Exempt, Evade, Enforce: Unpacking Property Tax Dynamics in the Short-Term Rental Market

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September 26, 2026

Abstract

How does third-party reporting shape property tax compliance? Local governments depend on property taxes, yet compliance relies on self-reported property use with little verification. Short-term rental (STR) hosts exploit this gap by managing rental activity to retain owner-occupied exemptions. Using STR data from 2015–2024 in Florida, I apply a bunching estimator at the 30-day exemption threshold and exploit an enforcement shock to detect tax evasion. Bunching is negligible before the shock but grows substantially after, with hosts cutting bookings by more than 16 nights. Results show how lenient third-party reporting generates meaningful compliance gains in decentralized tax systems.

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1 Introduction

Property taxes are the primary funding source for local governments, making their vulnerability to evasion, fraud, and misreporting especially problematic for local public finance.[1] This vulnerability originates from two intertwined challenges. First, property tax compliance depends on self-reported use of the property. Second, many jurisdictions lack the capacity to verify this information. Short-term rentals (STRs) amplify this vulnerability, as hosts can misreport or strategically manage rental activity to retain large owner-occupied exemptions. In this environment, third-party information reporting has the potential to play a decisive role in the behavior of STR hosts and the resulting tax revenue.

In this paper, I investigate how third-party reporting influences the compliance and evasion of property taxes in the short-term rental (STR) market. To examine this dynamic, I focus on property tax exemptions granted to owner-occupied homes rented fewer than a specified number of days, known as rental-day thresholds. I develop a conceptual framework in which hosts choose rental days to maximize profits in the presence of a tax notch, where crossing the threshold triggers a discrete increase in tax liability. In this context, optimal booking behavior reflects a tradeoff between marginal rental revenue and the expected tax penalty, with responses shaped by actual and perceived enforcement. These thresholds create sharp incentives for hosts to adjust rental activity to retain the exemption and provide a natural setting to study the impact of information reporting on taxpayer behavior.

To measure hosts' behavioral responses, I exploit the rental-day thresholds tied to tax exemptions using a bunching estimator and STR data from 2015–2024 in Florida (FL). I also estimate tax evasion by comparing booking behavior before and after the introduction of Airbnb's Voluntary Collection Agreements (VCAs) in 2015. A form of third-party reporting, the VCAs require Airbnb to remit sales and accommodation taxes to the appropriate tax jurisdictions on behalf of STR hosts, increasing third-party reporting to local governments. I use this variation as an enforcement shock to test whether increased reporting reduces evasion and induces hosts to adjust rental activity to remain eligible for tax exemptions.

I find that STR hosts respond sharply to both the increase in tax liability at the rental-day threshold and the increase in perceived audit probability from the VCAs. Before the Airbnb VCAs, STR hosts exhibit minimal to no bunching at the rental-day threshold. However, after the VCAs, Florida STR hosts cluster at the threshold, with approximately 4,600 additional STRs bunching at the cutoff. While only about 2–3 percent of STR hosts change their

[1] Property taxes are a fundamental funding source for local governments in the U.S., particularly counties (Yushkov 2024). Many local governments rely on property taxes to fund public services and public schools. On average, the property tax provides 30% of revenue for local governments and raised $581 billion in 2021 (Lincoln Institute 2024).

behavior, the average response of those hosts is to reduce bookings by 16 nights. These behavioral changes imply fiscal impacts of roughly $13.8 million over the sample period. As the VCAs are a relatively weak form of enforcement that improve tax remittance without directly notifying assessors of hosts exceeding rental-day thresholds, these findings highlight how even lenient reporting can generate sizable compliance gains and fiscal returns for local governments while reducing tax evasion and Airbnb bookings.

This paper contributes to the literature on tax compliance and information reporting by providing new evidence from local property tax systems. A large body of work shows that third-party reporting substantially reduces evasion in income and business taxation by limiting opportunities for misreporting (Kleven et al. 2011, Persson 2019). In contrast, less is known about the role of reporting in property taxation, where compliance often depends on self-reported property use and enforcement is decentralized. Existing causal evidence on property taxes focuses primarily on salience and enforcement intensity—such as reminders, lien threats, and social norms (Perez-Truglia & Troiano 2018, Hallsworth et al. 2017)—rather than on information reporting itself.

This paper also relates to the literature on STR regulation and taxation. Prior work studies how STR bans and taxes affect housing markets and platform activity (Koster et al. 2021, Bei & Celata 2023, Garz & Schneider 2023, Li et al. 2022), while a broader literature documents the externalities and regulatory challenges associated with STR growth. The study most closely related to this paper is Bibler et al. (2021), which shows that Airbnb's Voluntary Collection Agreements (VCAs) increase STR prices, reduce bookings, and affect entry and exit through improved tax enforcement. Nevertheless, this study and other literature in the STR space do not address property taxes, a key source of local public funding. I fill this gap by providing causal evidence on how third-party reporting shapes property-tax compliance and rental-day evasion in the STR market. By linking rental-day thresholds to enforcement, I identify a new margin of evasion in the STR market and provide causal evidence on how information reporting shapes property-tax compliance.

The next section provides background on the short-term vacation rental (STR) market and Florida property taxes. Sections 3 and 4 present the theoretical framework and the empirical methodology used for the analysis, respectively. After, I discuss the data in Section 5 and the results in Section 6. Section 7 positions the findings in the policy landscape, and Section 8 concludes.

2 Background

2.1 third-party Reporting on STRs: Airbnb Voluntary Collection Agreements

Short-term rentals (STRs) occupy a unique and often ambiguous regulatory space since they combine residential and commercial characteristics. Generally, STRs refer to residential properties rented to guests for stays of less than a month. These short stays are typically booked and rented through a third-party platform, such as Airbnb, Vacation Rental by Owner (VRBO), and Booking.com.[2] Due to their short-term stays, STRs are governed by local lodging or occupancy tax laws rather than long-term lease regulations.

Local governments have instituted various regulations on STRs to measure rental activity and dampen its negative effects. Some of these regulations include rental permitting requirements, additional taxes, zoning restrictions, and annual rental day limits.[3] In terms of community impacts, informal tourist accommodations like STRs impact the operation of zoning, traffic flow, parking, waste services, noise, and residential privacy. Furthermore, cities must consider how to provide sufficient water, safety, fire, and emergency services with fluctuating residency numbers and in times of overcrowding (Palombo 2015). Other concerns for STRs entry in a city include effects on the existing hotel market and a reduction in the long-term rental supply (Li et al. 2022, Gurran & Phibbs 2017*a*).[4]

In response to the new STR regulations, Airbnb has since enacted voluntary regulations on their platform that increase reporting to local governments. One of these regulations is the Voluntary Collection Agreements (VCAs). VCAs are agreements between Airbnb and

[2]Airbnb held roughly 43% of the U.S. short-term rental market in 2025, followed by VRBO at 21% and Booking.com at 8%. Together Airbnb and VRBO represent about two-thirds of U.S. listings (Rental Scale Up 2025). Globally, these three platforms control more than 70% of short-term rental revenue (Yahoo Finance 2025).

[3]For example, to protect its long-term rental supply, New York City has banned rentals of entire homes for less than 20 days. San Francisco mandates that hosts reside in their rental home for a minimum of 275 days annually. Similarly, Portland restricts the percentage of apartments in a building that can have STR permits and requires hosts to occupy their homes at least 270 days per year (Gurran & Phibbs 2017*a*).

[4]Previous research on STRs has focused on their disruption of existing firms, such as hotels and resorts (Dogru et al. 2019, Dogru, Hanks, Mody, Suess & Sirakaya-Turk 2020, Zervas et al. 2015, Yeung & Coyle 2016, Dogru, Hanks, Ozdemir, Kizildag, Ampountolas & Demirer 2020) and the housing and rental market (Barron et al. 2021, Koster et al. 2021, Liang et al. 2022, Franco & Santos 2021, Todd et al. 2022, Valentin 2021). This literature documents both benefits—such as enabling homeowners to remain in high-cost areas (Guttentag 2015) and increasing visitor spending (Oskam & Boswijk 2016)—and substantial costs, including neighborhood disruption (Gurran & Phibbs 2017*b*) and rising rents (Lee 2016). STR growth also strains public services (Ke et al. 2021, van Holm & Monaghan 2021, Reinhard & Roth 2024) and raises administrative costs for local governments (Office of the City Treasurer 2021, Arora et al. 2025). These fiscal pressures underscore why understanding enforcement and compliance rates for the property-tax base is essential for local public finance.

the local tax authority for Airbnb to collect sales and accommodation taxes directly on the platform and remit them to the proper authority. Prior to the VCAs, the STR hosts were solely responsible for collecting and remitting all taxes, such as accommodation, sales, and tourism taxes, to the appropriate levels of government (city, county, and/or state). Between 2014 and 2021, Airbnb established over 275 VCAs with state, county, and city governments to avoid stricter regulations like complete STR bans (Bibler et al. 2021).[5]

To detect property tax evasion in the STR market, this paper exploits the implementation of the Airbnb VCA with Florida on December 1, 2015.[6] I use the VCAs as a natural enforcement shock as well as a proxy for increased STR regulation and oversight by local governments. Although property taxes were not collected through Airbnb VCAs, entering into a VCA with Airbnb signals that the local government is increasing scrutiny and regulatory activity around STRs. This perceived increase in enforcement and visibility into rental activity extends the enforcement shock of VCAs to property tax compliance.

2.2 Property Tax Evasion through Fraudulent Owner-Occupied Exemptions

In detecting property tax evasion in the STR market, I focus on the evasion from fraudulent homestead exemption claims in Florida. The homestead exemption lowers a homeowner's annual property tax bill if their house is owner-occupied and the owner's principal residence. Homestead exemption is limited to one home per owner, so secondary homes and vacation houses do not qualify for homestead exemption.[7] These eligibility requirements also motivate the sample restrictions used throughout the paper. Specifically, the empirical analysis focuses on entire-home rentals managed by hosts with a single listing, who are the STR operators most likely to qualify for owner-occupied or homestead exemptions.

2.2.1 Property Taxes in Florida

Local governments in Florida levy residential property taxes based on a home's assessed value, the applicable district millage rates, and certain assessment limitations required by the Florida constitution. Due to limitations on the growth of assessed values, a home's

[5]Even with the implementation of VCAs, Airbnb does alert hosts that they may be responsible for remitting additional taxes based on their locality and tax jurisdiction. See https://www.airbnb.com/help/article/1036.

[6]According to Bibler et al. (2021), VCAs were generally announced only a few weeks prior to the effective date, limiting the scope for anticipatory behavioral responses.

[7]States usually consider a principal residence as the address listed on an owner's tax return, driver's license, and vehicle registration.

assessed value often does not equal the market value, except in a year of sale.[8] The total property tax liability equals the assessed value multiplied by the millage rate. More details on the calculation of Florida property taxes are available in Appendix F.

The Homestead Exemption provides substantial tax relief to Florida homeowners who claim a residential property as their permanent and primary residence. This exemption provides three distinct layers of property tax relief. First, $25,000 of property value is exempt from all property taxes, including school and non-school mills. Second, the homestead status exempts the portion of the property's value between $50,000 to $75,000 from non-school taxes.[9] These two tax provisions fall under Amendment 1 of the Florida Constitution, which passed in 2008.

The third tax savings that the homestead exemption provides is from the *Save Our Homes* (SOH) constitutional amendment from 1992. The SOH amendment restricts the annual growth in assessed value for a homestead at 3% or the rate of inflation, whichever is lower. Amendment 1 from 2008 expanded the SOH benefit to also allow homeowners to transfer up to $500,000 of accrued SOH savings to a new homestead within the state (Lincoln Institute of Land Policy and George Washington Institute of Public Policy 2024). Collectively, these provisions significantly reduce property taxes for eligible homeowners and accumulate those savings over time. The average savings from the homestead exemption in Florida on a $400,000 home can exceed $3,400 annually depending on the property's accrued SOH savings.[10]

Under Florida law, a property owner who rents their home for more than 30 days per year for two consecutive years is considered to have abandoned their homestead, thereby forfeiting the exemption.[11] A Florida Supreme Court case in April 2023 affirmed that even a homeowner renting part of their homestead is not entitled to any of the homestead exemption benefits (Lincoln Institute of Land Policy and George Washington Institute of Public Policy 2024). If the homestead exemption is lost, then the property is reassessed at full market value for the following tax year before any assessment caps are applied (Campo et al. 2024).

Florida law imposes substantial penalties for improper receipt of the homestead exemp-

[8] Amendment 2 of the Florida Constitution in 2018 made permanent a temporary provision that restricted growth in the assessed value of residential property to 10% for non-school taxes. Therefore, since the temporary provision began in 2008, assessed values have been capped each year until the assessed value equals market value or the home is sold.

