The Size and Scope of Commercial Property Tax Misvaluation*

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Abstract

We provide the first national evaluation of errors in the property tax valuation of US commercial real estate using tax roll data linked to confidential business microdata from the US Census. Misvaluation of commercial parcels is widespread across counties and firm industry, and substantially exceeds that of residential parcels: 90% of counties value commercial property less accurately than residential properties, and in the median county, aggregate commercial error is 66% larger than residential errors. These patterns are consistent with valuation challenges arising from thin markets for commercial property, a long-standing but largely untested hypothesis. In contrast, we find little evidence that assessment appeals or regulatory capture drive the national patterns. Because disparities in assessments translate directly into inequitable tax burdens, additional government capacity may be necessary to ensure equitable tax treatment.

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1. Introduction

Each year, US state and local governments collect over $650 billion by levying property taxes on real estate, a tax base currently valued at $80 trillion (U.S. Census Bureau, 2022, Federal Reserve, 2026). A distinguishing feature of the property tax is that the exact value of taxed property is often unknown because properties are sold infrequently. Consequently, local tax assessors must estimate the value to which the tax rate is applied. A decades-long empirical literature has documented systematic and persistent errors in the tax valuations of residential property, driven both by flaws in assessors' methods and by taxpayers' unequal propensities to appeal their valuations.[1]

Whereas much is now known about residential assessment accuracy, relatively little is known about assessment accuracy for commercial property, which represents nearly one-third of the total value of real estate (Federal Reserve, 2019, 2026). It is widely recognized that commercial parcels may be more difficult to value than residential parcels for several potential reasons. One reason is that commercial properties are sold relatively infrequently, providing fewer signals for use in modeling the value of unsold properties (Almy, 2022, Ghent, 2021, McMillen and Weber, 2008, Burge and Ihlanfeldt, 2005). A second potential reason is that the owners of commercial property may be better able to negotiate more favorable tax treatment—a concern raised by economists going back as far as the 19th century (Whitten, 1897) and documented in certain cases by present-day investigative journalists (Grotto and Kambhampati, 2017). Yet the nationwide magnitude and scope of errors in the valuation of commercial property remain unknown, possibly due to historical data limitations.

This paper is the first to document the prevalence and extent of assessment errors in commercial property using nationwide microdata. We augment this property data with a novel link to confidential US Census data covering the establishments that occupy commercial properties, allowing us to document correlations between valuation errors and establishment or firm characteristics. Using this dataset, we apply the conventional approach to assess valuation accuracy: we pair a commercial property's assessed valuation for a given tax year with a subsequent market transaction, ensuring that the price revealed by the market transaction does not affect the assessment.

To ensure comparability across locations and property types, we define our primary measure of assessment accuracy to be the "normalized assessment ratio" (NAR) for each property: the ratio between assessor-estimated market value and actual market value.[2] The interpretation of the NAR

[1] See Sirmans et al. (2008) for a survey of this literature.

[2] The NAR ensures comparability by adjusting for any uniform discount factor that is applied to assessment ratios, which is a common administrative practice. Specifically, it divides the realized assessment ratio by the

is intuitive—if assessments perfectly match market values, all properties would have an NAR of 1, and deviations from this benchmark are directly interpretable in percentage terms.

We find that commercial property is severely misvalued in the US. The inter-quartile range in commercial parcels is [.77, 1.53], compared to [.94, 1.34] for residential parcels. Valuation errors are substantially larger for commercial properties than residential properties in the vast majority of the country. More than 90% of the counties in our sample show more total misvaluation (relative to the size of the tax base) in commercial parcels than in residential. The median county has 66% higher misvaluation; and for the upper quartile of counties, the total error in commercial parcels is more than twice that in residential.

Our findings are consistent with the hypothesis that commercial valuation is a harder estimation problem: sales are infrequent, and sales prices capitalize property characteristics that assessors may be unable to observe. Focusing on large mistakes—NAR values more than 50% too high or too low—and comparing property classes within county, we find that at nearly every level of large-error prevalence among residential properties, the prevalence among commercial properties is higher. This within-county comparison absorbs factors common to both property classes, including assessor skill, bureaucratic capacity, and data availability, as well as (some) local economic factors such as market size — and therefore the consistently higher rate of large errors among commercial parcels points to an intrinsic difficulty in matching market values of commercial properties.

A second exercise examines heterogeneity across property characteristics. We find evidence of regressive patterns: lower-valued commercial properties exhibit systematically higher assessments. As with residential property, this pattern is particularly stark at the low end of the sales price distribution. Unlike residential property, however, we find a limited relationship between overvaluation and neighborhood demographic or economic characteristics. While extreme overvaluation is more common in tracts with the lowest share of white residents and in tracts with lowest household income, central tendencies appear to be largely flat across both distributions. Commercial assessments are slightly higher in highly productive tracts, as proxied by the prevalence of high-paying jobs.

To test whether the severe misvaluation of commercial properties is driven by firms' better ability to appeal their assessments (for example, by hiring sophisticated lawyers) or by regulatory capture, we analyze heterogeneity across firms who occupy commercial property. This analysis leverages establishment-level data from the US Census' Longitudinal Business Database and Busi-

county's realized median ratio.

ness Register, which includes location, industry, and employment counts.

Property occupied by larger firms does not seem to be more error-prone than for smaller firms. In particular, the distribution of NAR is very similar across single-establishment and multi-establishment firms. This finding is meaningful because one would expect that larger firms have more resources with which to appeal their assessment or engage in regulatory capture. In addition, one might expect that two categories of firms would be more knowledgeable about, or better positioned to navigate, an assessment appeals process: law firms and real-estate firms. Yet we find that these firms have significantly higher, rather than lower, assessment ratios on average. Similarly, valuation increases with the number of employees, another proxy for firm resources. Together, these patterns represent evidence against an explanation for severe commercial misvaluation related to appeals or corruption.

Although the central tendencies of errors are largely similar across industries, the degree of extreme error differs substantially, and these tails appear to contain meaningful information. In the set of industries showing the most extreme overvaluation, properties remain significantly overassessed relative to other industries even after the outliers are excluded. This points towards an unobservable heterogeneity challenge for assessors: while market transactions capitalize tenant-related information (see, e.g., Gupta et al., 2026, Liu et al., 2026, Brueckner and Rosenthal, 2026), establishment-level information is not typically contained in tax roll data and assessor access to supplementary information, whether through third-party datasets or owner-reporting requirements, varies across jurisdictions. Taken as a whole, our results suggest that commercial property poses a more difficult valuation problem than residential property.

Our analysis represents a significant advance in the state of knowledge on commercial property valuation. Previous studies have faced significant data limitations. In perhaps the most extensive prior academic study, Cornia and Slade (2006) find patterns of regressivity across approximately 5,000 commercial parcels in Maricopa County, Arizona. Using a model-based approach to recover the realized level of assessment, Burge and Ihlanfeldt (2005) find larger errors for commercial properties than other property classes within eight large counties in Florida, but the authors acknowledge the challenge of observing fewer than 100 sales in most of these counties.

Our study also complements the large literature on residential assessment inequality by showing that errors in the valuation of commercial property are larger, and arise from different sources. The seminal study in this literature, Paglin and Fogarty (1972), examined 400 properties within a single county. Subsequent work drew on increasingly detailed data and developed more sophis-

ticated methods (Clapp, 1990, Sirmans et al., 2008), continuing to the present day with national property-level data (Berry, 2021, Avenancio-León and Howard, 2022, Amornsiripanitch, 2020). In an interesting contrast with our results on commercial misvaluation, this literature documents that residential misvaluation often arises due to flaws in assessor methods (e.g., failure to incorporate neighborhood characteristics into hedonic models), and differences across taxpayers in propensity to appeal assessments.

2. Sources of Property Tax Variation

Within any tax jurisdiction, realized variation in property taxes can arise through multiple channels, both as a deliberate feature of a local tax system and from errors in administration. This section presents a framework that distinguishes the various channels and guides our empirical analysis.

For any given parcel i in locality j, the effective tax rate τ_i^e for a property with true market value M_i can be expressed as:

$$\tau_i^e = \frac{\tau_j(A_i - E_i)}{M_i} \quad \text{with } A_i = \alpha_j V_i \tag{1}$$

In the above, τ_j denotes the local *nominal* tax rate, which is applied to the property's assessment (A) net of any exemptions for which the owner/property may qualify (E). This equation distinguishes a property's true market value (M) from the property's assessed value (A), which is the value reflected in our data and on tax bills.[3] Importantly, some governments adjust the estimate of market valuation, V_i, with a scaling ratio α_j. Although we are not aware of any data source that reports target ratios for the over 3,000 assessing districts in the US, it is possible to infer α_j by analyzing valuations within a locality and tax year.

To further illustrate the sources of variation in tax burdens, Equation 1 can be rewritten as:

$$\tau_i^e = (\tau_j \alpha_j) \frac{V_i}{M_i} - \gamma_i \tag{2}$$

[3]Some localities deliberately use different names for V_i and A_i and reflect both on tax bills (e.g., Michigan and Florida).

