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Property Tax Pass-Through to Renters: A Quasi-Experimental Approach

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Abstract

Does a landlord's property tax bill affect a new tenant's rent? According to standard economic theory, it should not—the law of one price implies that identical rental units in the same market should be priced identically, despite heterogeneity in property tax costs. This paper provides new evidence that a landlord's property tax bill *does* affect rent for new tenants, violating the law of one price. I investigate the effect of heterogeneous property tax shocks on rents using a unique, quasi-experimental setting in California. California's Proposition 13 has created large discrepancies in property tax liability among otherwise similar rental units, and these discrepancies are exacerbated quasi-randomly around a sale. Using a novel, comprehensive dataset on new-tenant rents from the City of Berkeley, I find strong evidence that landlords faced with quasi-random, building-level property tax shocks pass through \$0.50–\$0.89 per \$1 of the property tax shock to renters. The results are robust to the inclusion of landlord size, renovations around a sale, and a property's purchase price. I propose and empirically motivate an explanatory model of heterogeneity in landlord sophistication that can rationalize the observed positive relationship between rent and property taxes.

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1 Introduction

Does a landlord's property tax bill affect a new tenant's rent? Standard economic theory suggests that it should not. Identical rental units in the same rental market should be priced identically, despite heterogeneous property tax costs—the law of one price should prevail. Political proponents of limiting property taxation, however, argue that property tax savings to landlords should pass through to renters.[1] The validity of this argument has far-reaching consequences for renters in the United States, as a majority of states now impose some sort of property tax cap.[2] This paper provides new evidence that a landlord's property tax bill *does* affect a new tenant's rent. Using a quasi-experimental setting from California and a novel unit-level rent dataset from the City of Berkeley, I find that landlords faced with quasi-random, building-level property tax shocks pass through \$0.50–\$0.89 per \$1 of the tax shock to renters. This violates a neoclassical understanding of the housing market, as similar units in the same rental market are priced differently depending on the amount of the property tax shock. While previous research on property tax incidence utilizes variation in property taxes *across* markets, this paper provides new evidence on how heterogeneous property tax burdens *within* a single market affect renters.

Proposition 13 (1978), a state law passed via California's referendum process, provides a natural quasi-experiment that can be used to evaluate the impact of a property tax shock on rents. Under Proposition 13, a property's taxable value is equal to its purchase price, which is allowed to increase by a maximum of 2% per year thereafter. As a result, the longer a property is held, the greater the gap between its market value and taxable value: Taxable value increases by 2% per year, while market value typically increases at a much faster rate.[3] Consequently, when a property is sold to a new owner, a large and quasi-random increase in property taxes occurs, with the amount of the change depending on the number of years since the property was last sold and the rate at which the property's market value outpaced its taxable value during those years. This creates very large discrepancies in property tax liability among otherwise similar rental properties. I combine property tax information with a novel dataset of unit-level leases in order to estimate the effect of a sale-triggered property tax change on rents. The rent dataset contains unit-level rents for approximately 25,000 rental units in the City of Berkeley from 1980 to 2022. This paper uses only new-tenant rent

[1] This was the argument made to renters in California to garner support for the passage of Proposition 13, a law drastically limiting property tax growth. See Figure A1.

[2] See Wong (2023).

[3] House prices increased 6.7% per year, on average, during the time period studied (FRED All-Transactions House Price Index for Oakland-Berkeley-Livermore).

observations from 1996 onward, which are freely set by the landlord with no rent control restrictions. The rent data are very unique in their scope and granularity, as rent data are not systematically collected.