[9] This $25,000 of the homestead's value is subject to property taxes that fund public schools.

[10] See Appendix G for a calculation of the average property tax savings from the homestead exemption in Florida.

[11] See Fla. Stat. §196.061(1). The 30-day threshold must be exceeded in two consecutive years; exceeding it in only one year does not result in the loss of homestead status. Reinstating the exemption is subject to additional filing and residency requirements, increasing the cost of losing homestead status.

tion.[12] Knowingly providing false information is a first-degree misdemeanor punishable by up to one year in jail or a $5,000 fine. Homeowners found to have improperly claimed the exemption within the prior ten years are liable for the unpaid taxes, a 50% penalty, 15% annual interest, and a recorded tax lien (Saint Lucie County Property Appraiser 2025, Sarasota County Property Appraiser 2025).

2.2.2 Opportunities for Fraud

Since homestead exemptions are granted and maintained until the home changes ownership, homeowners have an opportunity to engage in exemption fraud and tax evasion. A homeowner could claim the homestead exemption when they first move into the home and provide the proper documentation. As long as the assessor is not notified of a change in status or ownership, no annual verification or further documentation is needed. Later, the homeowner could list their home on a peer-to-peer accommodation platform, such as Airbnb and VRBO. Then, the homeowner could continue claiming the homestead exemption and receive the property tax benefits of a full-time, owner-occupied property regardless of how many days their home is rented.

3 Conceptual Framework

This section presents a conceptual framework for how a homeowner decides how many nights to rent their property as a STR in the presence of a property tax discontinuity. Property tax exemption thresholds, like the 30-day limit in Florida, introduce a notch in the property tax schedule. Crossing the threshold leads to a discrete jump in the homeowner's tax liability.

The following framework focuses on how a salient and enforceable threshold alters the intensive margin of STR behavior. Let homeowner i own a property with market value h_i. The homeowner rents out the property for N_i nights per year at a nightly price p and generates gross rental revenue $p \cdot N_i$. The homeowner faces operational costs $c_i(h_i, N_i)$, which depend on both the home's value and the number of rental nights. I assume costs increase with the home's value and number of rental nights. Accordingly, the first derivative of the cost function with respect to h_i and N_i are $\frac{\partial c}{\partial h_i} > 0$ and $\frac{\partial c}{\partial N_i} > 0$, respectively. The homeowner also faces a tax penalty $\Delta\tau(h_i, m_n)$ if they exceed the rental threshold N^*. This tax penalty is a function of the home's value and the applicable millage rate and has positive first derivatives as well ($\frac{\partial \Delta\tau c}{\partial h_i} > 0$ and $\frac{\partial \Delta\tau}{\partial m} > 0$).

[12] See Florida Statute 196.131(2) and 196.161(1).

Given this setup, homeowners will choose the N_i that maximizes their profit function. The profit function is:

$$\pi_i = p \cdot N_i - c_i(h_i, N_i) - \mathbb{1}_{N_i > N^*}[\Delta\tau(h_i, m_n)] \tag{1}$$

The indicator function $\mathbb{1}_{N_i > N^*}$ captures the presence of the tax notch. If the homeowner rents more than the threshold N^*, they face an immediate increase in property tax liability. Assuming the homeowner chooses N_i, their annual number of rental days, to maximize profits, the first-order condition (FOC) for an interior solution is:

$$\frac{\partial \pi_i}{\partial N_i} = p - \frac{\partial c_i(h_i, N_i)}{\partial N_i} \tag{2}$$

This implies that, in the absence of the notch, the homeowner rents until the marginal revenue equals marginal cost: $p = MC$.

A graphical representation of this profit-maximizing decision is depicted in Figure 1. The solid line up to N^* represents the payoff from renting when the homeowner retains the property tax exemption. The dashed line extending beyond N^* represents the counterfactual payoff schedule in the absence of the tax penalty. When the homeowner crosses the threshold, the tax penalty shifts the payoff schedule downward by Δtax. This creates a dominated region to the right of N^*: within this range, the homeowner receives a lower payoff from renting above the threshold than from locating at the threshold.

The indifference curves in Figure 1 illustrate how homeowners with different preferred levels of rental activity respond to the notch. A homeowner with relatively low demand for rental days, represented by IC_A, locates at $N_A = N^*$ and does not cross the threshold. A homeowner with a higher preferred number of rental days, represented by IC_C, chooses N_C even after accounting for the tax penalty because the additional rental revenue is large enough to offset the discrete tax cost. In contrast, a homeowner whose preferred rental activity would place them in the dominated region has an incentive to reduce rental days and bunch at N^* rather than pay the tax penalty. IC'_B represents this homeowner's counterfactual choice in the absence of the notch, where the homeowner would choose to rent N'_B nights, a rental level above N^*. Once the tax penalty is imposed, the feasible payoff schedule shifts downward above the threshold, and the homeowner instead locates at the kink, represented by IC_B. Homeowner B will choose to rent N^* nights, where the indifference curve IC_B intersects with the budget constraint at the notch. Thus, the notch creates a range of homeowners who would otherwise rent more than N^* and less than N_D but instead choose to locate at or just below the threshold.

This optimization framework implies that observed bunching around the threshold reflects

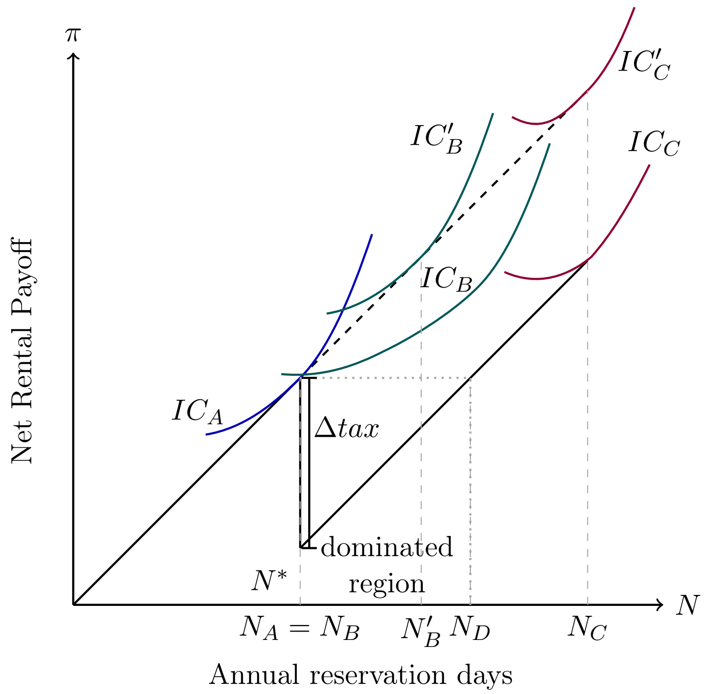


Figure 1: Bunching Incentives at Annual Rental Day Threshold

Notes: This figure illustrates the homeowner's choice of annual reservation days, N, in the presence of a property tax notch at N^*. The vertical axis measures net rental payoff, π. The solid line shows the feasible payoff schedule, while the dashed line shows the counterfactual payoff schedule absent the tax penalty. Crossing N^* triggers a discrete increase in property tax liability, Δtax, shifting the payoff schedule downward above the threshold. The dominated region is the range of rental days above N^* where the homeowner is better off bunching at the threshold than renting additional days and paying the tax penalty. The indifference curves IC_A, IC_B, IC'_B, IC_C, and IC'_C illustrate heterogeneity in homeowners' preferred rental intensity. The primed curves show counterfactual choices absent the tax penalty, while the unprimed curves show choices under the post-tax feasible payoff schedule. Homeowners whose unconstrained choices fall in the dominated region bunch at N^*, while homeowners with sufficiently high desired rental activity continue renting beyond the threshold despite the tax cost.

rational decision-making in environments with credible enforcement and high tax salience. For some homeowners, the discrete increase in taxes will dominate the marginal profit from additional rental nights. They will optimally choose to stop renting just below the threshold N^*. Others, whose rental revenue or cost structure makes it worthwhile, will rent beyond the threshold and forgo the exemption. Without credible enforcement, homeowners maximize profits by surpassing the rental day limit and underreporting rental activity.

If hosts behave according to this optimization logic, I should observe an excess mass of STR listings clustered just below the exemption limit. Hosts who prefer to retain the exemption will manipulate their annual rental days to remain below the cutoff, producing visible clustering as in Figure 2. A stronger enforcement regime and third-party reporting should strengthen incentives to remain below the rental day limit. Therefore, I anticipate a sharper bunching response and more pronounced clustering from STR hosts in the post-VCA period.

The degree of bunching provides a direct measure of hosts' responsiveness to the property tax notch. Using the excess mass at the threshold, I recover a reduced form elasticity of rental supply with respect to the property tax, as in the bunching literature. This elasticity captures how strongly hosts adjust their rental behavior in the presence of a property tax notch. Comparing elasticities before and after the VCAs reveals the sensitivity of hosts to third-party reporting in the property-tax system.

Although the above framework focuses on intensive-margin decisions, the rental-day threshold also has implications for the extensive margin decision of whether to participate in the market. Some homeowners may opt out of the STR market entirely due to the complexity of the thresholds or the potential jump in tax liability. Others may find that the tax-induced shift in their cost curve makes even short-term renting unprofitable. While this paper does not measure extensive-margin responses, these mechanisms provide a conceptual basis for understanding why such thresholds deter entry or encourage exit from the market.

4 Empirical Methodology

I employ a bunching estimator to measure the behavioral response of STR hosts to changing property tax rates in Florida. Similar to the approaches of Kleven & Waseem (2013) and Kopczuk & Munroe (2015), I exploit notches in the homestead exemption annual rental day limit to detect behavioral responses to property tax rates. I compare the actual distribution of annual rental nights (with the notch) to a counterfactual distribution (without the notch). I apply this bunching estimator to two periods: prior to the Airbnb VCA and after the

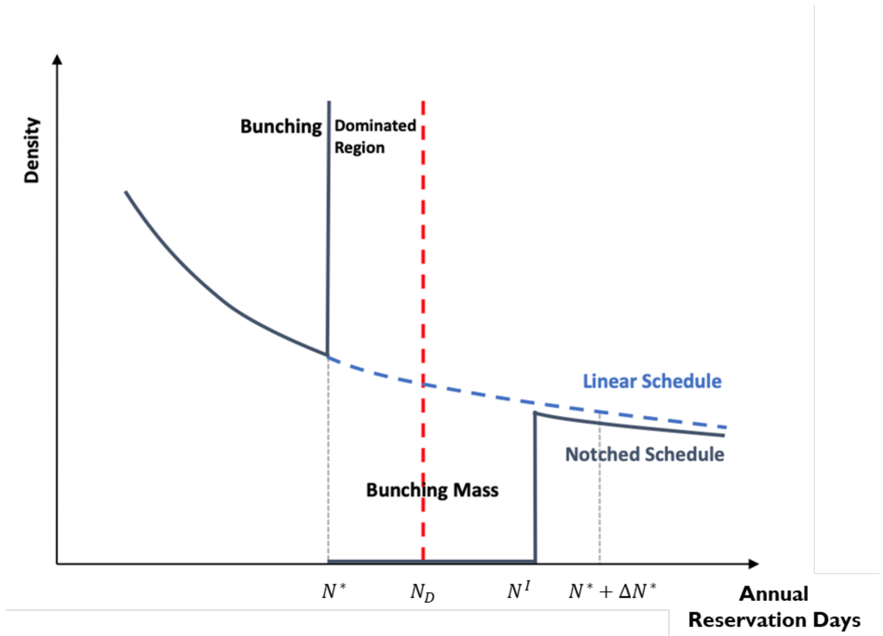


Figure 2: Bunching Conceptual Figure

Notes: This figure depicts perfect bunching behavior near a notched property tax threshold. STR hosts who would otherwise rent beyond N^* instead bunch just below the threshold due to a discrete jump in property tax liability. The shaded region represents the dominated region where no optimizing host chooses to locate. This figure is adapted from Figure 3b in Mavrokonstantis (2022).

VCA. By comparing the bunching results of the two periods which had different third-party reporting, I provide evidence of tax evasion in the STR market prior to the reporting increase.

Given the goals of this paper, a bunching estimator has several advantages over other causal inference methods to measure excess bunching and tax avoidance. The conceptual framework predicts that hosts facing a discrete increase in tax liability at the rental-day threshold will optimally locate just below the cutoff, generating excess mass in the distribution of rental days. The bunching approach directly tests this prediction and recovers both the number of responding agents and the magnitude of their behavioral adjustment. Another advantage of the bunching approach is that it exploits cross-sectional variation around the threshold to estimate how hosts respond to discrete changes in tax liability. Alternative approaches, such as difference-in-differences, would capture average changes in rental activity but would not identify the intensive-margin responses around the threshold that are central to this analysis.

