolute error, respectively, by home value. X-axis values further from (closer to) zero represent a higher (lower) value of the misperception measure.

Figure A6: Distribution (Kernal Density) of Property Tax Misperception by State Tax Rate Level
Panel A: Raw Error



Panel B: Absolute Error

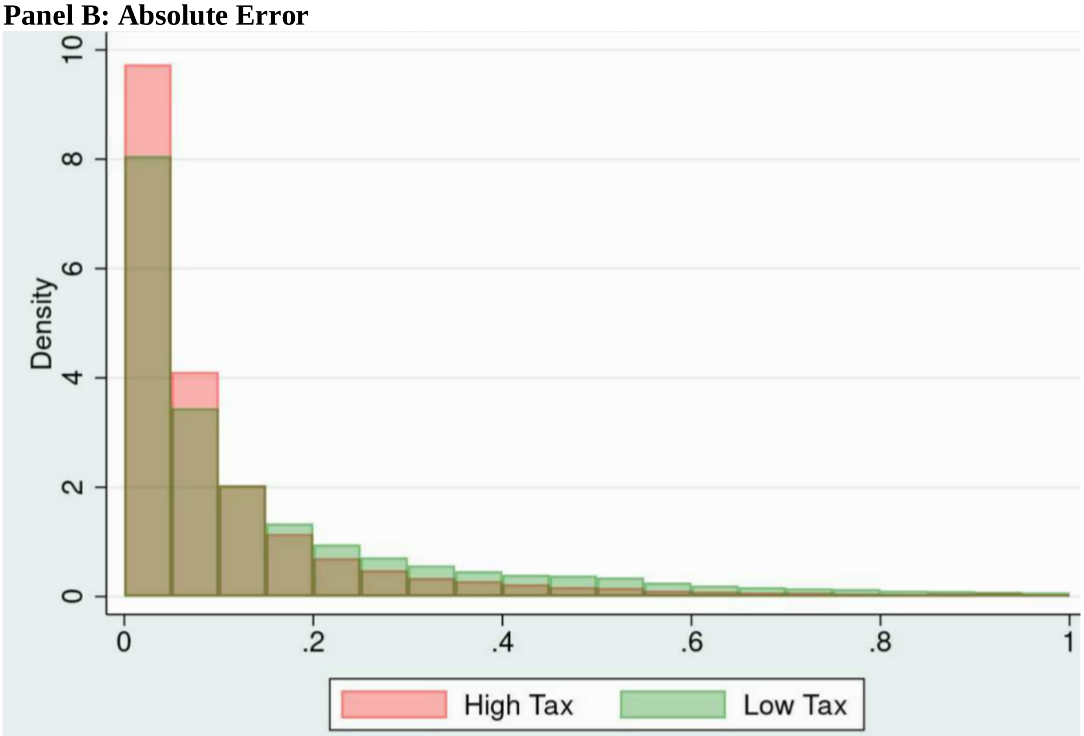


Figure A6 Panels A and B report the distribution (kernel density) of property tax misperception based on raw error and absolute error, respectively, across state tax rate levels. X-axis values further from (closer to) zero represent a higher (lower) value of the misperception measure.

Online Appendix II – Analysis to Develop the State Level Property Tax Misperception Indices