This formulation separates three sources of variation in effective tax rates. The parenthetical term, $\tau_j \alpha_j$, represents *geographical* variation in the core policy choice of a local property tax system: the intended rate of proportional taxation. The second source of variation is a friction arising from *administration* of the tax system: any misalignment between estimated and actual market value (V_i and M_i). The third source of variation is *intentional* within locality dispersion created by tax exemptions ($\gamma = \tau \frac{E}{M}$). Tax exemption policies are set within jurisdictions j, but applicability and eligibility often vary at the property or owner level, as in the case of an owner-occupier exemption.

In the formulation represented in Equation 2, the term V_i/M_i always equals 1 in a perfectly administered property tax system (i.e., one in which the government's estimate of market value is always correct). We use that benchmark to define a measure of valuation accuracy, which we refer to as the "normalized assessment ratio" (NAR):

$$\widehat{NAR}_i := \frac{\hat{V}_i}{M_i} = \frac{\frac{A_i}{\hat{\alpha}_j}}{M_i}. \tag{3}$$

In our data, we are able to observe A_i and M_i. Because we do not observe local target ratios, we compute $\widehat{\alpha}_j = median_j(\frac{A_i}{M_i})$ separately within property class for each county. This property-level measure of misvaluation allows comparison not only between parcels, but also across regions and across property classes. The NAR value is straightforwardly interpretable as over- or under-valuation in percentage terms: a NAR value of 1.1 would represent 10% overvaluation. See Section A.1.1 for additional discussion of the measure's properties, including its robustness to mismeasurement of the local target ratio.

3. Data and Empirical Approach

To analyze assessment errors, we use the universe of tax and assessment records, as well as the universe of deeds and transactions records. These data were assembled by BlackKnight and originally sourced from the publicly-available administrative records of local property assessors.[4] These data offer a number of important features that are standard across assessment and transaction datasets (e.g., CoreLogic, ATTOM).

The data contain an annual panel of assessed valuations and levied taxes for each property. In addition, we observe transaction records, including sale prices, for properties sold during this period. BlackKnight assigns a unique identifier to each parcel which enables linking properties

[4]Note that BlackKnight was acquired by ICE in late 2023, and its data portfolio is currently marketed under the label Mortgage Technology Property Data. The data we use was licensed from BlackKnight prior to this acquisition.

over time in both assessment and transaction datasets. To compute the measures of assessment accuracy described in the previous section, we pair a market transaction occuring in a given year with the pre-exemption property assessment applying to that same tax year. Because of the time required for local officials for produce, validate, and disseminate assessments, this pairing means that assessed valuations are unlikely to be mechanically impacted by information contained in the subsequent sale.

To study heterogeneity in assessment errors across firm types, we substantially enrich the (relatively standard) property-level data with confidential establishment-level data on businesses from the US Census Longitudinal Business Database and the Business Register. These data allow us to observe the industry type and employee count for businesses operating on commercial property. This linkage, which has not previously been used to study property assessments, uses a string match between parcel and establishment address. See Appendix A.1 for additional detail.

Our baseline analysis sample restricts to transactions from 2017-2019. This restriction is motivated by the observation that the COVID era involved a large shock to commercial property valuations (Gupta et al., 2026). Therefore, one obvious concern is that misalignment in commercial assessment valuations post-2020 may reflect rapidly-changing market conditions rather than long-term valuation error. However, in additional analyses, we reproduce our headline estimate of total assessment error using the 2020-2023 period, and find that the overall prevalence of misvaluation is strikingly similar.

4. Results

Figure 1 compares the sample distribution of NAR values between residential and commercial parcels. In accordance with Census disclosure regulations, each panel shows a Kernel Density Estimate (KDE) computed from the underlying microdata—the reader can interpret this as a smoothed histogram of parcel-level observations. In addition to the KDE, each panel also includes a density spike corresponding to an upper pseudo-quantile of the data (with the spike height scaled to correspond to the KDE estimate). Panel A shows NAR values for residential parcels. The dispersion around a value of 1 in this figure corresponds to the known inaccuracies in residential valuation. The interquartile range is [.941, 1.337], meaning that 25% of parcels receive an assessment more than 6% below market value, and 25% receive a valuation more than 34% above market value. The right tail spike depicts the share of extremely high valuations: 2% of parcels receive an assessment more than 4.5 times higher than the market value revealed in a subsequent transaction.

The increased prevalence of error in commercial assessments is immediately evident in Panel B. There is far more density both above and below one. The interquartile range is [.77, 1.53]: one-quarter of parcels are assessed more than 23% below market value, and 25% are assessed more than 53% above market value. Additionally, for commercial assessments, there is much more density in the range between 100% and 500% overassessment. As in Panel A, the KDE is paired with a density spike capturing extreme overvaluation, which is also much more prevalent for commercial property. Relative to residential parcels, a commercial parcel is more than two-and-a-half times more likely to receive a NAR that is 500% or more of market value.

At the risk of belaboring the point: an assessed valuation of five times market value is very wrong. If a model with access to all relevant information generates such an estimate, it is highly misspecified. That said, for extreme outliers, other explanations are possible. A property's value might be impaired by some adverse event (e.g., natural disaster) that also leads to a subsequent transaction. In this case, an assessment reflecting pre-impairment value and a market transaction capitalizing the negative shock would deliver a very high assessment ratio. Data errors are also possible: misrecording the decimal in either assessment or market value could also generate an assessment in the hundreds. Although fully understanding the cause of extreme outliers requires a parcel-by-parcel investigation (which is infeasible in our study), to fully explain the increased frequency of extreme outliers in commercial properties, the driver must differentially impact commercial and residential properties, which weighs against a number of alternate explanations, including data-entry error.

Going forward, to ensure that the analysis which follows is not driven by these extreme values we focus on pseudo-medians or pseudo-quantiles rather than means whenever possible, and to facilitate any analysis which implicitly relies on means (like regressions) we use winsorized NAR values, with a cutoff in both classes corresponding to the 95th pseudo-quantile in commercial parcels.

Dispersion Within County. The nationwide distribution speaks only very generally to prevalence: while a substantial share of commercial property is incorrectly valued, this could reflect large mistakes in a small number of (relatively large) regions. In most regions of the US, counties are the administrative entity charged with producing valuations. Therefore, our next set of comparisons explores outcomes between property class within county.

Systematic assessment errors appear to be widespread across the US. In Figure 2, Panels A and B analyze assessment accuracy in the form of binned scatterplots which compare within-county dispersion in NAR for commercial versus residential properties. Panel A measures dispersion in NAR

by standard deviation. The broad majority of localities exhibit more error for commercial properties than for residential. Across the 20 quantiles of residential assessment error, only the highest shows lower commercial error than residential error, and only marginally. In every other quantile, commercial assessments are less accurate than residential assessments, even where residential error is high.[5]

Panel B of Figure 2 uses an alternate measure of error: the share of properties with highly inaccurate assessments, defined as properties with NARs outside of 0.5 to 1.5 (i.e., 50% too high or 50% too low). Again, we plot the binscatter for twenty county-level quantiles with residential outcomes on the x-axis. Mirroring the pattern shown in Panel A, for nearly any level of residential inaccuracy, a greater share of commercial properties receive a highly inaccurate assessment. Again, only in the vigintile of counties characterized by the highest level of residential errors is there a slightly smaller share of parcels receiving a highly inaccurate valuation. Panels A and B of Appendix Figure A1 show the breakout by share high and share low. The relative prevalence of commercial error is bidirectional: given a county's level of over-assessment in residential properties, that same county generally has *more* over-assessment in commercial properties; and likewise for under-assessment.

Relative Error Between Classes. Finally, we produce a single county-level statistic that quantifies how much more total error there is in commercial parcels relative to residential parcels. The distribution of this statistic offers one particularly transparent way to characterize both the prevalence (across counties) and magnitude (within county) of commercial misvaluation. Conceptually, in a given county, we compare the aggregate deviation from true market value across all commercial parcels to the same aggregate across residential parcels. Operationally, the statistic is:

$$relative\ error_{county\ j} = \frac{aggregate\ comm.\ error_j}{aggregate\ res.\ error_j} = \frac{\sum_{i \in C_j} \left(\left| \frac{A_i}{\bar{\alpha}_j} - M_i \right| \right) \left(\sum_{i \in C_j} M_i \right)^{-1}}{\sum_{i \in R_j} \left(\left| \frac{A_i}{\bar{\alpha}_j} - M_i \right| \right) \left(\sum_{i \in R_j} M_i \right)^{-1}} \quad (4)$$

where sets C_j and R_j are commercial and residential parcels respectively in county j. The numerator (denominator) is the total error in commercial (residential) parcels, measured in dollar terms as deviation from market values and normalized by the size of the segment.[6]

[5] As noted, standard deviations are computed using winsorized NAR values to limit the extent that any small set of outliers can drive results. However, given the relative prevalence of extreme valuations in commercial parcels, this also means that the greater commercial dispersion reflected in Panel A is, in fact, a lower bound.

[6] Within each fractional component, the calculation is mathematically similar to the Price-Related Differential

The benchmark value of 1 for this relative error statistic would denote equal aggregate misvaluation between residential and commercial parcels. Importantly, that benchmark does not imply anything about absolute accuracy. All localities will have at least some error: perfect valuation is a theoretical knife-edge outcome. This statistic captures how much more or less error there is in commercial parcels relative to residential.