4.1 Main Bunching Estimation

The bunching estimator measures the excess mass of STR properties that bunch at the rental day limit. At this 30-day notch, the change in property tax rates occur. Because of the large jump in property taxes owed from crossing the rental day threshold, the tax schedule has a notch, as opposed to a kink.

First, I plot the distribution of annual STR days based on the actual data with the following equation:

$$c_j = \sum_{i=0}^{p} \beta_i (N_j)^i + \sum_{i=N_L}^{N_U} \gamma_i \mathbb{1}[N_j = i] + \sum_{r \in R} \rho_r \mathbb{1}[\frac{N_j}{r} \in \mathbb{N}] + \sum_{k \in K} \theta_k \mathbb{1}[N_j \in K \wedge N_j \notin [N_L, N_U]] + \epsilon_j \tag{3}$$

The STRs are put into j bins based on their annual rental days N, and each bin is a range of annual rental days. The number of STR observations in each bin is c_j. The first term in the equation, $\sum_{i=0}^{p} \beta_i (N_j)^i$, is the polynomial of order p with coefficients β_i that fits the binned data. The binned data are the counts of STR properties that fall into each bin. N_j is the maximum N in bin j of width δ.

The second term in the equation contains the bunching dummies that capture excess mass at the threshold. These dummy variables, γ_i, measure how much of the density is concentrated at the exemption limit relative to the rest of the distribution. N_L and N_U are the lower and upper bounds of the bunching region, respectively. They represent the area of the distribution that is impacted by the rental day limit. I estimate N_L and N_U by looking for visual changes in the rental day distribution.

The third and fourth terms in the estimation equation account for natural bunching patterns that are unrelated to the property tax threshold. The third summation term controls for round-number bunching through the coefficients ρ_r, where the set R includes round-number bunch points. The fourth summation term adjusts for any remaining fixed bunching points in the distribution through the set K, which contains prominent spikes outside the bunching region that are unrelated to the rental-day threshold. Including these terms improves the accuracy of the bunching estimator by isolating behavioral responses to the property tax threshold from other predictable, non-policy-related patterns in STR booking behavior. Based on the raw distribution of annual rental days in Florida, I include a fixed point control at 14 days and no round-number bunch points. The final term, ϵ_j, is the error term.[13]

Next, I estimate $\hat{c_j}$, the counterfactual binned count of STR properties. The counterfactual bin count is estimated as follows:

$$\hat{c_j} = \sum_{i=0}^{p} \beta_i (N_j)^i + \sum_{r \in R} \rho_r \mathbb{1}[\frac{N_j}{r} \in \mathbb{N}] + \sum_{k \in K} \theta_k \mathbb{1}[N_j \in K \wedge N_j \notin [N_L, N_U]] + \epsilon_j \tag{4}$$

The variables in Equation 4 are defined as above in Equation 3. However, the counterfactual

[13]More details about the empirical equations can be found in Appendix C.

estimation omits the bunching-region dummies γ_i to recover how the distribution would appear without the notch.

With the actual and counterfactual binned data, I then measure the excess number of STR hosts bunching at 30-days due to the notch. This excess bunching mass is estimated as:

$$\hat{B}_0 = \sum_{j=N_L}^{N^*} (c_j - \hat{c}_j) \tag{5}$$

c_j remains the observed count of STR properties between the bunching region $[N_L, N^*]$. $\hat{c}_j$ is the counterfactual count of STR properties and excludes the bunching region. Thus, $\hat{B}_0$ sums the difference between the actual distribution c_j and the counterfactual distribution $\hat{c}_j$ in the region affected by the rental day limit $[N_L, N^*]$. I refer to $\hat{B}_0$ as the bunching mass. Standard errors for $\hat{B}_0$ are bootstrapped 1,000 times.

In this context, $\hat{B}_0$ should be considered a lower bound for the number of bunchers for two reasons. First, some hosts have more than one property, in which case the total number of properties in my sample likely exceed the number of hosts. However, hosts can only have the homestead exemption on one residence. Thus, some STR properties in my sample would not be eligible for the homestead exemption regardless of annual rental days, which would attenuate my results.

Additionally, some STR hosts may choose not to rent and exit the market entirely because of the threshold. This market exit would impact the extensive margin of STR activity, which is not captured by these bunching estimates. So although these individuals are responding to the tax threshold, they would not be included in the estimate of the number of bunchers because they have exited the STR market.[14]

4.2 Estimation of Changes in Rental Behavior by STR Hosts

Next, I estimate how STR hosts change their rental behavior to stay under the rental day limit and avoid higher property taxes. $\hat{B}_0$ is the excess bunching mass calculated from Equation 5 and also estimates the number of extra STR properties clustering at the rental day limit. I examine the behavior of the average buncher by estimating b, the normalized excess mass. b is how many nights per year on average each STR host chooses not to rent to keep the homestead exemption. I estimate the average reduction in rental days as:

$$\hat{b} = \frac{\hat{B}_0}{\hat{c}_0} \tag{6}$$

[14]See the last paragraph of Section 3 for more detail about how the property tax threshold could impact the extensive margins of STRs.

The numerator $\hat{B}_0$ is the number of excess STRs at the notch in the bunching region. The denominator $\hat{c}_0$ is the counterfactual estimate of how many STRs would have located at the 30-day bin without the notch.

As not all STR hosts respond optimally to the tax threshold, I adjust b to account for these differing responses. I define "bunchers" as those who manipulate their rental days to remain under the homestead exemption rental day limit and "non-compliers" as STR hosts who don't adjust their behavior. I estimate bunchers and non-compliers according to the theoretical framework of Mavrokonstantis & Seibold (2022) and related bunching models. First, I recover the share of "non-compliers," α, which captures the share of STRs that fail to optimize due to friction in the market, ignorance of the threshold, or other adjustment costs that make it difficult for STR hosts to rent 30 days exactly. I estimate α by comparing the number of STRs that bunch at the rental day limit to the number of STRs that remain in the dominated region just above the threshold. This ratio provides an estimate of the proportion of hosts in the affected region who actively adjust their behavior in response to the property tax rule, as opposed to those who remain unaware of, constrained by, or indifferent to the threshold. Accordingly, the share of bunchers, denoted $\widehat{sharecompliers}$, corresponds to $1 - \alpha$, the share of STRs that respond to the threshold as "compliers."

To identify the region in which this adjustment should occur, I define a dominated region $[N^*, N_D]$. The dominated region is the area where it is not optimal to locate due to the changing tax liabilities at the threshold. I estimate the dominated region by dividing the average change in property taxes ($\Delta\lambda$) from crossing the threshold by the average nightly revenue. The result, $N_D - N* = \frac{\Delta\lambda}{avg.rate}$, is the average number of nights a property must rent to fully recoup the added tax burden.

Accounting for the different behaviors from STRs in the dominated region, I adjust the estimation of b as:

$$\hat{b}_{adj} = \frac{\hat{b}}{\widehat{sharecompliers}} \tag{7}$$

where $\widehat{sharecompliers}$, is the proportion of STRs in the affected region who respond to the rental day threshold. I divide b by the share of bunchers to recover the Local Average Treatment Effect (LATE). The LATE $\hat{b}_{adj}$ estimates how bunchers specifically reduce their rental nights in response to the homestead exemption rental day limit.

4.3 Tax Evasion: Rental Activity Before and After the VCA

To measure potential tax evasion, I employ the main bunching estimator with two additional subsamples: STRs operating before the Airbnb VCAs and those operating after. For Florida, the pre-VCA period includes 2015 only, and the post-VCA period includes 2017–2024, as Airbnb's agreement with Florida became effective December 1, 2015. Since Florida's homestead exemption is dependent on two consecutive years of rental activity, I exclude 2016 since it could be used to qualify exemption status for 2015 (before the VCA) and 2017 (after the VCA).

As in Bibler et al. (2021) and Marion & Muehlegger (2008), I rely on the enforcement change in tax remittance to detect tax evasion. If the bunching estimators differ between the pre- and post-VCA periods, this suggests that STR hosts previously evaded higher property taxes by misreporting or underreporting their rental activity. A stronger bunching response after the VCAs would indicate that increased reporting and enforcement made it more difficult for STR hosts to claim the homestead exemption fraudulently and avoid property taxes. Visually, the difference would manifest as a more pronounced spike to the left of the 30-day cutoff in the post-VCA period relative to the pre-VCA period, signaling that more hosts are deliberately staying below the limit to retain the property tax exemption.

4.4 Identifying Assumptions and Validation

There are three identifying assumptions necessary for using a bunching estimator to calculate excess mass, dominated regions, and potential evasion. First, the counterfactual distribution must be smooth so that any bunching can be attributed to a behavioral response. Second, bunchers originate from above the threshold and thus, a marginal buncher can be defined. Third, the market must have constant friction for the behavioral response of the marginal buncher to be estimated (Kleven & Waseem 2013). Constant friction allows a person or entity to move to any point along the distribution with the same amount of effort. In this context, this assumption translates to STR hosts being able to increase or decrease their bookings with the same amount of ease regardless of their current rental days.

I assess the first assumption by plotting the distribution of annual rental days for the restricted sample of hosts managing a single property.[15] The histogram in Figure 3 shows that the distribution of rental days is smooth outside the bunching region. Since the counterfactual in the bunching estimation is constructed by fitting a smooth function to observations away from the threshold, this smoothness supports the assumption that the counterfactual distribution is well-approximated by the observed data outside the cutoff. The second assumption is satisfied in the conceptual framework but cannot be tested empirically. By

[15] Restricting the sample to STR hosts managing a single property focuses the analysis on those most likely to be claiming the homestead exemption on their rental property. Further details on this sample restriction are provided in Section 5.

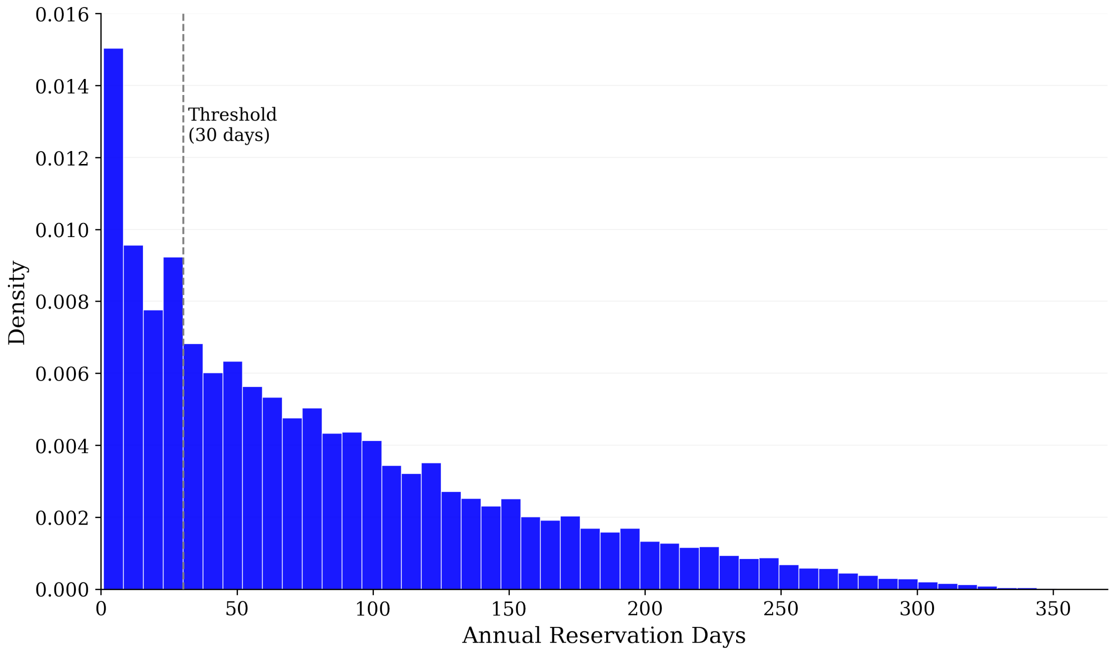


Figure 3: Distribution of Annual Reservation Days, 2015–2024
Notes: This figure displays a histogram of the distribution of annual reservation days for Florida STRs in the subsample. The subsample includes STRs that are a townhouse, condo, house, or villa and that have a host managing 1 unit. Dashed vertical lines indicate the short-term rental tax exemption threshold, 30 days. Observations with zero annual reservation days are excluded from the figure for clarity. Excluding zero, the mode for the distribution is 7 days.

definition, a "buncher" reduces their property's STR days in order to remain eligible for the homestead exemption.