Panel A – Absolute Error

	(1)	(2)	(3)	(4)	(5)
Bedrooms	0.005***	0.002**	0.001	0.001	0.001
Built 1971-1990	-0.006***	-0.005**	-0.003	-0.004**	-0.003
Built 1991-2000	-0.011***	-0.010***	-0.008***	-0.008***	-0.009***
Built 2011+	0.009	0.003	0.005	0.004	-0.001
Black			0.043***	0.040***	0.040***
Asian			-0.014***	-0.010**	-0.010**
Hispanic			0.012***	0.011***	0.011***
Medium Home Val	-0.037***	-0.036***	-0.024***	-0.023***	-0.027***
High Home Val	-0.064***	-0.061***	-0.039***	-0.033***	-0.043***
Married		-0.009***	-0.005***	-0.004***	-0.003**
Household Size		0.006***	0.003***	0.003***	0.003***
Years in Household		-0.001***	-0.001***	-0.001***	-0.001***
Age <=30			0.028***	0.022***	0.023***
Age 31-60			0.017***	0.012***	0.014***
At least college			-0.008***	-0.007***	-0.007***
Medium Income			-0.01***	-0.012***	-0.013***
High Income			-0.013***	-0.015***	-0.018***
Income/Home Val			0.017***	0.016***	0.020***
Mrtg No Tax				-0.013***	-0.012***
Mrtg With Tax				0.022***	0.023***
Tax rate (Prop_Taxes_Paid/ Home Value)					-0.022***
ln(Lot Size) (in acres)					-0.001
Square Footage					0.000
Bathrooms					0.004***
Number of Stories					0.002
Survey Year=2014	-0.007	-0.005	-0.006	-0.006	0.001
Survey Year=2015	-0.011	-0.008	-0.008	-0.008	-0.010
Survey Year=2016	-0.020	-0.018	-0.017	-0.017	-0.023**
Survey Year=2017	-0.029**	-0.026**	-0.025**	-0.025**	-0.032**
Alaska	-0.028**	-0.028**	-0.021	-0.023	0.001
Arizona	0.002	0.003	0.013**	0.011	0.023***
Arkansas	0.099***	0.098***	0.101***	0.102***	0.106***
California	-0.015**	-0.014**	-0.002	0.005	0.022***
Colorado	0.032**	0.033**	0.044***	0.042***	0.053***
Connecticut	-0.051***	-0.048***	-0.039***	-0.039***	0.004
Delaware	0.039***	0.038***	0.042***	0.040***	0.051***
DC	0.047***	0.050***	0.048***	0.047***	0.050***
Florida	-0.010	-0.008	-0.001	0.002	0.020**
Georgia	0.006	0.007	0.007	0.008	0.025***
Hawaii	0.094***	0.094***	0.113***	0.110***	0.115***
Idaho	0.041***	0.038***	0.048***	0.046***	0.048***
Illinois	-0.038**	-0.038**	-0.032**	-0.028**	0.013

Online Appendix II Panel A – Absolute Error – Continued					
Indiana	0.036***	0.033***	0.037***	0.038***	0.052***
Iowa	-0.021**	-0.023***	-0.017**	-0.017**	0.015
Kansas	-0.004	-0.005	0.001	0.001	0.023**
Kentucky	0.033**	0.032**	0.038**	0.040**	0.042**
Louisiana	0.033	0.032	0.034	0.034	
Maine	-0.034***	-0.037***	-0.027***	-0.026***	0.004
Maryland	0.009	0.011	0.020	0.021	0.038**
Massachusetts	-0.027***	-0.025***	-0.014**	-0.013	0.013
Michigan	0.039***	0.038***	0.042***	0.045***	0.064***
Minnesota	-0.028***	-0.028***	-0.021***	-0.021***	0.000
Mississippi	0.040	0.037	0.036	0.037	0.117***
Missouri	-0.021***	-0.021***	-0.016**	-0.017**	0.009
Montana	0.041***	0.039***	0.050***	0.048***	0.062***
Nebraska	-0.037***	-0.039***	-0.033***	-0.034***	0.005
Nevada	0.031***	0.032***	0.041***	0.041***	0.051***
New Hampshire	-0.069***	-0.069***	-0.060***	-0.058***	-0.013
New Jersey	-0.091***	-0.089***	-0.079***	-0.078***	-0.022**
New Mexico	0.002	0.001	0.008	0.006	0.027
New York	0.069***	0.069***	0.076***	0.076***	0.121***
North Carolina	0.001	0.001	0.005	0.005	0.022**
North Dakota	0.066***	0.063***	0.070***	0.070***	0.138***
Ohio	-0.001	0.000	0.005	0.007	0.043***
Oklahoma	-0.011	-0.012	-0.009	-0.008	0.005
Oregon	-0.041***	-0.042***	-0.030***	-0.028***	-0.004
Pennsylvania	0.038***	0.039***	0.045***	0.046***	0.079***
Rhode Island	-0.012	-0.009	0.001	0.003	0.038**
South Carolina	0.003	0.004	0.008	0.008	0.009
South Dakota	-0.027**	-0.030**	-0.023	-0.024	
Tennessee	0.041	0.043	0.047	0.050	0.072
Texas	0.009	0.008	0.010	0.015	0.043
Utah	-0.029***	-0.03***	-0.020***	-0.020***	-0.011
Virginia	0.018**	0.018**	0.024**	0.021**	0.032***
Washington	-0.014**	-0.013**	-0.002	-0.002	0.016**
West Virginia	0.020**	0.019**	0.024**	0.028**	0.031***
Wisconsin	-0.084***	-0.085***	-0.080***	-0.076***	-0.034**
Wyoming	-0.011	-0.012	-0.003	-0.005	0.001
Constant	0.207***	0.209***	0.183***	0.173***	0.183***
Adj. R-squared	0.032	0.034	0.041	0.046	0.050