We produce this relative error statistic for each county in the data. Panel C of Figure 2 shows the KDE estimate of the resulting distribution. The dotted red line shows the benchmark value of 1. Confirming the suggestive evidence of the binscatter, the total amount of error is larger in commercial parcels in nearly all localities. In accordance with Census disclosure requirements, this KDE is computed after trimming tails of the distribution. However, as noted in the subtitle of Panel C, we can characterize those tails (see also Table A1). Of 900 counties, only 80 have a relative error statistic that falls below 1. Nearly as many – 60 counties – have a relative error statistic that exceeds 3. The median county has a value of 1.67: an aggregate level of error that is 67% higher in commercial parcels than in residential; at the 75th percentile aggregate error is 113% higher.

While the analysis in this paper focuses on years 2017–2019, in large part to avoid anomalies driven by the Covid era, Panel C of Figure A1 in our Online Appendix shows the kernel density estimate of relative error for the 2020-2023 period. Relative misvaluation remains quite similar. The median county has 66% more error in commercial parcels; the interquartile range is 1.35–2.03; only 50 counties of 900 have less error in commercial parcels than in residential; and another 50 have a relative error statistic exceeding 300%.

These results illustrate that the misvaluation of commercial property is nationally widespread, and that the magnitude of error is typically substantially larger than for residential parcels. While data reporting issues or the (unobserved) presence of particularly unique local institutional tax policies could plausibly affect the econometric measurement of error in any single county, this figure shows a prevalence that points strongly to an overarching punchline: the accuracy of commercial assessments appears to be very substantially worse than that of residential assessments in most places. This finding represents an important contribution of this study. Previous studies of commercial assessments have hypothesized less uniformity in commercial valuations, but the limited empirical evidence has been based on single-county studies with hundreds or only a few thousand data points (Cornia and Slade, 2006, Burge and Ihlanfeldt, 2005).

measure which is commonly used by practitioners; the interpretation here is different, however.

4.1 Stylized Patterns of Commercial Misvaluation

Figure 3 analyzes errors along margins which are known to be consequential in residential assessments: the price level of the property, neighborhood demographics, and neighborhood incomes. Each panel plots 5 different pseudo-quantiles within a given set of NARs: psq10, psq25, psq50, psq75, and psq90. The reader should think of these as quantiles of the data, with an injection of noise as required by Census disclosure regulations.[7] Each set of pseudo-quantiles is produced for a bin within a binscatter split.

Panel A splits observations according to the level of transaction price with the lowest bin containing properties transacting below $75,000, and the highest bin contains properties transacting over $5M (the note to Fig 3 contains the cutpoints for each bin). Panel B assigns observations to within-county value deciles. In both panels A and B, patterns of assessment regressivity are evident. As on the residential side, extreme regressivity is most prominent as a feature of the lowest valued properties (Berry, 2021, Amornsiripanitch, 2020), although a regressive trend is also evident across middle- and higher-valued properties.

Interestingly, comparison of Panel A and B suggests that regressivity at the lowest-valued end of the distribution is larger when the value split is within county. This suggests that assessment models generate *relative* misvaluation: that is, while valuations for low-valued properties in absolute terms are substantially wrong (Panel A), accuracy is also worse for the set of properties at the bottom end of the county-level distribution, regardless of whether those properties are higher-valued in absolute terms.

Panels C and D explore inaccuracies related to neighborhood characteristics (note the different y-axis scale). Panel C plots pseudo-quantiles by 5 equal-support bins of tract-level non-white share.[8] Relative to documented patterns of racial disparities in residential assessments (Avenancio-León and Howard, 2022), there is reduced evidence of this pattern for commercial properties. Large overassessments – as captured by the 90th and 75th pseudo-quantile – are more extreme in tracts with the highest share of minority residents. But across the bottom four quintiles – which comprise the vast majority of neighborhoods – there is no obvious slope of assessments at the various pseudo-quantiles shown.

Panel D explores errors by tract-level median household income. Again, patterns appear

[7] Pseudo quantiles are produced by averaging the 11 values closest to the observation that corresponds to the mathematical quantile.

[8] Patterns of residential sorting in the US mean that there are many more tracts in the lowest quintile (0-20% share) than in upper quintiles.

muted relative to documented findings in residential assessments (Berry, 2021, Avenancio-León and Howard, 2022). Extreme over-assessment (psq90) is larger for the bottom two quintiles (household income below 25k and 50k respectively). At the 75th pseudo-quantile, however, assessments appear to be only slightly increasing as median household income shrinks. And in the poorest neighborhoods, under-assessment (psq25 and psq10) is also slightly increased.

Panel A of Table 1 explores additional neighborhood-level correlates of high valuations, using measures that proxy for the overall level of economic activity. The dependent variable is the assessment ratio – winsorized at approximately 95% to ensure that outliers don't drive regression fit. Valuations appear to be higher in areas of lower density. This would be consistent with larger errors in markets with fewer sales, which is a standard concern among assessors. Interestingly, valuations also appear higher in areas that have more jobs and more high-paying jobs: measures that can often proxy for central business districts and are not typically indicative of extremely thin markets.

In total, Figure 3 suggests that errors in commercial properties exhibit regressive patterns similar to those found in residential assessments, but show less correlation with other neighborhood demographic factors. This suggests that a large amount of commercial variation remains unexplained. In the next section, we explore correlation between valuation errors and characteristics of the firms that occupy these commercial properties.

4.2 Which Firms Bear the Incidence of Assessment Misvaluation?

Studies of residential assessment often examine how valuation errors are distributed across homeowners or groups of homeowners. For commercial property, the analogous question concerns the firms that occupy these parcels. In both cases, however, identifying who bears the cost of an assessment error is complicated by the distinction between ownership and occupancy. The tax assessment attaches to the real estate parcel, and is therefore a direct obligation of the property owner. Most single-family homes in the US—the focus of much of the residential assessment literature—are owner-occupied, but for rental properties the tax may pass through to tenants. Studies of residential pass-through offer mixed evidence, with estimates ranging from minimal to near-full (Carroll and Yinger, 1994, Schwegman and Yinger, 2020, Löffler and Siegloch, 2021, Baker, 2025).

As with residential property, the owner of a commercial property may or may not occupy the parcel. Some common commercial contracts, such as triple-net leases, explicitly pass the property tax along to the tenant. Empirical studies also find evidence of commercial property tax pass-

through, though as in the residential literature, estimates of magnitude vary (Wheaton, 1984, McDonald, 1993, Rolheiser, 2019). This section examines how the incidence of assessment errors varies with the characteristics of the firms occupying commercial parcels. None of our analysis relies on a particular estimate of pass-through, but the exercise implicitly assumes that at least some of the economic incidence of the property tax shifts onto tenant establishments.

Figure 4 shows splits along several margins. In panel A, on top, we show a box-whisker plot by NAICS two-digit industry. For any industry where the 90th pseudo-quantile exceeds our winsorized value, the dark green "W" denotes that the 90th psq exceeds that cutoff. This is the case for nearly all industries: the only exception is manufacturing (NAICS 31-33). At the 75th pseudo-quartile substantial variation across industries is evident, with several falling below two (valuation equal to double the market price) and several others stretching towards 3. At the pseudo-median, values by industry are all fairly similar.

As previously discussed, extreme outliers could reflect noise, such as data errors or a single county with a badly misspecified model, or they could reflect parcel features that are genuinely difficult to value. If outliers are purely noise, industries with very high outlying values should look like other industries once the outliers are removed. We test this by defining an indicator equal to one for parcels in industries whose unwinsorized 90th-percentile NAR exceeds 25, and zero otherwise.[9] To ensure that any relationship is not mechanical, we drop the parcels used to define the indicator and estimate:

$$NAR_i^{Winz} = \alpha + \beta 1\{Extreme\ Error\ Industry_i\} + \epsilon_i \tag{5}$$

where NAR^W is winsorized NAR. Column 1 of Table 1 shows the result. Even among the remaining, more accurately valued parcels, assessment ratios in high-outlier industries are 3.5% higher on average. This is inconsistent with a 'pure noise' interpretation. Instead, it suggests that some latent factor (or factors) correlated with industry leads valuations to be higher throughout the distribution, not just at the extremes.

Work on residential assessment has also illustrated the role of the appeals process (Weber and McMillen, 2010, McMillen, 2013, Plummer, 2014, Doerner and Ihlanfeldt, 2015, Nathan et al., 2020, Avenancio-León and Howard, 2022, Holz et al., 2025). The scale of potential savings as well as political economy factors would tend to suggest that appeals may be even more important

[9]These high-outlier industries are Wholesale Trade (42), Transportation and Warehousing (48-49), Information (51), Finance and Insurance (52), Real Estate and Rental (53), Professional, Scientific and Technical Services (54), Educational Services (61), and Arts, Entertainment, and Recreation (71).

for commercial parcels. A priori, one might expect two sets of firms to be more knowledgeable about appeals or more successful in navigating the process: law firms, or firms in real-estate sub-industries. In Panel B of Figure 4, we test for differences in valuation errors between these three groupings of firms. Pseudo medians are quite similar, but there is *more* dispersion on the high side for both law and RE firms than the grouping of all others. Column 2 of Table 1 confirms this in regression format: the categorical indicators for both Law and Real Estate firms are positive and statistically significant (though only at 10% for the latter group).