For the third assumption to be met, a buncher must be able to reduce their number of rented nights similarly at different points of the distribution. Since Airbnb gives hosts immense flexibility in booking, bunchers can reduce nights booked by declining further bookings, canceling existing bookings, and removing their STR listing altogether. These activities give them ease in moving above and below the rental day limit threshold. This ease in changing annual bookings applies no matter where the STR is in the annual rental day distribution. Thus, the third assumption also holds.

5 Data

Data for this project come primarily from AirDNA, a third-party provider for data on STRs globally. AirDNA supplies data on rental properties listed on Airbnb, VRBO, or both by scraping the platforms and gathering data from data partners. Data on Airbnb listings are provided monthly from 2015 until 2024, while VRBO listings are monthly from 2017-2024.

The variables from the AirDNA most pertinent for this paper are the number of bookings, number of reservations, reservation days, available days, and total revenue. I aggregate the monthly data to the annual level to create a dataset of 4,176,235 annual-property observations from 2015 to 2024.

I restrict the sample for my analysis to STRs most likely to respond to the homestead exemption rental day limit using the property characteristics in the AirDNA data.[16] First, I limit the sample by property type, retaining properties that are condos, houses, townhouses, and villas and excluding the other types.[17] Next, I limit the sample to entire-home rentals, as partial-home rentals are treated differently under homestead exemption laws.[18] Lastly, I keep hosts that manage only one rental unit.[19] I assume these hosts are more likely to be renting out their primary residence, which would qualify for the homestead exemption.[20] With these restrictions, the final sample has 1,168,880 property-year observations in Florida. The one-unit STR hosts account for approximately 30% of all STR reservations in Florida.

I supplement the STR data with data on Airbnb VCAs, typical home values, the Consumer Price Index (CPI), and property tax law. The implementation dates for the VCAs come from Bibler et al. (2020). The authors primarily gathered implementation dates from the Airbnb website or local news sources.

To quantify the average tax savings from the homestead exemption, To quantify the average tax savings from the homestead exemption, I use typical home values from Zillow Research (2025) and county and school millage rates from the Florida Department of Revenue, Property Tax Oversight (2025).[21] I adjust all revenue variables in U.S. dollars using the CPI with 2024 as the base year. Consequently, the revenue can be compared across time and accounts for inflation. The CPI values come from the CPI-U survey of Urban consumers from the Bureau of Labor Statistics' January 2025 estimations (U.S. Bureau of Labor Statistics 2025).

Additionally, I collect data on FL property tax laws, owner-occupied and homestead exemptions, and property tax rental day limits. I use a variety of government websites, such

[16]The individual property characteristics include number of bedrooms and bathrooms, rental type (private room, shared room, or entire house), location (city, metropolitan statistical area), property type (house, townhouse, apartment, villa, etc.), host type (how many units the host rents), and the first listing date.

[17]Some other property types include hotel, cottage, guest house, cabin, RV, loft, and tiny house.

[18]Prior to the 2023 court case, Florida county appraisers divided a home's use between owner-occupied and rented areas, granting the homestead exemption only to the portion serving as the owner's primary residence. Since most of the analysis period is pre-2023, I drop partial-home rentals from the sample.

[19]For about 1% of the sample, the data do not specify the host type. These properties are retained in the sample.

[20]See Appendix Table 2 for the number of observations remaining at each step of the sample restriction process.

[21]Additional sources for the Florida millage rate information are in Appendix J.

as the Florida Department of Revenue, and third-party sources like The Lincoln Institute of Land Policy to obtain this information. A full list of sources is available in Appendix J.

Summary statistics for STRs in Florida are presented in Table 3 in Appendix E. The average number of annual reservation days is 147 days per STR. STRs make on average $33,300 of revenue annually with an average nightly revenue of about $240.[22]

6 Results

6.1 Behavioral Responses to Notches and Third-Party Reporting

I compare the bunching behavior of STR hosts pre- and post-VCA to detect property tax evasion and changes in tax compliance. Bunching behavior in Florida differs starkly between the pre- and post-VCA periods as shown in Figure 4a and Figure 4b. Table 1 reports the estimates for Florida's pre- and post-VCA periods.

Bunching is minimal in the pre-VCA period (2015), with no statistically significant clustering of STRs at the 30-day rental threshold. However, after the VCA goes into effect, bunching behavior becomes much more pronounced. In the post-VCA period from 2017–2024, approximately 4,600 extra STRs cluster just below the 30-day threshold, and marginal bunchers reduce their bookings by 16.46 nights. These results are statistically significant at the 1% and 5% level and suggest that STR hosts in Florida adjusted their rental behavior after increased reporting and tax remittance by Airbnb. This behavior change is also consistent with the predictions of the conceptual framework.

Two robustness checks support the main estimates. First, because AirDNA began collecting VRBO listings in 2017, the start of the post-VCA period, I repeat the analysis using Airbnb listings only (Appendix H). Second, I replace the polynomial counterfactual with the rescaled distribution of hosts with 21 or more units, who are ineligible for the homestead exemption (Appendix I).[23] Both estimates are smaller than the main post-VCA estimate of 0.450 in Table 1 but remain positive and statistically significant at the conventional levels.

While the bunching estimates cannot directly quantify the amount of property tax evasion, they provide a basis for approximating its fiscal impact. Assuming each bunching host retains an average property tax benefit of $3,000 annually, the implied property tax revenue loss from the bunching behavior is roughly $13.8 million in Florida (4,600 × $3,000) from

[22] For the estimates of nightly price, I divide a STR's annual revenue by its annual reservation days. The result estimates the average revenue the STR host receives per night of renting the STR.

[23] The hosts with 21+ units could be claiming the homestead exemption on their current residence and renting it out. If all hosts did this, this eligibility would be at most 5% of the sample of STRs with hosts managing 21 or more units.

	Florida (30-day limit)	
Year(s)	2015	2017–2024
Estimated Excess Mass	-1.171	4,589.321***
	(7.957)	(1,416.941)
Normalized Excess Mass	-0.019	0.450**
	(0.126)	(0.184)
Share of Bunchers	-0.022	0.027
Adj. Normalized Excess Mass (LATE)	0.826	16.464
N	1,283	193,148

Table 1: Bunching Estimation Results: Likely Homeowners with 1 Unit

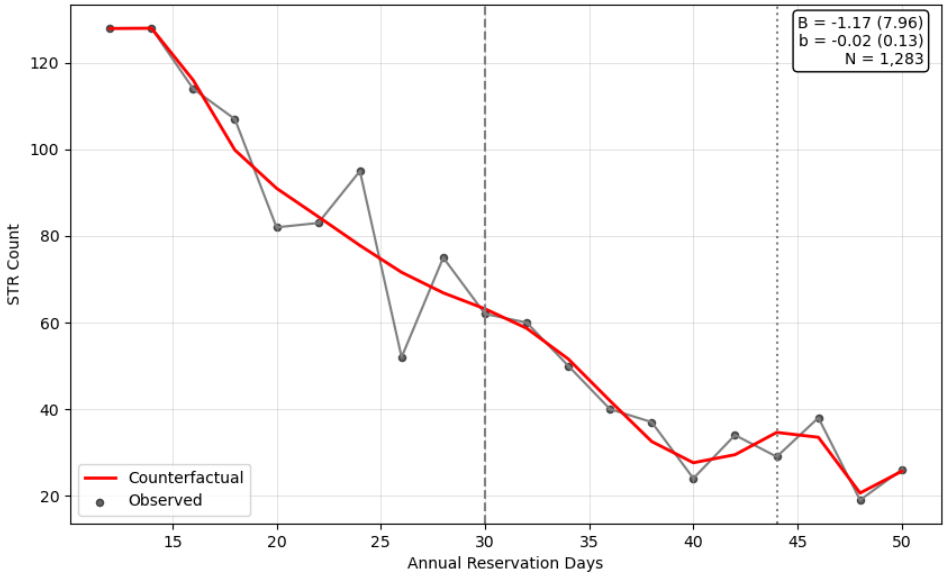
Notes: This table reports bunching estimator results for the "Likely Homeowners with 1 Unit" subsample—STRs that are a townhouse, condo, house, or villa managed by a host with 1 unit. Data are from AirDNA. The columns estimate bunching at the 30-day rental limit (bin width: 2 days; 10 bins on each side; fixed point control for 14). N is the number of observations in the bin range. Estimated excess mass is the number of additional STRs located at the threshold. Normalized excess mass is the average number of rental nights forgone at the cutoff. Share of bunchers is one minus the ratio of observed to counterfactual counts in the dominated region (the bin just above the threshold), capturing the fraction of STRs that respond to the cutoff (compliers). The adjusted normalized excess mass is the LATE—normalized excess mass divided by the share of bunchers—capturing how many rental nights the average buncher forgoes due to the cutoff.
$p < 0.10$*, $p < 0.05$**, $p < 0.01$***.

2015 to 2024. These figures represent the potential cost of hosts maintaining exemptions while renting near the threshold for the 9-year period. Similarly, the corresponding unreported rental revenue can be approximated as \$15.5 million in Florida (4,600 $\times$ 14 $\times$ \$240). These approximations represent the value of economic activity potentially concealed to avoid the higher tax rate. Although these calculations are illustrative, they highlight the potential magnitude of local tax revenue loss and rental revenue loss associated with property tax evasion in the STR market.

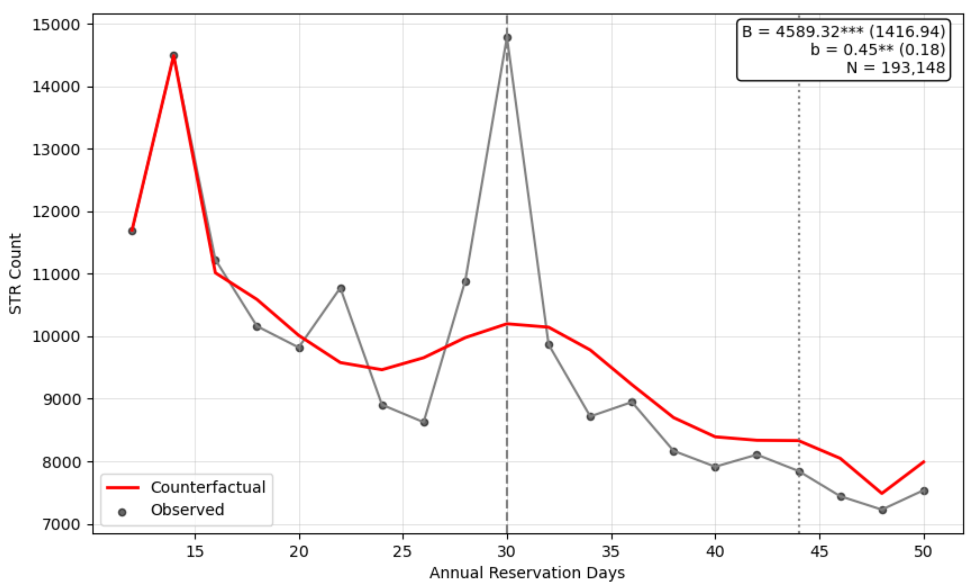
6.2 The Dominated Region and Optimizing Frictions

Next, I assess whether the behavior of STR hosts is consistent with the profit-maximizing behavior depicted in the Conceptual Framework of Section 3. According to the Conceptual Framework, STRs that locate in the dominated region are not profit-maximizing and thus, could improve their profits by locating outside the region. Given the average annual tax savings of \$3,000 from the homestead exemption, the dominated region is [30, 44] days for Florida. Therefore, an average property must rent 14 days in Florida to recoup the cost of the additional property tax.

By comparing the dominated regions with the typical buncher's response, I find that



(a) Pre-VCA (2015)



(b) Post-VCA (2017–2024)

Figure 4: Bunching at the 30-Day Property Tax Threshold Before and After Airbnb VCAs
Notes: The figures plot the distribution of annual reservation days for likely homeowner-hosts with one unit. The gray dotted line marks the 30-day homestead exemption threshold. Black dots represent actual binned counts; the red line shows the counterfactual distribution from the bunching estimator. Bin width is 2 days. I include a fixed point control at 14 days. Ten bins are used on each side of the threshold. The thin light gray line denotes the dominated region. B is estimated excess mass at the threshold and b is normalized excess mass. Standard errors from a residual bootstrap with 1,000 replications are in parentheses. p<0.10*, p<0.05**, p<0.01***.

bunchers in Florida respond rationally to the change in tax rate at the rental day threshold. The average reduction in nights for Florida STR hosts is 16.46 nights, which is only about 2.5 days more than the 14 day width of the dominated region. Accounting for operational costs would explain why Florida bunchers would bunch more than 14 nights, since the 14 night estimate is based on revenue only, not profits.