Online Appendix II Panel B – Raw Error

	(1)	(2)	(3)	(4)	(5)
Bedrooms	-0.005***	-0.005***	-0.004***	-0.004***	0.002
Built 1971-1990	-0.004**	-0.004**	-0.004**	-0.004**	0.000
Built 1991-2000	-0.014***	-0.013***	-0.014***	-0.014***	-0.002
Built 2011+	-0.028***	-0.019**	-0.021**	-0.020**	-0.004
Black			0.043***	0.040***	0.040***
Asian			-0.014***	-0.010**	-0.010**
Hispanic			0.012***	0.011***	0.011***
Medium Home Val	-0.010***	-0.010***	-0.01***	-0.010***	-0.025***
High Home Val	-0.014***	-0.013***	-0.013***	-0.017***	-0.036***
Married		-0.005***	-0.005***	-0.005***	-0.006***
Household Size		-0.001	0.000	0.000	0.000
Years in Household		0.001***	0.001***	0.001***	0.001***
Age <=30			-0.020***	-0.016***	-0.015***
Age 31-60			-0.009***	-0.006***	-0.002
At least college			-0.004**	-0.004**	-0.002
Medium Income			-0.001	0.001	-0.003
High Income			-0.001	0.000	-0.01***
Income/Home Val			0.001	0.001	0.026***
Mrtg No Tax				0.008***	0.009***
Mrtg With Tax				-0.015***	-0.014***
Tax $rate_{ACS}$ (Prop_Taxes_Paid/ Home Value)					-0.090***
ln(Lot Size) (in acres)					-0.005**
Square Footage					0.000
Bathrooms					-0.004**
Number of Stories					-0.001
Survey Year=2014	-0.027	-0.029	-0.028	-0.028	0.016
Survey Year=2015	-0.013	-0.014	-0.014	-0.014	0.018**
Survey Year=2016	-0.005	-0.007	-0.007	-0.007	0.018**
Survey Year=2017	0.005	0.003	0.003	0.003	0.023**
Alaska	-0.031**	-0.031**	-0.031**	-0.030**	0.07***
Arizona	-0.056***	-0.059***	-0.061***	-0.061***	-0.033***
Arkansas	-0.113***	-0.114***	-0.115***	-0.116***	-0.041**
California	-0.103***	-0.106***	-0.111***	-0.116***	-0.065***
Colorado	-0.066***	-0.069***	-0.069***	-0.068***	-0.061***
Connecticut	-0.070***	-0.075***	-0.076***	-0.076***	0.086***
Delaware	-0.105***	-0.104***	-0.106***	-0.105***	-0.077***
DC	-0.040***	-0.043***	-0.044***	-0.043***	-0.033***
Florida	-0.041***	-0.044***	-0.047***	-0.049***	0.004
Georgia	-0.035***	-0.038***	-0.040***	-0.041***	0.005
Hawaii	-0.093**	-0.097**	-0.108**	-0.106**	-0.112**
Idaho	-0.032	-0.032	-0.032	-0.031	-0.012
Illinois	0.000	-0.003	-0.005	-0.007	0.159***