To estimate the effect of a sale-triggered property tax change on rents, I first employ an event study design to establish the presence of both a property tax increase and a rent increase after a sale event. The event study shows that property taxes increase by 60% on average after a sale. Rents increase by 6% on average after a sale, and the positive effect on rent persists over the next five years. Second, I utilize a difference-in-difference design that is closely related to a standard cost pass-through specification, leveraging two sources of variation (treated/control and dosage of treatment). I compare rents of similar buildings that were either sold between new-tenant rent observations (treated) or not sold between new tenants (control). Additionally, buildings that are sold (treated) incur different 'dosages' of treatment in terms of the change in property tax burden, based on how long ago the property last sold. My preferred specification yields an elasticity of rent to taxable property value of 0.05. This implies that a 100% increase in property taxes following a sale causes rents to increase by 5%. This elasticity equates to tax shifting of $0.53 per $1 of additional per-unit tax. Although sales are not strictly random events, my preferred specification includes a series of fixed effects that allow me to compare rent changes in buildings with different property tax burdens in the same neighborhood over the same period.[4]

I validate these difference-in-difference results using an instrumental variables approach, in which I directly utilize the quasi-random variation in the length of time between the current sale and most recent previous sale of sold buildings. This specification addresses a potential threat to identification, which is that some property-specific amenity change around a sale causes a property's purchase price (and thus property taxes) and potential rents to increase simultaneously. I instrument for the change in property tax burden around a sale with the number of years between the current sale and the previous sale for sold properties, which should be unrelated to any property-specific amenity change. This specification exploits the fact that a longer length of time between the current and previous sale will cause a larger percentage change in property taxes upon sale.[5] Again, this specification includes a series of fixed effects such that it compares rent changes in buildings with differing sale-triggered

[4] Also, sales are common (60% of buildings are sold in the sample, see Table 1), I can rule out pre-trends in rent before a sale (see Figure 5), and I provide direct evidence on renovations around a sale (see Section 4.2).

[5] As an example, a building sold this year and two years ago will incur a much smaller change in property taxes than a building sold this year and twenty years ago, because the building sold two years ago was reassessed much more recently.

property tax shocks in the same neighborhood over the same period. The IV results suggest more pass-through than in the OLS specification, \$0.89 per \$1. Both the IV and OLS results hold even when conditioning on a sold property's sale price, thus exploiting the difference between two properties that sell for exactly the same price but incur different tax shocks.

Additionally, the results are robust to differences in rent-setting behavior between small 'mom-and-pop' landlords and larger landlords. I find that landlord size has a small but significant effect on rent-setting behavior that is independent of the effect of sale-triggered property tax increases, with larger landlords setting slightly higher rents than their smaller counterparts. Further, the results are robust to the inclusion of permitted renovations around a sale, as measured by city building permits.[6]

The pass-through result presented in this paper suggests an important question: How are different rent levels sustained in similar apartments? I propose and empirically motivate a model in which incumbent, long-term landlords are inattentive to market-rate rents due to a lack of informative tax cost shocks. Property taxes for these landlords are not informative about a property's market value or its potential rents, causing these landlords to set below-market rents based on a property's current tax bill. These below-market rents create an opportunity for high-sophistication landlords to purchase properties from inattentive landlords, increasing both property taxes and rents. Thus, upon sale, the new landlord corrects the below-market rent by updating to the correct market-rate rent, but will herself become inattentive over time. This model explains 1) the positive relationship between rent and property taxes, and 2) why below-market taxes lead to below-market rents. Further, this model implies a novel mechanism for pass-through via landlord churn.

The empirical and theoretical results presented in this paper have clear policy implications. First, property tax caps such as Proposition 13 do provide rent rebates via below-market rents to tenants with long-term, incumbent landlords. However, it is also clear that property tax caps are a blunt policy instrument, in that who receives these rent rebates is unknown and likely random. The explanatory model proposed in this paper suggests that the repeal of a property tax cap such as Proposition 13—and its replacement with a system that taxes property based on its market value—would lead to rent increases, but also increased state tax revenue that could be used to provide targeted rental assistance to low-income renters.

[6] Following Diamond et al. (2019) and Benmelech et al. (2023).

1.1 Contribution

This paper adds to an active literature documenting behavioral pricing in the owner-occupied housing market. In a seminal work, Genesove and Mayer (2001) study the Boston condominium market and find that loss aversion relative to a property's original purchase price is a large and significant driver of pricing behavior.[7] This suggests that sellers are very sensitive to their individual gains/losses over their home's original purchase price. A more recent paper from Andersen et al. (2022) uses rich data from the Danish housing market to document a similarly high degree of loss aversion and reference-dependent behavior from home sellers.