The presence of any STRs in the dominated region, while surprising, could be due to several factors. First, because of data limitations, I cannot identify which STRs are truly owner-occupied or actually claiming the exemptions, so the estimated responses may include ineligible properties. I do not expect a behavioral or bunching response from properties that are ineligible for the homestead exemption at the rental-day limit. Second, since the homestead exemption in Florida is forfeited after exceeding the 30-day threshold in two consecutive years, some hosts may rationally locate in the dominated region in a given year if they plan to remain below the threshold the following year.[24] For these two reasons, the estimates in this study should be interpreted as lower bounds on bunching and tax evasion.

Second, optimizing frictions likely explain part of the observed mass in the dominated region. Optimizing frictions occur when hosts face informational or logistical constraints that prevent precise optimization around the cutoff. For example, a host may intend to exceed the rental threshold, and does, but does not receive enough bookings to pass the dominated region. In which case, the host remains stuck in the dominated region although it would be optimal to avoid that region. In that case, some STRs in the dominated region may reflect unrealized rental demand or imperfect adjustment rather than deliberate noncompliance or ignorance of the threshold.

6.3 Reduced Form Elasticity Estimates: Rental Nights to Tax Rate

While the previous results described rental behavior of STR hosts, the reduced-form elasticity captures how sensitive STR rental activity is to changes in property taxes. I calculate the elasticity as follows:

$$\epsilon_{N,t} = \frac{\%\Delta N}{\%\Delta T} = \frac{\hat{b}/N^*}{\Delta\lambda/\lambda} \tag{8}$$

The percentage change in rental nights $\%\Delta N$ is the average reduction in nights $\hat{b}$ in response to the cutoff. I also estimate this with $\hat{b}_{adj}$, which is the reduction in nights by STR hosts

[24]To the extent this behavior occurs in Florida, some observations in the dominated region classified as non-compliers may instead reflect hosts strategically planning their rental activity given the two-year rule. This would attenuate the estimated share of bunchers and bias the corresponding LATE estimates toward zero.

who are bunchers and more responsive to the rental day limit. I find the percentage change in property taxes $\%\Delta T$ by dividing the change in taxes from losing the homestead exemption, $\Delta\lambda$, by the total tax liability with the homestead exemption, λ. I interpret the elasticities as the percentage change in rental nights for the STR host from a 1% increase in the property tax rate. The calculations for the elasticity estimates are included in Appendix G.

For STRs just below the 30-day threshold in Florida, the average STR reduces rental activity by approximately 0.45 nights. Using the illustrative examples in Appendix G, this corresponds to an average elasticity of 1–2.80 %. The range of the estimate depends on the amount of the SOH protection that the homestead has accumulated over time.

For marginal bunchers in Florida, the effect is substantially larger. These hosts reduce their bookings by 16.46 nights at the threshold. From a tax increase of $3,500, a 1% increase in property taxes leads to a 37 % decrease in rental nights for marginal bunchers.[25] The FL elasticity estimates should be interpreted as illustrative because the tax-savings calculations likely understate the true value of the homestead exemption for many Florida homeowners. The examples in Appendix G include only county and school district millage rates and therefore provide a lower-bound estimate of the tax savings associated with homestead status. In practice, municipal and special district taxes may further increase the cost of losing the exemption. Moreover, the value of the exemption depends critically on the amount of accumulated SOH protection, which varies substantially across homeowners and can generate much larger tax increases than those reflected in the illustrative examples. Overall, the elasticity results highlight how sensitive Florida STR hosts are to the tax exemption threshold.

7 Discussion

Rental-day limits tied to property tax exemptions shape STR host behavior in meaningful ways, as shown by the bunching patterns in Florida. Hosts exhibit clear signs of adjusting their booking activity to preserve tax benefits, with responses that grow more pronounced over time.

These behavioral responses likely reflect the interplay of several mechanisms, including the size of the financial incentive. The homestead exemption in Florida is particularly strong due to the SOH cap. Over several years, the SOH protection can save a homeowner tens of thousands of dollars, particularly in high-value markets. Upon losing the Florida homestead exemption, the property is immediately reassessed at market value for all future

[25]The elasticity for marginal bunchers also has a range in this case, depending on the amount of SOH protection. See Appendix G for further examples.

tax years. Therefore, the homeowner not only faces a higher current property tax bill but also forfeits the accumulated assessment limitation benefits that constrain future tax growth. Consequently, the cost of exceeding the rental-day threshold depends not only on current tax savings but also on the amount of accumulated SOH protection. Homeowners who have held their properties for many years may have assessed values substantially below market values, making the loss of homestead status particularly costly. These future tax consequences likely amplify the response to the threshold.

Differences in host behavior over time also stem from variation in information and tax salience. Homestead exemption eligibility is not verified annually, and many hosts may be unaware that the exemption is conditional on staying below the rental-day limit. In one Florida county, for example, a tax appraiser reported that 80% of exemption fraud cases in 2017 stemmed from ignorance rather than deliberate evasion (Thomson Reuters Institute 2018). This suggests that relatively low-cost interventions—such as information and awareness campaigns—could meaningfully improve compliance without resorting to more costly audits or higher financial incentives. For instance, in North Alabama, the Alabama Mountain Lakes Tourist Association partnered with Granicus to send notification letters to over 2,500 STR owners reminding them of their lodging tax obligations. Within two months, the area saw a 21% increase in billed revenues through the compliance system, and an 8% increase in statewide STR tax collection among the 16 counties covered (Granicus 2023). This case study suggests that when noncompliance stems from lack of information rather than intentional evasion, broad awareness campaigns reduce tax fraud even absent expensive software tools, such as Granicus' Host Compliance.

Alongside tax salience, enforcement plays a key role in shaping bunching behavior. STR hosts exhibit stronger bunching after the implementation of Airbnb's Voluntary Collection Agreements (VCAs). The bunching patterns before and after the VCAs provide compelling evidence that improved reporting and oversight reduce opportunities for tax evasion. Before VCAs, hosts could misreport rental activity with little risk of detection. After VCAs increased tax remittance and the perceived visibility of STR activity to local authorities, bunching intensified, which is consistent with hosts adjusting real or reported activity to remain compliant. This underscores the importance of credible enforcement: even in decentralized tax systems, third-party reporting and data coordination between platforms and tax authorities can materially improve compliance.[26]

Furthermore, the elasticity estimates reveal how STR activity responds to taxation at the

[26]See Thomson Reuters Institute. "Homestead Exemptions for Airbnb Hosts are Complicated — and Often Illegal." *Thomson Reuters*. https://www.thomsonreuters.com/en-us/posts/investigation-fraud-and-risk/homestead-exemptions-airbnb-illegal/.

margin. The average host is inelastic, but marginal bunchers are highly elastic—reducing bookings by roughly 16 nights. These findings indicate that while overall STR supply may not collapse under higher property taxes, targeted enforcement near exemption cutoffs can meaningfully alter behavior. For local governments, these responses translate into meaningful cumulative fiscal stakes: approximately $13.8 million in lost property tax revenue over the study period in Florida. I do not interpret this figure as the net fiscal impact of STRs since short-term rentals may also generate sales, accommodation, and other tourism-related tax revenues. Therefore, this estimate only quantifies the property-tax consequences of compliance and enforcement of owner-occupied tax exemptions, an important source of local government revenue.

These findings should be interpreted with caution given certain limitations of the data. Most notably, the data do not identify STRs with the homestead exemption, so estimates in this study represent lower bounds on bunching and tax evasion. Future research with property-level tax records or verified exemption claims could mitigate these issues. Additionally, the bunching estimates in this paper capture only the intensive-margin effect of property tax policy on STR supply and therefore likely understate the overall effect.[27] More research is needed to understand the extensive-margin effects of property tax thresholds.

8 Conclusion

This paper provides new evidence that short-term rental hosts respond to property tax incentives and enforcement, revealing both compliance and evasion margins largely overlooked in prior research. Using data from Florida, I examine how hosts respond to rental-day thresholds tied to large property tax exemptions. Applying a bunching estimator at the 30-day limit and exploiting the introduction of Airbnb's Voluntary Collection Agreements (VCAs) as an enforcement shock, I measure how hosts alter rental activity along both compliance and evasion margins.

I find that even lenient third-party reporting reduces evasion and increases compliance. STR hosts adjust their rental activity to remain below exemption thresholds, with large, highly responsive reductions in rental nights. After the implementation of Airbnb's tax remittance agreements, hosts exhibit sharper bunching behavior, suggesting that third-party reporting tightened compliance.

[27] The intensive margin captures how existing STR hosts adjust the number of nights they rent their properties in response to property tax policy. However, property tax thresholds may also affect the extensive margin by discouraging entry into the STR market or encouraging existing hosts to exit altogether. Because the bunching estimator relies on observed rental activity, it cannot capture homeowners who choose not to enter the STR market because of the risk of losing owner-occupied tax benefits.

These behavioral responses shed light on the mechanisms underlying property-tax compliance in platform markets. Behavioral responses depend critically on the size, salience, and enforceability of the tax benefit. When exemptions are valuable and backed by credible oversight, hosts adjust rental behavior sharply to maintain eligibility. When enforcement is weak or exemptions insufficiently salient, thresholds lose traction, and the risk of tax evasion rises.

At the local public finance level, these findings also have meaningful implications for STR regulation. They illustrate how rental-day thresholds influence host behavior, particularly when paired with credible enforcement mechanisms such as third-party reporting. Because the hosts analyzed here account for a large share of STR bookings, even small behavioral adjustments can have important fiscal implications for local governments. STR activity can increase demand for police, EMS, and public safety services (Ke et al. 2021, van Holm & Monaghan 2021, Reinhard & Roth 2024), while also raising pressure on emergency departments, waste systems, and other municipal operations (Arora et al. 2025, Office of the City Treasurer 2021). These strains make the integrity of the property tax base especially consequential in tourism-heavy areas. Therefore, local governments investing in data-sharing and third-party reporting can yield returns well beyond their cost. The additional reporting ensures that property tax exemptions function as intended and provide relief to eligible homeowners rather than becoming a source of revenue loss that strains essential public services.

The results also point to promising directions for policy and future research. Integrating STR-platform data with property-tax records could help assessors verify exemption claims more efficiently. Experimental variation in threshold levels or audit intensity could identify where enforcement resources yield the largest improvements in compliance. Additional work examining extensive-margin decisions—such as whether homeowners enter the STR market at all or shift toward room rentals—would further illuminate how exemption rules shape behavior.

For policymakers seeking to preserve the intent of owner-occupied tax exemptions, there are several pathways forward. First, threshold levels should balance administrative cost against the behavioral responses they induce. Second, simple exemption rules provide more salient cutoffs and penalties and are easily understood by homeowners. Third, enforcement should be supported by routine data-sharing agreements that enhance detection at low cost. In an era where platform economies blur the line between private and commercial use, effective enforcement and transparent data-sharing will determine whether property tax exemptions remain instruments of fairness or loopholes for tax evasion.

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A Appendix: Additional Short Term Rental Industry Background

This appendix provides additional background on the short-term rental (STR) industry and enforcement practices that inform the empirical analysis. It summarizes the structure and market concentration of major STR platforms and discusses variation in local enforcement capacity relevant to property tax compliance.

The modern STR industry emerged with the founding of Airbnb in 2007, when Brian Chesky and Joe Gebbia began renting out an air mattress in their living room as a bed and breakfast. The following year, they launched the Airbnb platform (Lagorio-Chafkin 2010). On the Airbnb platform, people seeking temporary accommodations can connect with hosts offering their spare rooms or entire homes for lodging. Hosts choose the price per night for their accommodations, and Airbnb collects fees from both hosts and guests (Koster et al. 2021).

Other platforms, such as Vacation Rental by Owner (VRBO) and Booking.com, offer similar services. Because of the technological innovations underlying these platforms, STR hosts can operate with relatively low overhead costs and compete directly with traditional accommodation providers, including hotels and bed and breakfasts (Guttentag 2015, Morgan & Kuch 2015, Orsi 2013).

As a result, the STR market has become highly concentrated among a small number of platforms. In 2025, Airbnb held roughly 43% of the U.S. short-term rental market, followed by VRBO at 21% and Booking.com at 8%. Together, Airbnb and VRBO account for about two-thirds of U.S. listings (Rental Scale Up 2025). Globally, these three platforms control more than 70% of short-term rental revenue (Yahoo Finance 2025). This concentration underscores the importance of platform-level reporting and data-sharing for understanding STR activity and tax compliance.