Indiana	0.004	0.004	0.004	0.004	0.036***
Iowa	-0.098***	-0.098***	-0.098***	-0.098***	0.030**
Kansas	-0.100***	-0.100***	-0.100***	-0.100***	-0.008
Kentucky	-0.042***	-0.042***	-0.042***	-0.043***	-0.006
Louisiana	-0.089***	-0.088***	-0.089***	-0.089***	
Maine	-0.105***	-0.103***	-0.102***	-0.104***	0.007
Maryland	-0.003	-0.008	-0.009	-0.009	0.031
Massachusetts	-0.074***	-0.079***	-0.079***	-0.079***	0.014
Michigan	0.036**	0.034**	0.034**	0.032**	0.133***
Minnesota	-0.073***	-0.075***	-0.075***	-0.075***	0.001
Mississippi	-0.077**	-0.076**	-0.076**	-0.076**	-0.105
Missouri	-0.067***	-0.069***	-0.069***	-0.069***	0.007
Montana	-0.007	-0.006	-0.005	-0.004	0.035
Nebraska	-0.051***	-0.05***	-0.049***	-0.049***	0.071***
Nevada	-0.032***	-0.034***	-0.038***	-0.038***	-0.022***
New Hampshire	-0.045***	-0.047***	-0.047***	-0.048***	0.122***
New Jersey	-0.049***	-0.053***	-0.056***	-0.056***	0.117***
New Mexico	-0.072***	-0.073***	-0.075***	-0.074***	-0.053***
New York	0.044	0.0400	0.037	0.037	0.185***
North Carolina	-0.038***	-0.039***	-0.040***	-0.04***	0.001
North Dakota	-0.011	-0.009	-0.008	-0.008	0.055***
Ohio	-0.063***	-0.065***	-0.065***	-0.067***	0.059***
Oklahoma	-0.053***	-0.052***	-0.053***	-0.054***	0.003
Oregon	-0.11***	-0.111***	-0.113***	-0.114***	-0.056***
Pennsylvania	-0.112***	-0.115***	-0.116***	-0.117***	-0.004
Rhode Island	-0.11***	-0.115***	-0.114***	-0.116***	0.013
South Carolina	0.007	0.006	0.005	0.005	0.008
South Dakota	-0.088***	-0.084***	-0.083***	-0.082***	
Tennessee	0.020	0.018	0.017	0.015	0.068
Texas	0.000	-0.002	-0.004	-0.007	0.124***
Utah	-0.074***	-0.075***	-0.075***	-0.075***	-0.055***
Virginia	-0.092***	-0.093***	-0.094***	-0.093***	-0.039**
Washington	-0.09***	-0.093***	-0.095***	-0.095***	-0.038***
West Virginia	-0.043***	-0.041***	-0.041***	-0.044***	-0.03**
Wisconsin	-0.028**	-0.027**	-0.027**	-0.029**	0.132***
Wyoming	-0.052***	-0.051***	-0.050***	-0.049***	-0.031**
Constant	0.081***	0.073***	0.083***	0.089***	0.151***
Adj. R-squared	0.022	0.023	0.024	0.026	0.053
N	435,000	431,000	431,000	431,000	293,000

Online Appendix II Panels A and B report estimates of the misperception determinant regressions using absolute error and raw error, respectively, and showing each individual state fixed effect. Columns differ based on the determinants included. Col. (1) focuses on accounting for a limited of home characteristics (the quality of the home) and as we move to later columns we include additional household characteristics with Col. (5) being the most comprehensive (and, as a result, restrictive with the data). Alabama is the omitted state and reference group. We define the variables in Table 1. Standard errors are omitted for brevity. The symbols ***, **, and * denote statistical significance at the 1%, 5% and 10% levels (two-tailed), respectively.

Online Appendix III – Property Tax Misperceptions Index Values by State

State	Quality Adj. Index	QAI RANK	Household Adj. Index	HAI RANK	State	Quality Adj. Index	QAI RANK	Household Adj. Index	HAI RANK
Alabama	-0.09	27	-0.85	42	Montana	0.92	6	0.78	9
Alaska	-0.78	40	-0.82	40	Nebraska	-1.00	44	-0.72	36
Arizona	-0.04	24	-0.25	25	Nevada	0.67	17	0.45	12
Arkansas	2.35	1	1.93	5	New Hampshire	-1.79	48	-1.19	46
California	-0.46	35	-0.27	27	New Jersey	-2.33	50	-1.42	47
Colorado	0.70	16	0.54	10	New Mexico	-0.04	24	-0.14	23
Connecticut	-1.35	47	-0.74	38	New York	1.61	3	2.32	2
Delaware	0.87	5	0.49	14	North Carolina	-0.07	26	-0.27	27
DC	1.07	10	0.46	12	North Dakota	1.53	4	2.77	1
Florida	-0.34	30	-0.32	29	Ohio	-0.12	28	0.28	16
Georgia	0.06	22	-0.19	24	Oklahoma	-0.36	31	-0.72	36
Hawaii	2.22	2	2.16	4	Oregon	-1.10	46	-0.95	44
Idaho	0.92	6	0.41	15	Pennsylvania	0.84	12	1.22	6
Illinois	-1.03	45	-0.51	32	Rhode Island	-0.39	33	0.15	19
Indiana	0.80	13	0.51	11	South Carolina	-0.02	23	-0.61	34
Iowa	-0.61	36	-0.46	31	South Dakota	-0.76	38	-0.85	
Kansas	-0.19	29	-0.25	25	Tennessee	0.92	6	1.04	7
Kentucky	0.72	14	0.25	18	Texas	0.13	20	0.28	16
Louisiana	0.72	14	-0.85		Utah	-0.81	42	-1.14	45
Maine	-0.93	43	-0.74	38	Vermont	.	.	.	.
Maryland	0.13	20	0.15	19	Virginia	0.35	19	-0.01	21
Massachusetts	-0.76	38	-0.51	32	Washington	-0.44	34	-0.43	30
Michigan	0.87	10	0.83	8	West Virginia	0.40	18	-0.04	22
Minnesota	-0.78	40	-0.85	42	Wisconsin	-2.16	49	-1.74	48
Mississippi	0.89	9	2.22	3	Wyoming	-0.36	31	-0.82	40
Missouri	-0.61	36	-0.61	34					