Finally, recognizing that firm size may change incentives, monitoring, or average lease terms, we compare single-establishment firms ("SU") to multi-establishment ("MU") firms. There is no evidence of difference, either in Panel C of Figure 4 or in the regression counterpart (Col 3 of Table 1). In columns (4–5) of Table 1, we find that valuations do appear to increase in the number of employees.

4.3 Implications for Inequality in Taxation

Substantial misvaluation implies that the realized tax burden on an individual commercial parcel can differ markedly from its intended burden. A natural follow-up question is whether these parcel-level errors also aggregate into a wedge in tax burdens between property classes, and whether the data suggest that localities intend to tax the two classes differently in the first place. We compare county-level median tax rates for commercial and residential property, and to disentangle intent from error, we pay particular attention to states without split-roll taxation, where state law requires both classes to be assessed and taxed identically.[10] The remainder of this section briefly summarizes the results of this analysis. See Appendix Section A.2 for an expanded discussion.

We find that within counties, nominal tax rates (taxes levied relative to assessed value) are similar for commercial and residential property, with commercial rates slightly higher (Appendix Figure A2). In non-split-roll states, because nominal rates do not depend on market value, this gap is not attributable to misvaluation, but rather likely reflects exemption policy, consistent with the widespread use of residential homestead exemptions (Ihlanfeldt and Rodgers, 2022, McMillen and Singh, 2026). In the full national sample, which includes states free to tax the classes differently by letting τ_j vary by class, we find little evidence that localities commonly choose to do so.

Effective tax rates (taxes levied relative to market value) exhibit a similar pattern (Appendix Figure A2). In non-split-roll states, the comparison between nominal and effective rates isolates the

[10] We identify ten such states using the Lincoln Institute of Land Policy's Significant Features of the Property Tax database: CT, DE, IN, ME, NV, NJ, NH, OH, VT, and WA.

contribution of assessment error, and so similarity in this sample indicates that misvaluation does little to shift median class-level tax burdens. Effective rates in the full national sample additionally capture deliberate differences in tax burden introduced by selecting different α_j by class; here too, we find little evidence that a majority of localities choose to do so.

Pooling all parcels, the nationwide median effective rate is 1.54% for commercial property and 1.16% for residential property (Table A1). This raw comparison will reflect the exemption differences discussed above, but likely also a relative concentration of commercial parcels in higher-tax jurisdictions. Taken together, the within-county comparisons in this section suggest that most localities do not set sharply different rates by property class, and that misvaluation, while large and widespread, is symmetric enough that it largely washes out of class-level medians.

5. Discussion: Why Are Errors So Large?

Our study raises the question of why assessments of commercial properties are so inaccurate. A priori, two general hypotheses appear regularly in policy discussions and surface also in the limited academic work. The first recognizes that commercial property is relatively illiquid, meaning few transactions occurring within a smaller set of parcels to begin with (McMillen and Weber, 2008, Ghent, 2021, Almy, 2022). As a straightforward consequence, assessors have fewer statistical inputs with which to build a valuation model, leading to reduced accuracy. This class of explanations for commercial inaccuracy extends to regularly observed features of county valuation approaches: faced with a limited ability to identify comparable properties – whether through high-touch selection or mass valuation technique (some form of hedonic regression) – counties may turn to a capitalization approach, which is much more common for commercial parcels than for residential (IAAO, 2025). While this may seem to offer the advantage of needing to estimate a smaller number of parameters, valuations then become quite sensitive to both cap rate and income flows.

The second set of explanations holds that owners of commercial property have stronger incentives and greater ability to influence their assessments, for example by hiring politically-connected intermediaries (see, e.g., Grotto and Kambhampati 2017) or by pursuing sophisticated legal strategies generally unavailable to homeowners.[11] In jurisdictions with large concentrations of commercial property, this influence could extend to regulatory capture, systematically shifting the tax burden from commercial to residential parcels.

Although investigative journalists have convincingly documented that commercial property own-

[11] For an example of the latter, see the "dark store theory" as described in, e.g., Fanning et al. (2018)

ers do work to lower their assessments, our results suggest that owner influence over the assessment process is not the first-order explanation for the national gap between commercial and residential accuracy. We find that properties occupied by larger firms and firms specializing in law or real estate do not tend to receive substantially more favorable valuations. Moreover, systematic manipulation by commercial property owners would push assessments down, yet the national distribution of commercial errors is right-skewed, with more overvaluation than undervaluation. Likewise, if owners were systematically succeeding, commercial property would bear lower effective rates within county, especially in states without split-roll taxation; instead we find that commercial rates are similar or slightly higher than residential rates. Our findings are most consistent with commercial property posing a more difficult valuation problem. In the substantial majority of counties, commercial assessments are less uniform than residential assessments, and this within-county comparison absorbs factors common to both property classes, such as assessor skill, effort, record-keeping, and bureaucratic capacity.

One potential non-economic contributor to the large variation we document warrants mention: the quality of the data itself may be worse for commercial parcels than for residential. There are reasons to believe this might be the case. Commercial transactions typically have a broader range of transaction structures than residential parcels, and if a county lacks fidelity in recording information like partial-interest or deeds-type flags, then these structures may produce inaccurate signals of true market value for a transacted parcel. It is worth emphasizing that this is not merely an issue for the econometrician—as noted by Ihlanfeldt (2004), states quite commonly use ex-post ratio studies (which closely parallel our construction of NAR values) as an input to oversight processes that discipline local errors and allocate funding to restore compliance with state statues. Since the data used in this study are the same data that assessors have access to, any difference in data quality between residential and commercial properties is meaningful in and of itself, because it implies a disruption in the ability of oversight bodies to diagnose and address assessment inequities.

In total, our study shows that the prevailing approach to valuing commercial property is neither adequate to meet both legal standards for identical treatment of commercial and residential property (as in non-split-roll states) nor consistent with internationally-established standards for assessment uniformity (IAAO, 2013). The severe deficiencies we document suggest that additional expansion of government capacity may be necessary in order to ensure equitable tax treatment.