Against this backdrop, enforcement of homestead exemption rules varies substantially across counties, and publicly available data on audit rates or investigative capacity remain limited. However, emerging evidence suggests that enforcement has intensified in some jurisdictions as advances in data analytics have made it easier for property appraisers to cross-reference tax rolls, booking activity, and other administrative records to identify suspicious properties (Thomson Reuters Institute 2018). Some counties have created dedicated fraud-investigation units or citizen hotlines, such as the Orange County Property Appraiser's office, which reports recovering more than $550 million in improper exemptions after hiring former law-enforcement professionals and encouraging anonymous tips from residents (Erb 2016). Similarly, the Duval County, Florida property appraiser identified approximately 1,900 homes erroneously claiming the homestead exemption in 2017, resulting in \$11 million in recovered taxes (Thomson Reuters Institute 2018).

B Appendix: STR Market in Florida

This appendix provides additional background on the short-term rental (STR) market in Florida that informs the empirical analysis. The figures below document the growth and geographic distribution of STRs in Florida over the sample period. The following discussion describes the regulatory environment surrounding Airbnb's Voluntary Collection Agreements and their relationship to property tax enforcement.

Figure 5 presents the share of STRs in the major FL metro areas. Generally, STRs are concentrated in coastal cities in Florida as well as in Orlando. Figure 6 shows the growth of STRs in Florida by host type from 2015-2024. Most of the STR growth comes from hosts managing one property or more than 20 properties.

The homestead exemption and its associated 30-day rental day limits both predate Airbnb, which launched in 2008, and the widespread adoption of short-term rentals (STRs). In the mid-2010s, Airbnb began collecting and remitting accommodation and sales taxes on behalf of STR hosts to local governments through VCAs. Consequently, these governments received more information about STR activity within their jurisdictions.[28] Even though VCAs do not remit property taxes, I use the VCAs as a proxy for greater oversight, regulation, and enforcement in the STR market, which should lead to more enforcement in property tax collection as well.

[28]The extent to which local governments in Florida use this data for enforcement is not fully documented. In some cases, counties have leveraged this information to identify exemption fraud. For example, task forces such as the one in Orange County, Florida cross-referenced property tax records with Airbnb listings to uncover fraudulent homestead exemptions. See Kelly Philips Erb, "Investigations, Tips Lead To More Than \$550 Million In Property Tax Fraud Recovery," *Forbes*, 2016. https://www.forbes.com/sites/kellyphillipserb/2016/06/02/investigations-tips-lead-to-more-than-550-million-in-property-tax-fraud-recovery/.

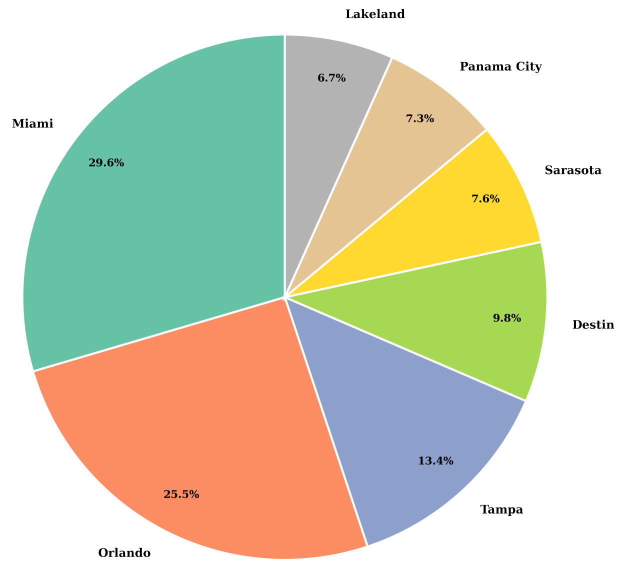


Figure 5: Metro Areas for STRs in FL in 2024

Notes: This figure shows the percentage of STRs in Florida in the major metropolitan areas across the state. Data is from AirDNA for the year 2024. The STRs included in the figure represent only two-thirds of the total STRs in Florida.

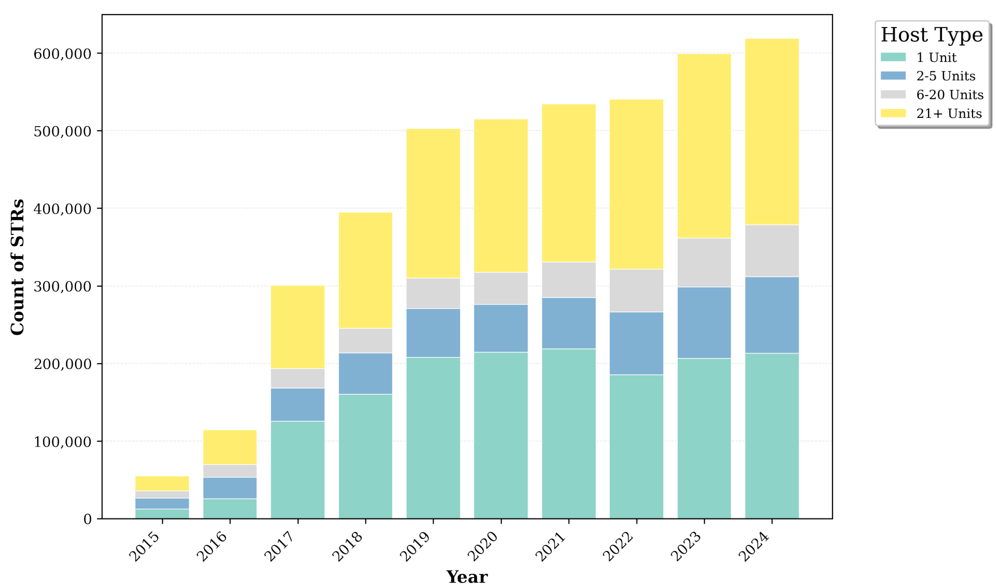


Figure 6: Number of STRs in FL

Notes: This figure displays the number of STRs in Florida per year from 2015-2024 as reported by AirDNA. The bars in the chart are divided based on the host type, which is how many STR units the host is managing.

C Appendix: Bunching Estimator Details

This appendix presents the technical details of the bunching estimator underlying the empirical results. I outline how the distribution of annual STR rental days is binned and modeled, how excess mass at the exemption threshold is identified, and how the counterfactual distribution is constructed and adjusted to satisfy the integration constraint.

I plot the distribution of annual STR days based on the actual data with the following equation:

$$c_j = \sum_{i=0}^{p} \beta_i (N_j)^i + \sum_{i=N_L}^{N_U} \gamma_i \mathbb{1}[N_j = i] + \sum_{r \in R} \rho_r \mathbb{1}[\frac{N_j}{r} \in \mathbb{N}] + \sum_{k \in K} \theta_k \mathbb{1}[N_j \in K \wedge N_j \notin [N_L, N_U]] + \epsilon_j \tag{9}$$

The STRs are put into j bins based on their annual rental days N, and each bin is a range of annual rental days. The number of STR observations in each bin is c_j. The first term after the equal sign is the polynomial of order p with coefficients β_i that fits the binned data. The binned data are the counts of STR properties that fall into each bin. N_j is the maximum N in bin j of width δ.

The second term in the equation are the bunching dummies that capture excess mass at the threshold. These dummy variables, γ_i, measure how much of the density is concentrated at the exemption limit relative to the rest of the distribution. N_L and N_U are the lower and upper bounds of the bunching region, respectively. They represent the area of the distribution that is impacted by the rental day limit. I estimate N_L and N_U by looking for visual changes in the rental day distribution.

The last two terms in the estimation equation account for natural or mechanical bunching that is unrelated to the property tax threshold. The third summation term controls for round-number bunching through the coefficients ρ_r. The set R includes round values where STR hosts may cluster bookings. For instance, STRs frequently offer discounts for week-long stays, leading to visible spikes in the distribution of annual rental days at multiples of seven. The coefficients ρ_r capture the average excess mass at these round-number points. Including this control allows the estimator to separate tax-induced bunching at the 30-day limit from predictable, calendar-driven clustering in the data.

The fourth summation term adjusts for fixed bunching points elsewhere in the distribution that are not related to the rental day threshold or a natural bunching point. The set K includes prominent spikes in the rental day distribution that fall outside the bunching region $[N_L, N_U]$ but could otherwise distort the estimated distribution. The coefficients θ_k measure and absorb these unrelated concentrations of mass, ensuring that the fitted values are not biased by excess clustering at other points in the distribution. Similar to round number bunching, these fixed bunching points are visually detectable upon examining the rental day distribution.

Next, I estimate $\hat{c_j}$, the counterfactual binned count of STR properties and adjust the counterfactual to meet the integration constraint correction. The counterfactual bin count is estimated as follows:

$$\hat{c_j} = \sum_{i=0}^{p} \beta_i (N_j)^i + \sum_{r \in R} \rho_r \mathbb{1}[\frac{N_j}{r} \in \mathbb{N}] + \sum_{k \in K} \theta_k \mathbb{1}[N_j \in K \wedge N_j \notin [N_L, N_U]] + \epsilon_j \qquad (10)$$

The variables in Equation 10 are defined as above in Equation 9. However, the counterfactual estimation omits the bunching-region dummies γ_i to recover how the distribution would appear without the notch. The integration correction constraint accounts for bunchers' response to the notch. When bunchers come from above the threshold and locate at the notch, then the proceeding bins have less STRs than what would have existed without the notch. This correction shifts $\hat{c_j}$ upward to compensate, so that the missing mass under the counterfactual equals the excess bunching at the notch (Chetty et al. 2011, Mavrokonstantis & Seibold 2022).

D Appendix: Sample Construction

Table 2 details the number of observations remaining at each step of the sample restriction process for Florida. Beginning with the full AirDNA dataset, I sequentially restrict to listings likely owned by homeowners, listings managed by hosts operating five or fewer units, entire-home listings, and finally listings managed by hosts operating a single unit. This last restriction constitutes the main estimation sample used throughout the analysis.

Table 2: Sample Restrictions: Florida

Sample Restriction	Observations
Full sample	4,176,235
Likely homeowner or property type missing	3,148,586
Host manages 1–5 units or missing	1,634,717
Entire home listing	1,461,251
Host manages 1 unit or missing (main sample)	1,168,880

Notes: Each row reports the number of listing-year observations remaining after applying the indicated restriction. Restrictions are applied sequentially.

E Appendix: Descriptive Statistics

Table 3 presents the descriptive statistics for Florida STRs in the restricted sample. The average Florida rental has 3 bedrooms and 2.5 baths and has been operating for almost 5 years. Average annual reservation days is 147, and the occupancy rate is approximately 50%. Florida STRs on average generate $33,300 of revenue annually. Accordingly, the average nightly rate in Florida is about $240 with higher average rates in Miami and lower ones in Orlando and Tampa. The average length of a reservation in Florida is 6.2 days.

Table 3: FL Descriptive Statistics: Likely Homeowners with 1 Unit, 2015-2024

Variable	All of FL	Orlando	Miami	Tampa
A. Property Characteristics				
Num. of Bedrooms	3.09	4.49	2.41	2.32
Bathrooms	2.54	3.51	2.07	1.87
Share of House Listings	0.49	0.48	0.54	0.51
Share of Condo Listings	0.34	0.14	0.36	0.41
Share of Properties on Airbnb and Vrbo	0.08	0.05	0.09	0.12
Years as a STR	5.11	4.95	4.77	4.93
B. Other Characteristics				
Annual Number of Reservations	31.44	34.60	35.78	33.20
Annual Reservation Days	147.01	150.89	140.49	158.27
Average Stay in Days	6.17	5.06	5.26	6.69
Average Occupancy Rate	0.53	0.55	0.52	0.56
Annual Revenue in Dollars	33,311.62	30,557.57	36,297.71	32,508.11
Revenue / Revenue Potential	0.81	0.82	0.81	0.80
Average Nightly Rate	236.16	213.37	283.48	207.39
Observations	1,168,880	239,183	136,272	89,119

*Notes: This table presents summary statistics for a subsample of Florida STRs from 2015-2024. The "Likely Homeowners with 1 unit" subsample consists of STRs that are a townhouse, condo, house, or villa and that have a host managing 1 unit. The reported statistics are means. The variables in Panel B are weighted by the number of annual reservation days for each property. Data comes from AirDNA.

F Appendix: Property Tax Calculations

Today, the property tax remains a fundamental funding source for local governments in the U.S., particularly for counties (Yushkov 2024). Many local governments rely on property taxes to fund public services and public schools. On average, the property tax provides 30% of revenue for local governments and raised \$581 billion in 2021 (Lincoln Institute 2024). The different assessment ratios and millage rates from the homestead exemption are meant to redistribute the property tax burden more equitably. However, levying an equitable property tax requires understanding the extent and potential for tax evasion.

Thirty-three states offer a version of the homestead exemption for owner-occupied residential property. For most of the 33 states, these exemptions are granted to all homeowners. However, select states restrict the program to certain groups, such as veterans, people over 65, first responders, and low-income earners (Lincoln Institute 2024).