Online Appendix III reports the state level property tax misperception indices, the Quality Adjusted Index and Household Adjusted Index, derived from the standardized state fixed effect coefficients (mean = 0, std dev = 1) from Col. (1) and (5), respectively in Online Appendix II. The QAI values are increasing in the degree of property tax misperception not explained by the quality/characteristics of the home (Col. (1) in Online Appendix II). The HAI values are increasing in the degree of property tax misperception that is not explained by either the quality/characteristics of the home or characteristics of the household (Col. (5) in Online Appendix II). Rankings are associated with degree of misperceptions (1 = most misperception (least accurate), 50=least misperception (most accurate)).

Online Appendix IV - Simplified Meta-Analysis of the Property Tax Capitalization Literature With Additional Controls

	Texas Excluded (No Income Tax)		*Control for State Offering Tax Credit*				*Control for Financial Literacy Requirements*			
Period:			*All*		*Studies > 1990*		*All*		*Studies > 1990*	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
QAI	-0.164***		-0.159**		-0.600***		-0.126**		-0.572***	
	(0.057)		(0.064)		(0.143)		(0.058)		(0.131)	
HAI		-0.212***		-0.203***		-0.870***		-0.172**		-0.735***
		(0.066)		(0.066)		(0.138)		(0.062)		(0.194)
Tax Credit			-0.035	0.015	-0.339**	-0.289*				
			(0.187)	(0.172)	(0.135)	(0.121)				
Financial Literacy Requirement							0.394	0.299	0.748***	0.332
							(0.257)	(0.252)	(0.100)	(0.210)
Year	0.016***	0.016***	0.016***	0.017***	0.045***	0.037***	0.016***	0.015***	0.038***	0.032**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.011)	(0.008)	(0.003)	(0.004)	(0.009)	(0.009)
Constant	-0.032	0.018	0.014	0.021	-1.362**	-0.885**	-0.085	-0.027	-1.412***	-0.897**
	(0.089)	(0.103)	(0.176)	(0.176)	(0.451)	(0.324)	(0.101)	(0.109)	(0.376)	(0.311)
Observations	27	27	31	31	10	10	31	31	10	10
R-squared	0.350	0.387	0.332	0.364	0.808	0.845	0.360	0.379	0.856	0.812

This appendix table presents estimates from a simplified meta-analysis, following the same as in Panel A Linear Probability Model, except we drop studies from Texas in columns 1 and 2 since this state does not have an income tax. Column 3 through 6 include an indicator control for whether the state offered a property tax deduciton/credit for state income taxes (https://www.urban.org/sites/default/files/publication/51451/1000852-Property-Tax-Credits-Offered-Through-State-Income-Tax-Systems.PDF). Columns 7 through 10 include a control for the proportion of high schools in the state with a financial literacy requirement in their curriculum (either as a standalone course or embedded – as described in Urban (2020)). Columns 5, 6, 9, and 10 restrict the sample to only studies publised after 1990. We use robust standard errors, and standard errors are reported in parentheses. The symbols ***, **, and * denote statistical significance at the 1%, 5% and 10% levels (two-tailed), respectively.