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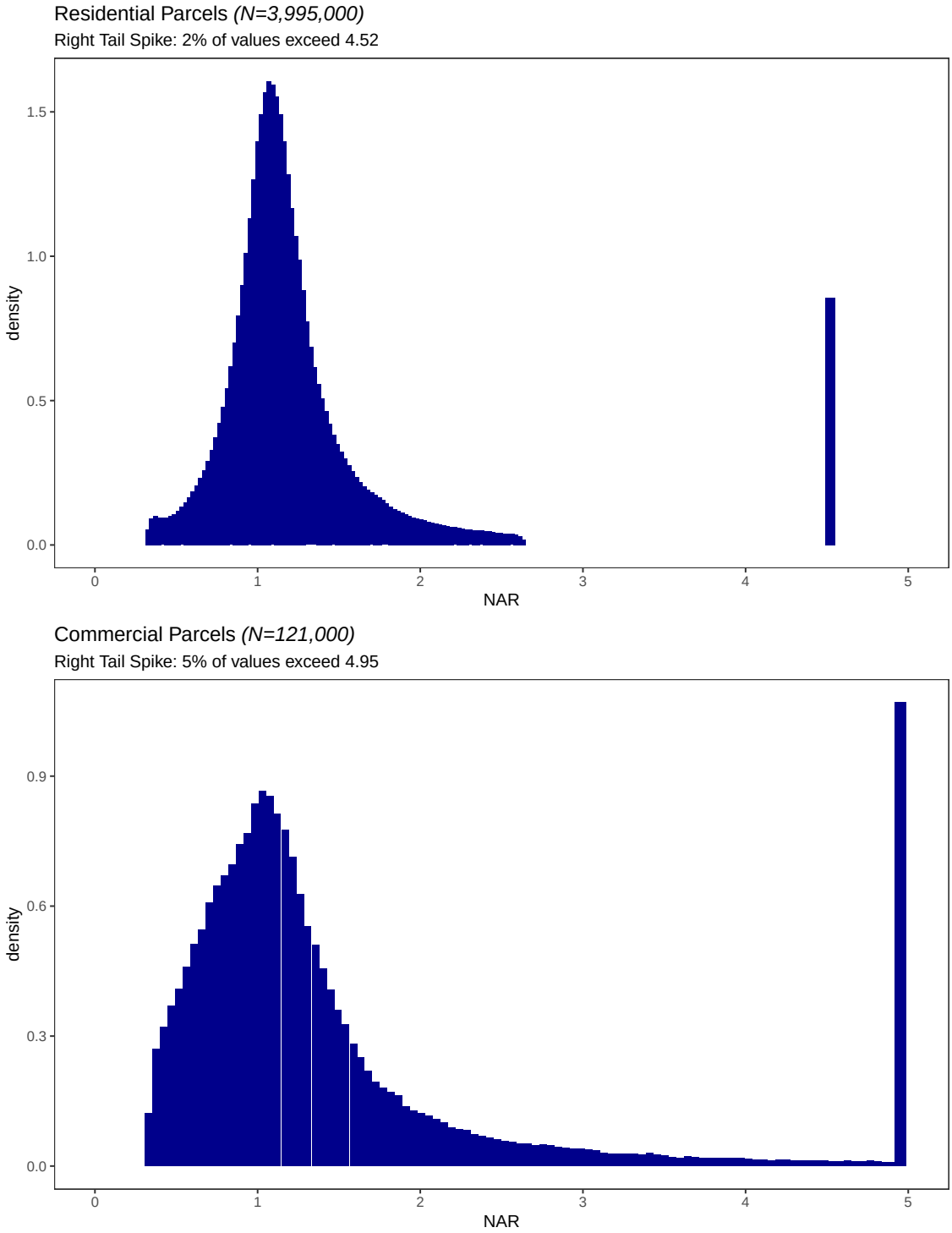
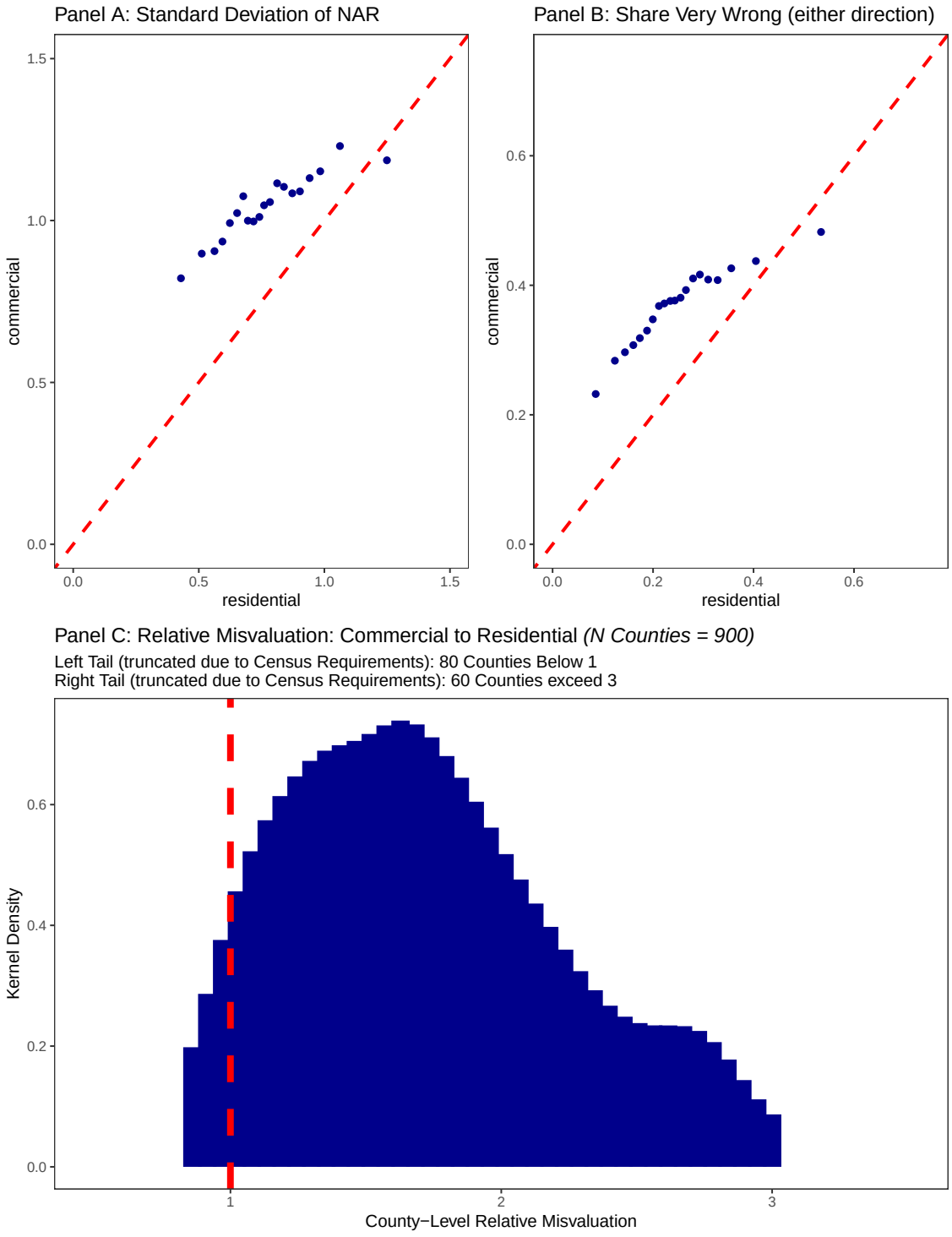
Figure 1: Kernel Density Estimate of NAR, Microdata



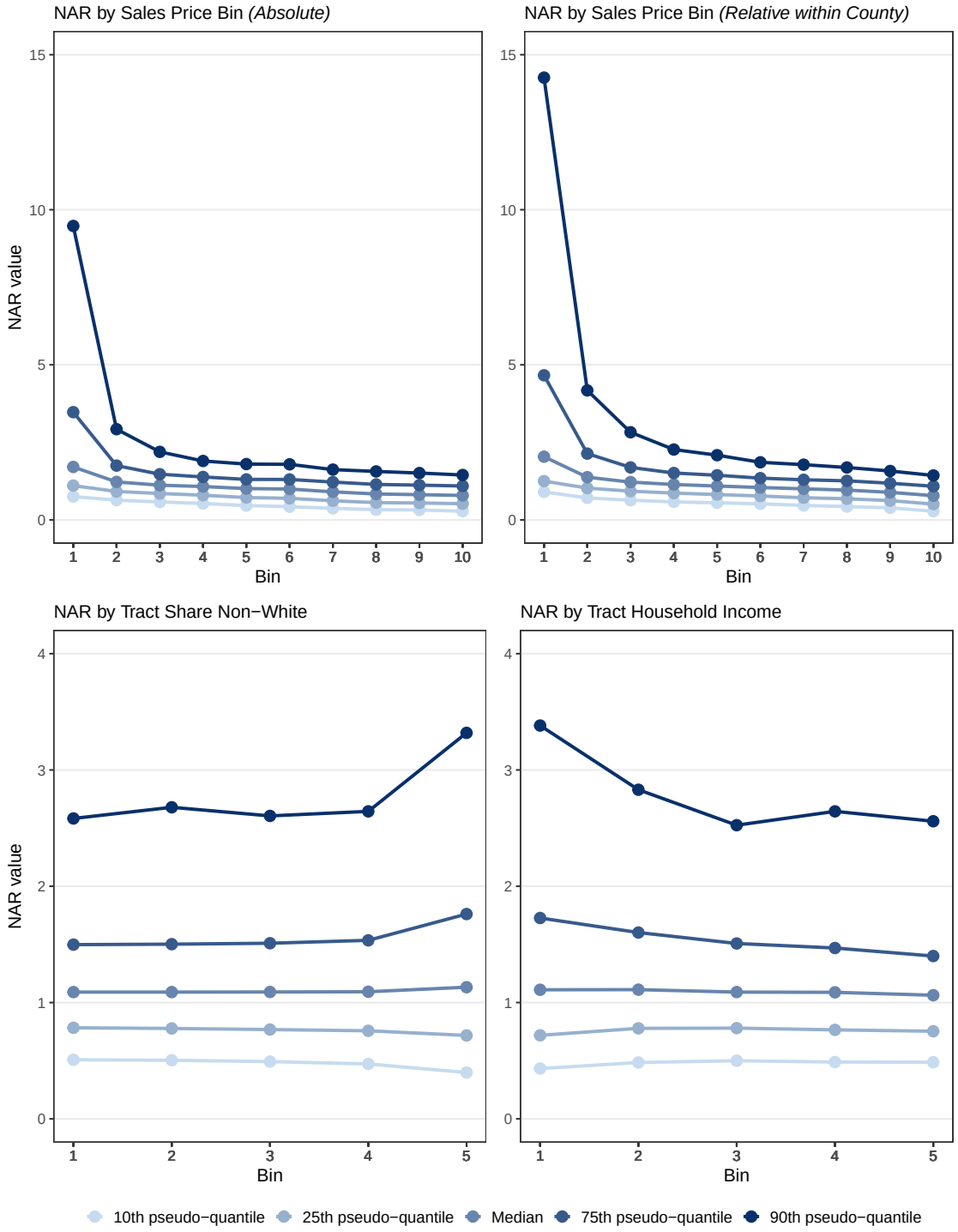
Notes: This figure plots a kernel density estimate (KDE) of the distribution of the normalized assessment ratio (NAR) for residential (top panel) and commercial (bottom panel) parcels transacting in 2017–2019. In accordance with Census disclosure requirements, each KDE is estimated after trimming tails of the microdata. The spike at the right of each panel shows the share of parcels in the untrimmed microdata with NAR above the indicated upper pseudo-quantile, with height scaled to the density estimate. Parcel counts are rounded.