Florida Property Taxes

Florida's constitution limits school mills and non-school mills (e.g., county and city) to 10 each unless voters have approved a higher rate. Additionally, the new millage rates must be less than 110% of the rollback rate, which is the millage rate that would raise the same revenue as the previous year. For education funding, the Florida legislature sets a uniform school millage rate for the state, effectively mandating the amount of funds that each school district must raise for school operations.

Below, I present a mathematical representation of the tax liability for a non-homestead property and a homestead property in Florida. The total property tax liability for an non-homestead home in Florida in year t can be expressed as:

$$A_t = min(h_t, A_{t-1} \cdot 1.10) \tag{11}$$

$$\lambda_t = A_t \cdot (\frac{m_n + m_s}{1000}) \tag{12}$$

where the first equation defines the assessed or taxable value A_t for home h_t in year t. For non-homestead, the assessed value is the lesser of the home's market value h and the 110% of the previous year's assessed value A_{t-1}. The millage rates are split into two parts: m_n, the non-school millage rate applied to county and municipal services, and m_s, the millage rate specifically levied for school funding.

The corresponding tax liability for an owner-occupied homestead property is:

$$A_t = min(h_t, A_{t-1} \cdot min(1.03, 1 + CPI_t)) \tag{13}$$

$$A_{t,F} = A_t - 25,000 \tag{14}$$

$$\lambda_t = A_{t,F} \cdot (\frac{m_n + m_s}{1000}) - E \cdot \frac{m_n}{1000} \tag{15}$$

$$E = \begin{cases} 25{,}000, & \text{if } A_t > 75{,}000, \\ A_t - 50{,}000, & \text{if } 50{,}000 < A_t \leq 75{,}000, \\ 0, & \text{if } A_t \leq 50{,}000. \end{cases} \tag{16}$$

The assessed value for the homestead A_t in year t is the minimum of the market value of the home h and the capped assessed value based on the SOH protection. Under SOH, the capped assessed value for year t is the previous year's assessed value A_{t-1} multiplied by 1.03 or 1+CPI, whichever is lower. Since the Consumer Price Index (CPI) determines the inflation rate for year t, I use CPI_t as shorthand for the inflation rate. The homestead exemption exempts the first $25,000 of assessed value to be exempt from all mills. Therefore, the taxable value used to determine tax liability for year t is $A_{t,F} = A_t - 25,000$. In total property taxes, a homeowner pays the non-school m_n and school millage m_s rates on the $A_{t,F}$ minus the last term in the equation, $E \cdot m_n$. The last term $E \cdot \frac{m_n}{1000}$ exempts up to $25,000 from the non-school millage m_n for homestead properties over $50,000.

G Appendix: Average Property Tax Savings

G.1 Homestead Exemption and Save Our Homes (SOH) Protections

Under Florida law, when a homestead exemption and its associated Save Our Homes (SOH) protections are forfeited (for example, by renting the property for more than 30 days per year for two consecutive years under Fla. Stat. §196.061(1)), the property is immediately reassessed at full market value and loses the homestead exemptions.

Let h_t denote the market value of the home in year t, A_t the SOH-capped assessed value, m_n the non-school (local) millage rate, and m_s the school millage rate.

The annual tax liability **with** the homestead exemption and SOH protections is:

$$\lambda_{t,\text{HS}} = (A_t - 25{,}000) \cdot \frac{(m_n + m_s)}{1000} - 25{,}000 \cdot \frac{m_n}{1000} \tag{17}$$

and **without** the exemption (after reassessment to market value):

$$\lambda_{t,\text{noHS}} = h_t \cdot \frac{(m_n + m_s)}{1000} \tag{18}$$

The difference between the two represents the annual property tax increase from losing the exemption:

$$\Delta\lambda_t = (h_t - A_t + 25{,}000) \cdot \frac{(m_n + m_s)}{1000} + 25{,}000 \cdot \frac{m_n}{1000} \tag{19}$$

Numerical Examples The illustration below uses an average house value of $h_t = \$400{,}000$ and the average population-weighted, county-only millage rates from the Florida Department of Revenue, Property Tax Oversight (2025): $m_n = 8.349$, and $m_s = 5.946$.[29]

$$\frac{m_n + m_s}{1000} = 0.014295, \quad \frac{m_n}{1000} = 0.008349$$

Example A (moderate SOH gap): $A_t = \$300{,}000$

$$\Delta\lambda_t = (400{,}000 - 300{,}000 + 25{,}000) \times 0.014295 + 25{,}000 \times 0.008349 = 1{,}995.60$$

The annual property tax **with the homestead exemption** is:

$$\lambda_{t,\text{HS}} = (300{,}000 - 25{,}000) \times 0.014295 - 25{,}000 \times 0.008349 = 275{,}000 \times 0.014295 - 208.725 = 3{,}722.40$$

Thus, the homeowner pays roughly \$3,720 annually with the exemption and would pay \$5,720 without it, yielding an annual savings of approximately \$2,000.

[29] m_s is the population-weighted average school millage rate, equal to the sum of School Board Operating and School Board Debt Service levies. m_n is the population-weighted average non-school, non-municipal millage rate, which includes county government operating, debt service, dependent special districts, independent special districts, and municipal service taxing units (MSTUs). Both rates are computed from the Florida Department of Revenue *Millage and Taxes Levied Report* (Florida Department of Revenue, Property Tax Oversight 2025) and exclude municipal levies. Homeowners residing within city limits face a higher total millage burden. Population weights are county-level estimates from the Bureau of Economic and Business Research (U.S. Census Bureau 2023).

Example B (large SOH gap): $A_t = \$200{,}000$

$$\Delta\lambda_t = (400{,}000 - 200{,}000 + 25{,}000) \times 0.014295 + 25{,}000 \times 0.008349 = 3{,}425.10$$

The annual property tax **with the homestead exemption** is:

$$\lambda_{t,\mathrm{HS}} = (200{,}000 - 25{,}000) \times 0.014295 - 25{,}000 \times 0.008349 = 175{,}000 \times 0.014295 - 208.725 = 2{,}292.90$$

So the homeowner pays roughly \$2,290 annually with the exemption and would pay \$5,720 without it, resulting in annual savings of about \$3,430.

These values correspond directly to the λ (denominator) and $\Delta\lambda$ (numerator) terms used in the elasticity calculation for Florida. The tax with the exemption ($\lambda_{t,\mathrm{HS}}$) serves as the reference base when expressing the property tax increase as a percentage change.

The examples demonstrate how the SOH cap compounds over time: longer ownership periods and greater appreciation produce larger differences between assessed and market values, thereby increasing the effective tax savings from the homestead exemption. The cumulative savings over multiple years can easily reach tens of thousands of dollars for long-tenured homeowners in high-growth markets.

Remarks.

- The algebra in (19) explicitly reflects the *immediate* reset of assessed value to the market value h_t when homestead/SOH protections are lost; the reassessment is the reason the leading term contains $h_t - A_t$.

- The examples above are annual increases (not cumulative present values). If one reports the cumulative additional tax burden over T future years after reassessment, one should sum the annual $\Delta\lambda_{t+\tau}$ for $\tau = 0, \ldots, T-1$ while accounting for subsequent growth in millage rates and assessed values (because, after the reset, the reassessed basis is h_t and the former SOH cap no longer applies). This cumulative amount can reach several tens of thousands of dollars for long-tenured owners with large SOH gaps — but it is *not* the annual figure.

Elasticity Calculations for Florida Using the elasticity formula:

$$\epsilon_{N,t} = \frac{\%\Delta N}{\%\Delta T} = \frac{\hat{b}/N^*}{\Delta\lambda/\lambda} \tag{20}$$

For the **STR from Example A**, $\hat{b} = 0.45$ nights and $N^* = 30$:

$$\epsilon_{N,t} = \frac{0.45/30}{1,995/3,722} = \frac{0.015}{0.536} = 0.0280 = 2.80\%$$

Thus, a 1% increase in property taxes leads to a 2.8% decrease in rental nights.

For the **STR from Example B**, $\hat{b} = 0.45$ nights and $N^* = 30$:

$$\epsilon_{N,t} = \frac{0.45/30}{3,425/2,293} = \frac{0.015}{1.49} = 0.0101 = 1.01\%$$

So, a 1% increase in property taxes leads to approximately a 1% decrease in rental nights. This is a unit elastic response.

Similarly, I calculate the elasticity for **marginal bunchers** in each example. The marginal buncher reduces their rental nights by approximately 16.46 nights annually.

For the **STR from Example A**, $\hat{b}_{adj} = 16.46$ nights and $N^* = 30$:

$$\epsilon_{N,t} = \frac{16.46/30}{1,995/3,722} = \frac{0.549}{0.536} = 1.024 = 102\%$$

A 1% increase in property taxes leads to a 102% decrease in rental nights for the marginal buncher.

For the **STR from Example B**, $\hat{b}_{adj} = 16.46$ nights and $N^* = 30$:

$$\epsilon_{N,t} = \frac{16.46/30}{3,425/2,293} = \frac{0.549}{1.49} = 0.368 = 36.8\%$$

In this case, a 1% increase in property taxes leads to a 37% decrease in rental nights by the marginal buncher. As expected, marginal bunchers are more responsive to the threshold than the average STR.

G.2 Summary of Estimated Property Tax Savings

Table 4 summarizes the key statutory parameters and the estimated average annual property tax savings from the homestead exemption in Florida. The estimates incorporate both the standard homestead exemption and the SOH assessment cap, use illustrative examples for typical assessed-value gaps, and account for the immediate reassessment of the property to full market value when the exemption is lost.

Table 4: Comparison of Average Property Tax Savings for Owner-Occupied Homes

Parameter / Measure	**Florida (Homestead + SOH)**
Median Home Value ($)	400,000
Assessment Ratio (Owner-Occupied)	— (uses SOH-capped A_t)
Assessment Ratio (Non-Owner)	— (reset to full market value h_t)
Assessment Growth Cap	3% or CPI (SOH)
School Millage Exemption	None beyond first $25,000
Typical Non-School Millage (m_n)	8.349 mills
Typical School Millage (m_s)	5.946 mills
Homestead Exemption Amount	Up to $50,000 (two tiers)
SOH Benefit Included	Yes (explicitly modeled $h_t - A_t$ gap)
Estimated Annual Tax Savings	$2,000–$3,500
Representative Monthly Savings	$160–$280
Key Legal Threshold	>30 days rental for 2 consecutive years
Primary Legal Reference	Fla. Stat. §196.061; Furst v. Rebholz (2023)

Notes: Florida calculations use illustrative millage rates of $m_n = 8.349$ and $m_s = 5.946$ mills, and market-to-assessed-value gaps ($h_t - A_t$) of $100,000–$200,000. Florida values reflect the immediate annual increase in property tax liability after reassessment to full market value when homestead and SOH protections are lost (see Eq. 19). Cumulative losses over multiple years can be substantially larger as the reassessed property continues to appreciate without the SOH cap.

H Appendix: Airbnb-Only Robustness Check

A potential concern with the main analysis is that AirDNA began scraping VRBO listings in 2017, coinciding with the start of the post-VCA period in Florida. If VRBO listings systematically differ from Airbnb listings in their bunching behavior, the introduction of VRBO data in 2017 could confound the pre/post comparison rather than reflecting a true behavioral response to the VCA. To assess this, we replicate the main analysis restricting the sample to Airbnb listings only.

Figure 7 displays the bunching estimates of annual reservation days for the Airbnb-only sample from 2017–2024. The pre-period figure is not shown here as it is identical to the pre-period figure in the main analysis. Because AirDNA did not scrape VRBO listings prior to 2017, the pre-period samples are Airbnb-only by construction. The results are qualitatively consistent with the main analysis, though the estimated excess mass is attenuated relative to the full sample.