Figure 2: Much Larger Misvaluation In Commercial Properties



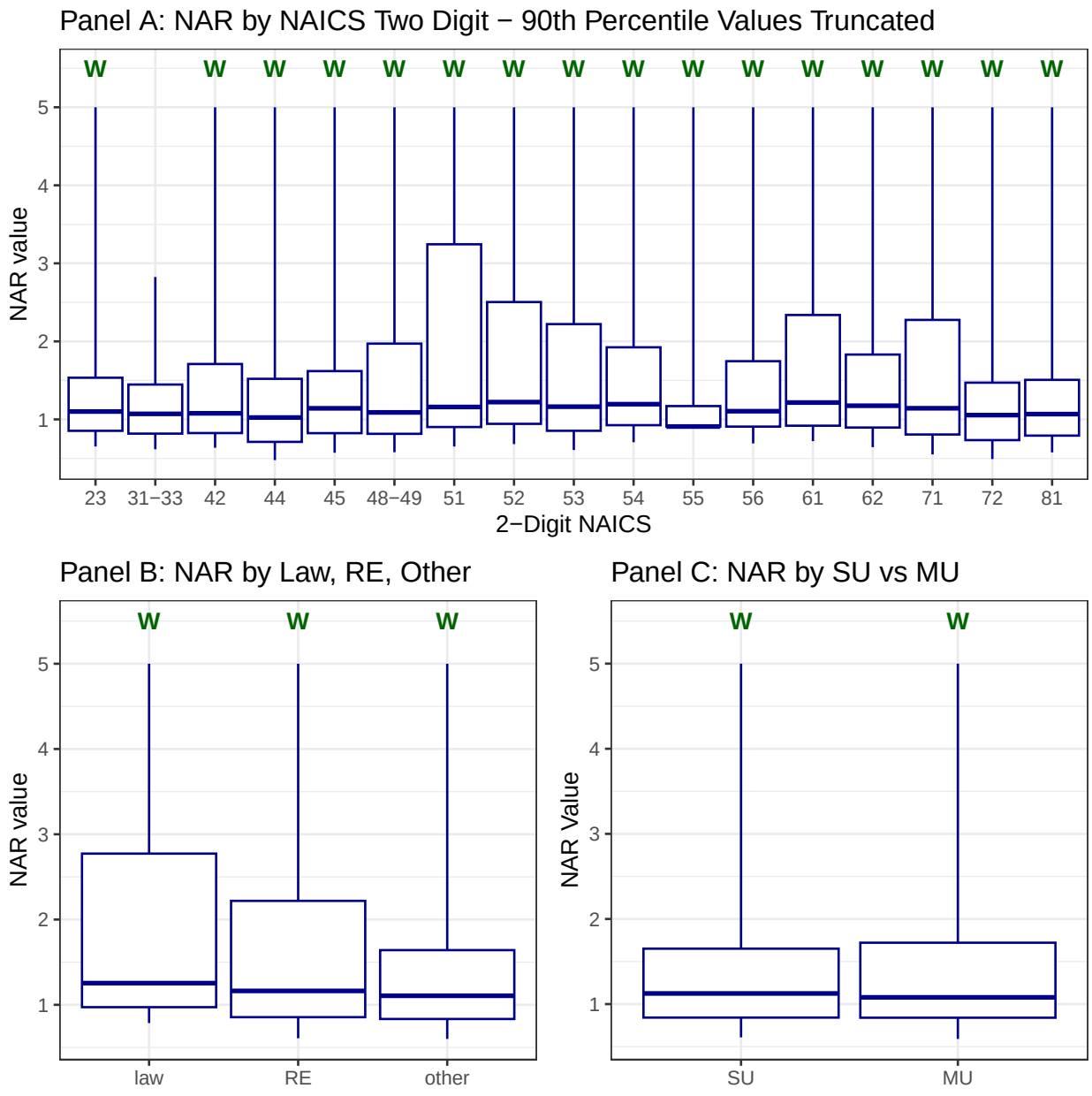
Notes: Panels A and B are binned scatterplots comparing within-county assessment error for commercial parcels (vertical axis) and residential parcels (horizontal axis). Counties are grouped into 20 equal-sized bins based on the residential measure. Panel A measures error as the standard deviation of winsorized NAR. Panel B measures error as the share of parcels with NAR below 0.5 or above 1.5. The dashed line is the 45-degree line. Panel C plots the kernel density estimate of the county-level relative misvaluation statistic (Equation 4). The dashed line at 1 marks equal error in both classes. Due to Census requirements, tails are truncated in the KDE estimate. The number of (untrimmed) counties above and below benchmark values are reported in the panel subtitle.

Figure 3: Misvaluation by Property Value and Tract Characteristics



Notes: Each panel plots the 10th, 25th, 50th, 75th, and 90th pseudo-quantiles of commercial NAR within bins. Pseudo-quantiles are the average of the 11 observations closest to the corresponding quantile, as required by Census disclosure rules. Panel A bins parcels by transaction price with upper cutpoints (in thousands) of: 75, 150, 300, 500, 750, 1000, 1500, 2500, 5000, top-coded. Panel B bins parcels by within-county deciles of transaction price. Panel C bins parcels by tract non-white population share in 20-percentage-point intervals. Panel D bins parcels by tract median household income in $25,000 intervals (top bin: above $100k). Vertical-axis scales differ between the top and bottom panels.

Figure 4: Misvaluation by Tenant-Firm Characteristics



Notes: This figure shows box-whisker plots of commercial NAR by characteristics of the establishment occupying the parcel. Establishment detail comes from the US Census Longitudinal Business Database and Business Register, and is linked to BlackKnight parcel by address. Boxes span the 25th to 75th pseudo-quantiles, and the horizontal line marks the pseudo-median; whiskers extend to the 10th and 90th pseudo-quantiles. A green "W" indicates that the 90th pseudo-quantile exceeds the winsorization cutoff of approximately 5. Panel A groups parcels by two-digit NAICS industry. Panel B compares legal services firms (Law), real estate firms (RE), and all other firms. Panel C compares single-establishment (SU) and multi-establishment (MU) firms.

Table 1: Additional Parcel-Level Correlates of Valuation Errors

Panel A: Geographic Factors

	(1)	(2)	(3)	(4)	(5)	(6)
Tract - Density	-0.012***					
	(0.003)					
Population Density Decile		0.000				
		(0.015)				
Tract - High Paying Jobs (000s)			0.001***			
			(0.000)			
High Paying Jobs Decile				0.027*		
				(0.015)		
Tract - Jobs (000s)					0.001***	
					(0.000)	
Jobs Decile						0.021
						(0.015)
County FE	Y	Y	Y	Y	Y	Y
Observations	20500	20500	20500	20500	20500	20500
Adjusted R-squared	0.321	0.310	0.319	0.310	0.319	0.310

Panel B: Firm, Establishment, and Industry Factors

	(1)	(2)	(3)	(4)	(5)
High Outlier-NAICS	0.035***				
	(0.013)				
Legal Industry NAICS		0.362***			
		(0.086)			
Real Estate NAICS		0.194*			
		(0.108)			
Multi-Establishment			0.049		
			(0.060)		
Employee Bin (Continuous)				0.020*	
				(0.012)	
Number of Employees					0.000*
					(0.000)
County FE	Y	Y	Y	Y	Y
Observations	18500	20500	20500	20500	20500
Adjusted R-squared	0.214	0.312	0.310	0.310	0.310

Notes: This table reports OLS regressions of winsorized commercial NAR on parcel-level characteristics. Panel A uses tract-level measures of economic activity. Columns 2, 4, and 6 use the parcel's decile assignment as a continuous independent variable. Panel B uses characteristics of the occupying establishment. In column (1), the regressor is an indicator for industries whose unwinsorized 90th-percentile NAR exceeds 25; properties with these extreme values are then excluded from the regression sample. Columns (4) and (5) measure establishment size by number of employees, using a continuous bin-assignment variable and number of employees, respectively. Observation counts are rounded in accordance with Census disclosure requirements. Standard errors, clustered by county, are in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

A. Online Appendix

A.1 Data: BlackKnight and Census Establishment Records

Our property data come from BlackKnight (currently marketed as Mortgage Technology Property Data) which assembles assessment, tax, and deed records originally sourced from the publicly available administrative records of local property assessors and recorders. These data share the main features of other commonly used assessment and transaction microdatasets (e.g., CoreLogic, ATTOM), and span the near-universe of parcels in the U.S.

We classify parcels as commercial or residential based on assessor land use codes reported in BlackKnight. We impose four notable filters on commercial properties. First, we exclude multifamily properties from the commercial (and also the residential) samples. Prior studies have variously classified these as primarily residential or as a subset of commercial property. As some of our analyses rest on comparing commercial and residential outcomes, it is undesirable to have a large subset of parcels with ambiguous classification. Second, we exclude parcels with agricultural land use codes, as agricultural land sometimes receives explicitly different tax treatment in state legislative codes. Third, we exclude parcels assigned a vacancy code. Finally, within the set of commercial land use codes, we remove any parcel assigned a subcode that corresponds to municipal infrastructure: e.g., airports, highways, road, or bus terminals. For residential land-use codes, we restrict to single-family homes and townhomes–excluding large multifamily for the reason outlined.

We construct our analysis sample by starting with transactions listed in the deeds data and imposing multiple filters designed to remove transactions that will not provide an accurate signal of market price. In addition to removing any observation with a missing sales price, we draw upon multiple BlackKnight indicators to remove transactions that are not occurring at arms length for full consideration. We exclude partial-interest and intra-family transactions, along with sales recorded at nominal prices. We exclude any transaction denoted as a "multiple-APN" transaction, to avoid using a transaction price that reflects the transfer of real property beyond the focal parcel. Finally, we keep only transactions which specifically note that the sales price is either explicitly recorded on the relevant transfer document or has been backed out from transfer tax information.

For each observation that passes these filters, we then match the parcel-transaction observation to the assessment records, which are a panel dataset at the property-by-tax-year level. We associate each market transaction occurring in year t with the property assessment applied for tax year t. As noted in the main text, the timing with which local officials produce and disseminate tax valuations

means that an assessment applied to year t is unlikely to be mechanically impacted by a transaction occurring in that same year. Assessed values in BlackKnight are reported prior to any exemptions. The data contain an indicator for whether a parcel receives one of several exemption types but do not record the size of the reduction. We drop fully tax-exempt parcels, which typically have no reported taxes levied.

Finally, we drop any county in which we have fewer than 25 commercial transactions or fewer than 100 residential transactions. Our baseline sample uses data from 2017 to 2019, and contains approximately 121,000 commercial properties and 3,995,000 residential properties across 900 counties.

A.1.1 NAR Construction

Following equation 3, we construct $\widehat{NAR}_{ij} = \frac{A_{ij}}{\widehat{\alpha}_j} M_i^{-1}$ for each property-transaction observation. As noted, A and M come directly from the data. To enable comparisons across locations, we recover $\hat{V}$, the tax official's estimate of market value at a one-to-one valuation ratio by adjusting each A_i with an empirical estimate of the local scaling ratio: $\hat{\alpha_j} = median_j(A_i/M_i)$. Because α_j can vary by property class, we compute this median separately for commercial and residential parcels within each locality.

An appealing feature of this formulation of NAR is that even if the empirical measure of $\widehat{\alpha}_j$ differs from the true unobserved target ratio, this measurement error will not lead us to find any additional dispersion in valuations within a locality j. That is, our estimates of the total amount of assessment error in a locality are robust to mismeasurement of the target ratio. WLOG, the data yield $\widehat{\alpha}_j = \beta\alpha_j$. If $\beta \neq 1$, this would suggest a gap between the intended effective rate of taxation and τ_{ij}^e, the rate actually achieved by tax officials, but as shown in Equation 3, all empirically measured NAR values would still be a constant value (i.e., β^{-1} rather than 1), and this in turn would reflect zero dispersion in valuations.

This robustness entails a cost, however: by construction, our analysis will not capture any distortion that arises from a uniform level shift in assessments. To illustrate with a concrete example: consider a locality that intends to target .7 for both commercial and residential properties, but instead realizes a perfectly uniform assessment ratio of .8 for all commercial parcels while hitting the target exactly on residential properties. Our analysis would interpret the absence of dispersion in commercial parcels as reflecting completely accurate assessments. However, relative to the (unobserved) intention to place equal tax burden on both classes, valuation error would

lead commercial parcels in this locality to be overtaxed. While analysis of NAR values would not capture this, a comparison of effective rates ($tax\ levied_i/M_i$) would uncover differences between classes. This is one motivation for the county-level analysis of effective rates in Section 4.3.

The largest potential threat to interpreting NAR values is that a locality would set different α_j targets within property class. In this case, $median_j(A_i/M_i)$ would recover a value close to one of the targets, causing all properties subject to the other target to look erroneously valued. Although we have seen nothing to suggest that practice is common, it may exist in some jurisdictions. However, to the extent that this form of measurement error exists, it will affect only the single county that implements such a policy. Our primary results show consistent patterns across 900 counties, suggesting that they are not driven by idiosyncratic local practices of this kind. In addition, our conclusions are largely unaffected when we restrict our sample to non-split roll states, for which such a difference is particularly unlikely given the legal standard of equal treatment.

A.1.2 Census Establishment Data

To study heterogeneity in assessment errors across firm types, we link the property data to confidential establishment-level data from the US Census Bureau's Longitudinal Business Database (LBD) and Business Register (BR). To our knowledge, this linkage has not previously been used to study property assessment. We link parcels to establishments by matching the parcel address in BlackKnight to the establishment's physical (rather than mailing) address in the BR.

Before matching, we standardize addresses in both sources, for example by normalizing case and punctuation and standardizing street suffixes and directionals. We then require an exact match on the full address, including street number, street name, city, state, and ZIP code. This criterion is quite strict: 123 E Main ST South would not match 123 E Main ST, or 123 Main ST South, or 123 E Main Ave South, even within the same city and zip code. Matching is further complicated by the fact that BlackKnight associates each commercial parcel with a single address, whereas large commercial structures often have multiple entrances, or multiple street numbers, within the same building.

Because our analysis focuses on central tendencies across firm characteristics, we do not use fuzzy string matching or geocoding. Although these methods could raise the match rate, they would also introduce false matches, and we judge that the resulting measurement error would outweigh the gain in sample size. The overall match rate therefore reflects the stringency of the procedure: of approximately 121,000 commercial parcels, we obtain approximately 20,500 parcel-

establishment matches.[12] Although the matched sample is considerably smaller, requiring exact agreement on every component of the address ensures that match quality is high.

A.2 County Level Analysis of Nominal and Effective Rates

This appendix presents the full analysis summarized in Section 4.3. We compare nominal and effective rates within county. In drawing these comparisons, we place a special focus on states without split-roll taxation—states in which commercial and residential property are treated identically by law. States with split roll taxation can deliberately assess and/or tax commercial and residential property at different levels. To identify states without split-roll taxation, we use the Lincoln Institute of Land Policy's Significant Features of the Property Tax database. Using the notation from Equation 2, we classify states as those without split-roll taxation in which legislative codes: (i) constrain α_j and τ_j to be equivalent between classes, and (ii) do not impose any caps on assessment growth that could generate wedges in effective tax rates. There are 10 such states: CT, DE, IN, ME, NV, NJ, NH, OH, VT, and WA.

We find that on average, local governments tax commercial and residential property at similar levels. Panel A of Figure A2 presents, for non-split-roll states, a binned scatterplot that compares the median *nominal rate* (i.e., $t_j = \frac{tax\ levied_i}{A_i}$) for residential properties and for commercial properties within each county. Because the nominal rate does not depend on true market value, any deviation from the 45-degree line must come from exemption policy.[13] Panel A shows that most points lie slightly above the 45-degree line, meaning that commercial properties bear a slightly higher tax rate. This pattern remains largely unchanged in the national sample (Figure A2, Panel B), where states have the additional flexibility of allowing τ_j to vary by class.

The pattern of higher commercial nominal rates is consistent with the general observation that tax exemptions for residential properties (especially owner-occupied properties) are widespread across states (Ihlanfeldt and Rodgers, 2022, McMillen and Singh, 2026). Exemptions are typically flat reductions of X_j that can be deducted from A_i before applying τ_j to produce a billed amount. Because BlackKnight reports assessment values prior to exemptions (which enables our NAR construction), a property receiving an exemption will appear to have a lower nominal rate to the econometrician: *tax levied* is reduced, and A is unaffected. Therefore, to the extent that exemptions are more prevalent for residential properties, or that the exemption cap of X_{res} tends to be larger relative to market values than any X_{comm}, this would reduce residential rates relative

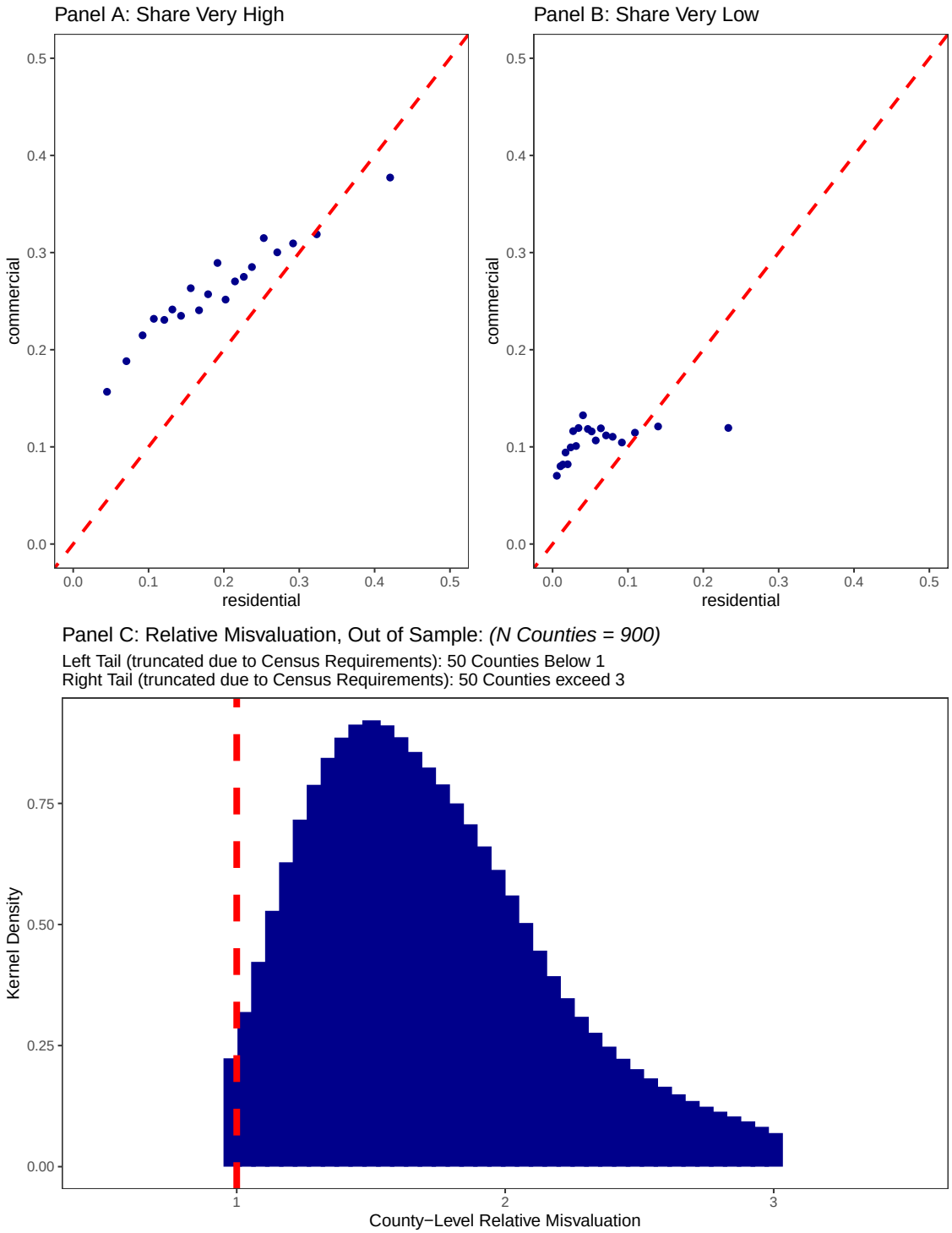
[12] All counts derived from Census data are rounded in accordance with Census Bureau disclosure avoidance rules.
[13] Or, potentially, from local non-compliance of the state codes constraining equal treatment between classes.

to commercial, leading to exactly the pattern shown in Panel A of Figure A2.