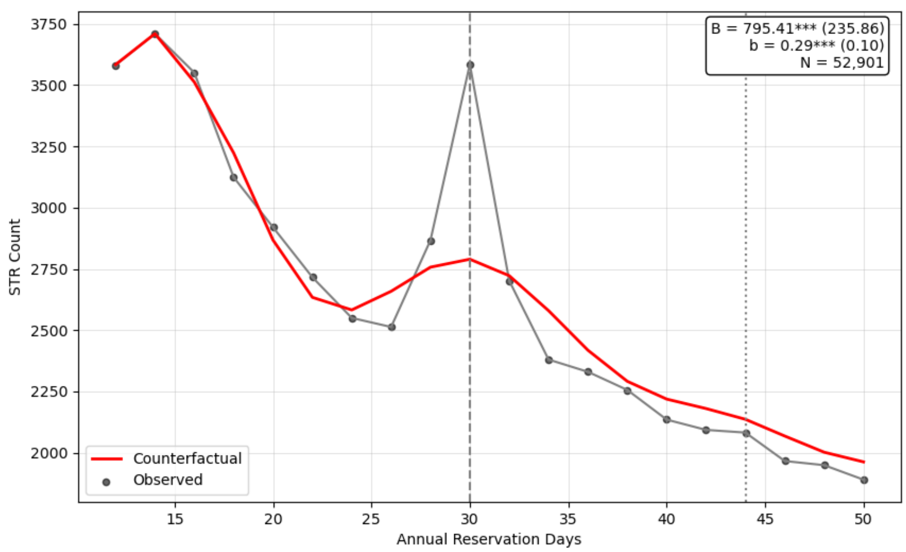


Figure 7: Distribution of Annual Reservation Days, Airbnb Only, 2017 -2024

Notes: The figure plots the distribution of annual reservation days for likely homeowner-hosts with one unit. The gray dotted line marks the 30-day homestead exemption threshold. Black dots represent actual binned counts; the red line shows the counterfactual distribution from the bunching estimator. Bin width is 2 days. I include a fixed point control at 14 days. Ten bins are used on each side of the threshold. The thin light gray line denotes the dominated region. B is estimated excess mass at the threshold and b is normalized excess mass. Standard errors from a residual bootstrap with 1,000 replications are in parentheses. Years of analysis are 2017-2024.
p<0.10*, p<0.05**, p<0.01***.

Table 5: Bunching Estimates, Airbnb-Only Sample

	Florida (30-day limit)	
Year(s)	2015	2017–2024
Estimated Excess Mass	-1.171	795.408***
	(7.957)	(235.862)
Normalized Excess Mass	-0.019	0.285***
	(0.126)	(0.098)
Share of Bunchers	-0.022	0.007
Adj. Normalized Excess Mass (LATE)	0.826	38.147
N	1,283	52,901

Notes: This table replicates Table 1 restricting to Airbnb listings only. The pre-period for Florida is 2015 and the post-period is 2017–2024. Standard errors from a residual bootstrap with 1,000 replications are in parentheses. N is the number of observations in the bin range. Estimated excess mass is the number of additional STRs located at the threshold. Normalized excess mass is the average number of rental nights forgone at the cutoff. Share of bunchers is one minus the ratio of observed to counterfactual counts in the dominated region (the bin just above the threshold), capturing the fraction of STRs that respond to the cutoff (compliers). The adjusted normalized excess mass is the LATE—normalized excess mass divided by the share of bunchers—capturing how many rental nights the average buncher forgoes due to the cutoff. The adjusted normalized excess mass for 2017–2024 is large because the estimated share of bunchers is small (0.007), which makes the adjustment imprecise; the normalized excess mass is the better basis for comparison with Table 1. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

I Appendix: Hosts with 21 or More Units as the Counterfactual Robustness Check

As an alternative to the main estimation, I use the distribution of annual reservation days among hosts with 21 or more units as the counterfactual for one-unit hosts. Because the homestead exemption applies only to a permanent residence, these hosts can claim it on at most one of their many properties, so their distribution near the threshold should reflect factors unrelated to the exemption, such as demand for monthly stays or platform features. Consistent with this, estimating the main specification for hosts with 21 or more units gives a normalized excess mass of 0.146 (0.065) in 2015 and 0.197 (0.078) in 2017–2024. They bunch at 30 days both before and after the VCA, so their bunching is not a response to it. The estimation uses the same periods as the main analysis (2015 before the VCA and 2017–2024 after), the same bin width of 2 days, and the same 10 bins on each side of the threshold, and the bunching window is the bin that ends at the 30-day threshold.

Because hosts with 21 or more units list many more properties than one-unit hosts, the two distributions must be put on the same scale. Let m_j be the number of listings of hosts with 21 or more units in bin j, n_j the number of one-unit listings, and W the bunching window. I first convert the comparison counts to shares, $s_j = m_j / \sum_k m_k$, and then rescale them by a single constant so that, across the bins outside the bunching window, the counterfactual sums to the one-unit count:

$$\hat{c}_j = s_j \cdot \frac{\sum_{k \notin W} n_k}{\sum_{k \notin W} s_k}. \tag{21}$$

The counterfactual therefore takes its shape from hosts with 21 or more units and its level from one-unit hosts, and the level is determined only by bins that the threshold should not affect. The excess mass is $B = \sum_{j \in W}(n_j - \hat{c}_j)$, and the normalized excess mass is $b = B/\hat{c}_{z^*}$, where $\hat{c}_{z^*}$ is the counterfactual count in the threshold bin. This is the same normalization used for the main estimates. Standard errors come from the same residual bootstrap as the main estimates, with 1,000 replications. The bootstrap holds the shape of the comparison distribution fixed, so the standard errors do not reflect sampling variation among hosts with 21 or more units.

Table 6 compares these estimates with the main estimates, and Figure 8 plots the one-unit distribution against the rescaled comparison distribution. Before the VCA, one-unit hosts show no significant bunching relative to hosts with 21 or more units, with a normalized excess mass of 0.134 (0.385), consistent with the main pre-VCA estimate of −0.019 (0.126). After the VCA, the estimated excess mass is 2,424.8 (473.9) listings and the normalized excess mass is 0.196 (0.039), significant at the 1 percent level. This estimate is smaller than the main post-VCA estimate of 0.450 (0.184), but it remains positive, statistically significant, and more precisely estimated.

The smaller estimate is expected. Because hosts with 21 or more units also bunch at the threshold, their bunching is built into this counterfactual, so the estimate measures bunching by one-unit hosts over and above the bunching of hosts with 21 or more units. This removes any clustering near 30 days that is common to both groups, and the gap between the two estimates (0.254) is comparable to the post-VCA normalized excess mass of 0.197 for hosts with 21 or more units, although the two are not directly additive because each is normalized by a different counterfactual count.

This comparison distribution is also an imperfect counterfactual away from the threshold. Above about 40 days, the number of one-unit listings falls off somewhat faster than the number of listings of hosts with 21 or more units. For these reasons, I treat this design as a robustness check rather than the main specification. Because it nets out all bunching shared with hosts who do not respond to the VCA, and because the main sample cannot separate eligible from ineligible properties, the estimate of 0.196 should be interpreted as a conservative lower bound on the response of one-unit hosts who claim the homestead exemption.

Table 6: Bunching Estimates for One-Unit Hosts Using Hosts with 21 or More Units as the Counterfactual

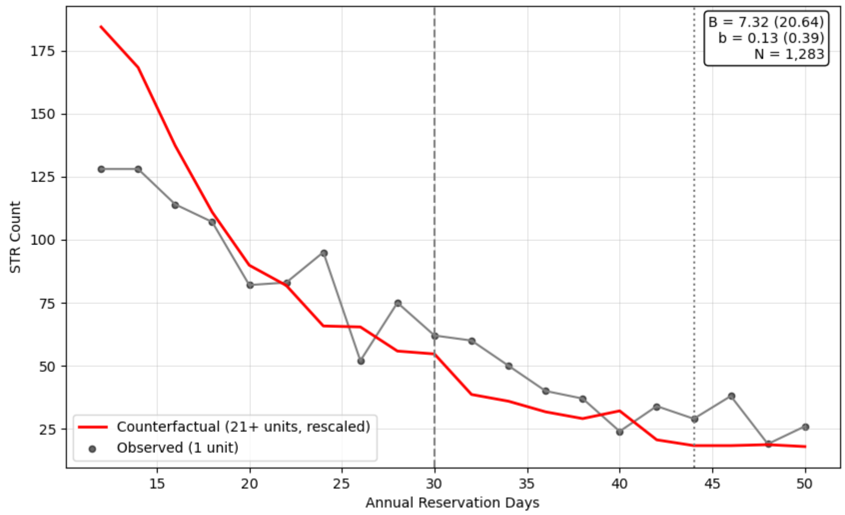
Counterfactual	Polynomial (Main Estimates)		Hosts with 21+ Units	
Year(s)	2015	2017–2024	2015	2017–2024
Estimated Excess Mass	-1.171	4,589.321***	7.317	2,424.777***
	(7.957)	(1,416.941)	(20.645)	(473.884)
Normalized Excess Mass	-0.019	0.450**	0.134	0.196***
	(0.126)	(0.184)	(0.385)	(0.039)
Share of Bunchers	-0.022	0.027	-0.554	0.021
Adj. Normalized Excess Mass (LATE)	0.826	16.464	-0.242	9.495
N (1 Unit)	1,283	193,148	1,283	193,148
N (21+ Units)			3,336	220,473

Notes: This table reports bunching at the 30-day rental limit for the main sample of likely homeowner-hosts with 1 unit under two counterfactuals. The first two columns repeat the main estimates, where the counterfactual is a polynomial fit to the one-unit distribution (Table 1). The last two columns use the distribution of likely homeowner-hosts with 21 or more units and entire-home listings, converted to shares and rescaled so that it matches the one-unit count outside the bunching window. Data are from AirDNA. Bin width is 2 days, with 10 bins on each side of the threshold. N (1 Unit) and N (21+ Units) are the numbers of observations in the bin range for each group. Estimated excess mass is the number of additional STRs located at the threshold. Normalized excess mass is the average number of rental nights forgone at the cutoff. Share of bunchers is one minus the ratio of observed to counterfactual counts in the dominated region (the bin just above the threshold), capturing the fraction of STRs that respond to the cutoff (compliers). The adjusted normalized excess mass is the LATE—normalized excess mass divided by the share of bunchers—capturing how many rental nights the average buncher forgoes due to the cutoff. Standard errors from a residual bootstrap with 1,000 replications are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

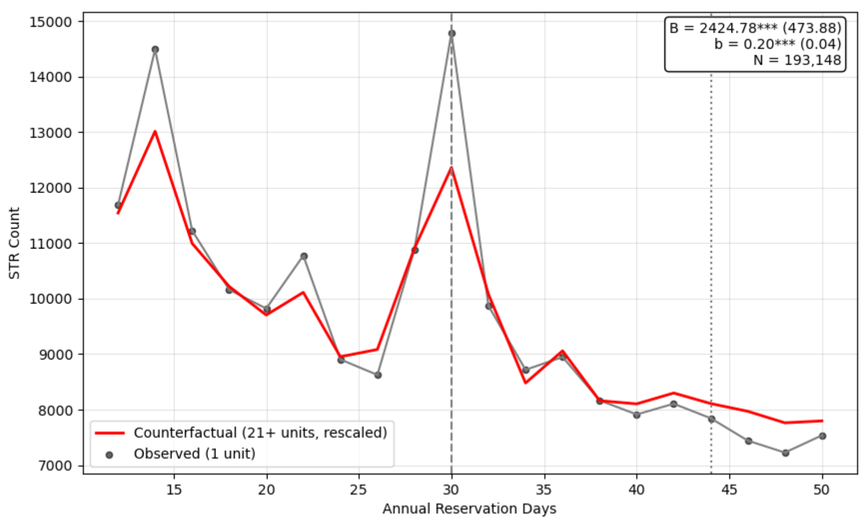
J Appendix: Additional Data Sources

I list the various web and news sources used for the rental day limit data and information on property tax law.

- *Zillow Research.* "Zillow Home Values." `https://www.zillow.com/home-values/58/vt/`
- *WSVN.* "Rented House Through Airbnb and Lost Homestead Exemption." `https://wsvn.com/news/help-me-howard/rented-house-through-airbnb-and-lost-homestead-exemption`
- *Florida Statutes.* Section 196.061(1), "Rental of Homestead to Constitute Abandonment." `http://leg.state.fl.us/Statutes/index.cfm?App_mode=Display_Statute&Search_String=&URL=0100-0199/0196/Sections/0196.061.html`



(a) Pre-VCA (2015)



(b) Post-VCA (2017–2024)

Figure 8: Bunching Among One-Unit Hosts Using Hosts with 21 or More Units as the Counterfactual

Notes: The figures plot the distribution of annual reservation days for likely homeowner-hosts with 1 unit and entire-home listings. Black dots represent actual binned counts. The red line shows the counterfactual: the distribution of likely homeowner-hosts with 21 or more units in the same period, converted to shares and rescaled to match the one-unit count outside the bunching window. The dashed gray line marks the 30-day homestead exemption threshold, and the dotted gray line at 44 days marks the dominated region. Bin width is 2 days, with 10 bins on each side of the threshold. B is estimated excess mass at the threshold and b is normalized excess mass. Standard errors from a residual bootstrap with 1,000 replications are in parentheses. p<0.10*, p<0.05**, p<0.01***.

- *Florida Department of Revenue.* "Homestead Exemption." https://floridarevenue.com/faq/Pages/FAQDetails.aspx?FAQID=1635&IsDlg=1

- *Florida League of Cities.* "History of Florida's Property Tax." http://www.floridaleagueofcities.com/docs/default-source/Civic-Education/historyoffloridaspropertytax.pdf