Our data also allow us to analyze differences in the effective rate of taxation ($t_j^e = \frac{tax\ levied_i}{M_i}$). This generates a valuable comparison for non-split roll states: in Panel A, deviations from the 45-degree line are attributable to exemptions, while in Panel C, deviations can be driven by exemptions or assessment error. The difference, therefore, is attributable to misvaluation.

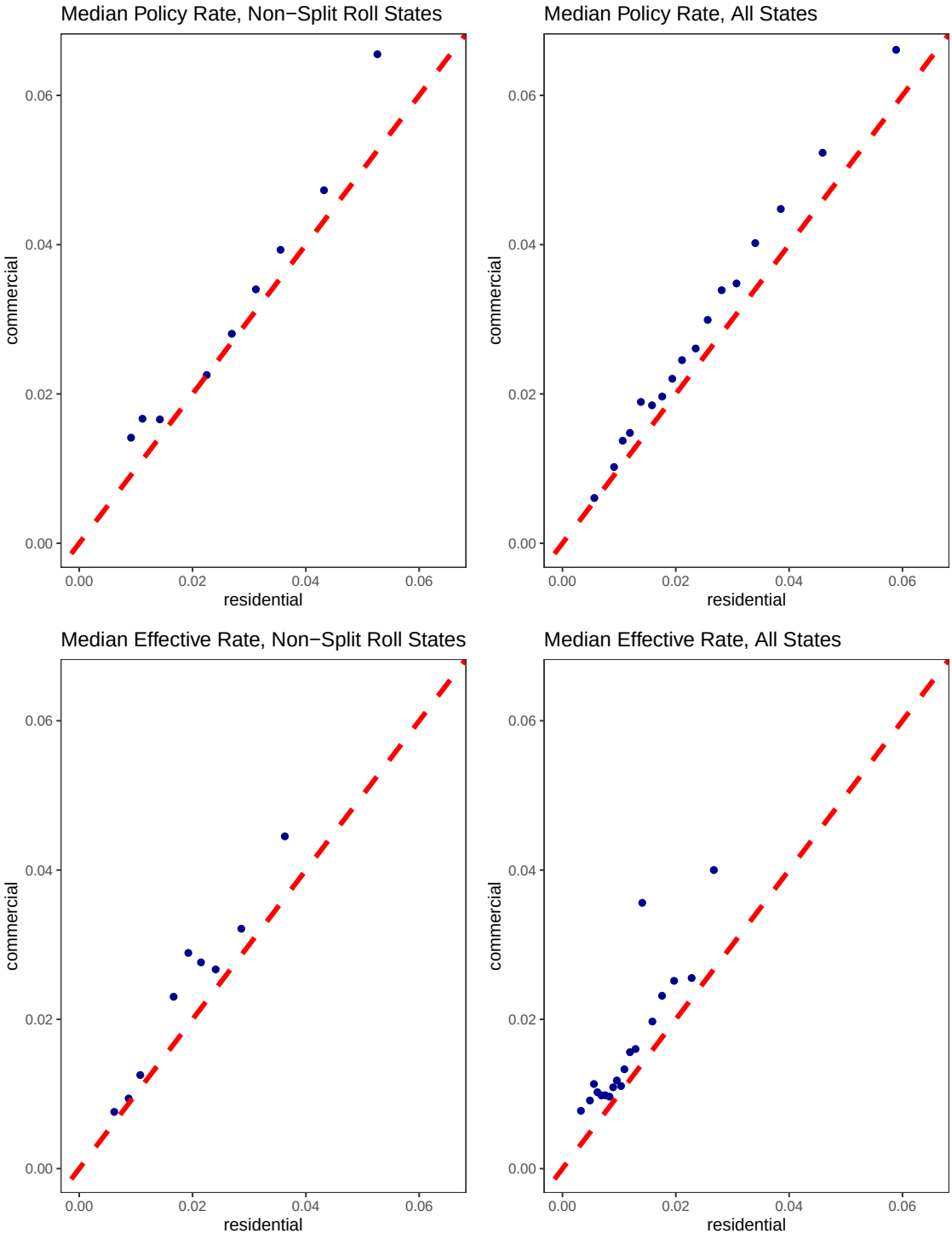
As with nominal rates, we find that effective rates of taxation are also similar between commercial and residential properties. While misvaluation can have very large impact on individual parcels, Panel C suggests that the overall impact of commercial assessment error on county-median effective rates is limited. The binscattered commercial rates in Panel C lie only slightly higher above the 45-degree line than in Panel A. Panel D considers effective rates for all states. This adds another degree of freedom that could potentially generate rate differences by class: a deliberate policy decision to impose different tax burden on commercial relative to residential by choosing class-specific α_j. For most of the sample, there is no evidence to support this being a common choice. Two points in the binned scatterplot are consistent with a deliberate choice to tax commercial parcels more heavily; however in this set of counties, our analysis is not sufficient to distinguish between assessment error and intention.

Figure A1: Breakout of Share High and Share Low; Relative Error Out-of-Sample



Notes: Panels A and B are binned scatterplots, constructed as in Figure 2, showing the share of parcels with NAR above 1.5 (Panel A) and below 0.5 (Panel B) for commercial (vertical axis) and residential (horizontal axis) parcels. The dashed line is the 45-degree line. Panel C replicates Panel C of Figure 2 using transactions from 2020–2023. Due to Census requirements, tails are truncated in the KDE estimate. The number of (untrimmed) counties above and below benchmark values are reported in the panel subtitle.

Figure A2: Summary Comparisons of Tax Rates



Notes: Each panel is a binned scatterplot of county-level median property tax rates for commercial parcels (vertical axis) against residential parcels (horizontal axis). The nominal rate (Panels A and B) is tax levied divided by assessed value; the effective rate (Panels C and D) is tax levied divided by sale price. Panels A and C restrict to the 10 states without split-roll taxation (CT, DE, IN, ME, NV, NJ, NH, OH, VT, and WA), identified using the Lincoln Institute of Land Policy's Significant Features of the Property Tax database. Panels B and D include all states. The dashed line is the 45-degree line.

Table A1: Summary Statistics

Panel A: Microdata: NARs

	N - Parcels	N - Counties	Pseudo-Median	Unwinsorized Mean	Winsorized Mean[a]	SD	Share Winsorized*
Commercial Parcels	121,000	900	1.094	5.280	1.396	1.105	5.0%
Residential Parcels	3,995,000	900	1.114	1.537	1.258	0.771	2.0%

[a] For commercial parcels, the 95th pseudo-quantile value is 4.95; commercial and residential parcels are winsorized at approximately this value. The exact winsorization cutoff is unreported due to Census disclosure protocols.

Panel B: Microdata: Tax Rates

	N - Parcels	N - Counties	Pseudo-Median Effective Rate
Commercial	121,000	900	1.54%
Residential	3,995,000	900	1.16%

Panel C: County Level: Relative Error Comparisons

					Less Error in Commercial		More than 3x Error in Commercial	
	N - Counties	Pseudo-Median	25th Pseudo-Quantile	75th Pseudo-Quantile	Number	Share	Number	Share
Core Sample (2017–2019)	900	1.666	1.295	2.132	80	8.9%	60	6.7%
Out-of-Sample (2020–2023)	900	1.653	1.349	2.025	50	6.0%	50	6.0%

Notes: Panel A reports summary statistics for the NAR of parcels transacting in 2017–2019. Winsorized statistics cap NAR at approximately the 95th pseudo-quantile of the commercial distribution (4.95); the exact cutoff is withheld in accordance with Census disclosure requirements. Panel B reports the pseudo-median effective tax rate (tax levied divided by sale price). Panel C summarizes the county-level relative misvaluation statistic (Equation 4) for the core sample and for transactions from 2020–2023. The final columns report the number and share of counties with less aggregate error in commercial than in residential parcels (statistic below 1) and with more than three times as much (statistic above 3). Parcel and county counts are rounded in accordance with Census disclosure requirements.