Fewer papers have attempted to study the rental market, due to the fact that very few data on unit-level rents exist. Survey data have been used to establish rent stickiness (Gallin and Verbrugge (2019), Genesove (2003)) while Baker and Wroblewski (2024) also document rent stickiness in the same near-universal sample of renters in Berkeley, California, used in this paper. Giacoletti and Parsons (2022) use a cross-sectional sample of rental listings in California to investigate reference dependence and liquidity constraints in rent-setting. They find that landlords who purchased rental properties during a housing market peak set rents 2-3% higher than landlords with similar properties purchased during a housing market downturn. They show that this behavior can be rationalized with reference-dependent preferences relative to a property's purchase price, but not liquidity constraints.[8] Hughes (2022) utilizes quasi-exogenous changes in mortgage financing to understand the impact of changes in financing costs on a sample of U.S. renters, finding that landlords increase rent revenues around both cost-increasing and cost-decreasing events. Similar to the mechanism proposed in this paper, he proposes information updating around the event as a potential explanation.

In concurrent work from Watson and Ziv (2024), the authors use tax policy changes to test for landlord pricing power in the New York City rental market. They investigate two tax policy changes that created building-specific changes in tax burden, and find that landlords pass through 75–130% of these idiosyncratic tax shocks to tenants. I estimate a pass-through rate of \$0.50-\$0.89 per \$1, or a 50–89% pass-through rate, in line with their estimates. A key contribution of this paper is the scope and granularity of rent data—this paper has near-universal coverage of rents for the City of Berkeley, and does not rely on

[7] This work in fact showed that loss aversion was a much more important driver of pricing behavior than the loan-to-value ratio of the mortgage, as studied in Genesove and Mayer (1997).

[8] This is similar to Genesove and Mayer (2001), who find reference dependence to be much more important than differences in liquidity constraints.

survey data that sample rent infrequently. As a result, I am able to use within-property variation in property tax costs.

This paper also relates to the longstanding literature on property tax incidence. Numerous papers have sought to determine if the landlord or tenant bears the majority of the property tax (see Oates and Fischel (2016) and England (2016) for reviews of the literature). Papers in this literature typically examine nearby areas with different tax rates or frequent tax rate changes, and compare the median rents in these areas while controlling for local public services provided. Estimates of pass-through from previous studies are inconclusive, with estimates ranging from \$0 to over \$1 of pass-through per \$1. In a seminal paper, Carroll and Yinger (1994) investigate the effects of property tax changes on rental prices in the Boston area in 1980. They find little evidence of tax shifting, with a \$1 increase in property tax yielding a \$0.09–\$0.16 increase in rents. Recent working papers find larger estimates of pass-through that vary by housing supply elasticity, ranging from \$0.50–\$1.39 per \$1 of tax (Löffler and Siegloch (2021), Rolheiser (2019)). These general equilibrium estimates of pass-through are not directly comparable to the partial equilibrium estimates of this paper and Watson and Ziv (2024), but it is surprising that they are so similar in magnitude.

The remainder of the paper will proceed as follows. Section 2 provides background on the setting and data sources used in this paper. Section 3 presents empirical results. Section 4 presents the results of robustness checks. Section 5 describes a theoretical framework to rationalize the empirical results. Section 6 concludes.

2 Background and Data

2.1 Property Taxes

I acquire property tax data from the Alameda County Assessor's Office, spanning 1987–2022. The assessor data include each Berkeley property's parcel number, address, total taxable value, the owner's name and address, and the date of the latest document filed by the owner related to the property.

Property tax liability is equivalent to approximately 1.25% of a property's assessed taxable value in Berkeley.[9] Proposition 13 caps taxable value increases at 2% per year unless the property is sold. Figure 1 shows an example of this in two similar multi-unit apartment buildings on the same block.[10] First, looking at Property 1 (1725 Oxford Street, represented

[9] City taxes account for the additional 0.25% above California's stated 1% property tax rate.

[10] Figure A7 shows the kitchens of a representative unit in each building, which appear quite similar.

by the red solid line), property taxes increase steadily at 2% per year until the building is sold in 2017, at which point property taxes jump from $9,400 to $95,000 per year, a 910% increase. Property 2 (1749 Oxford Street, represented by the blue dashed line) exhibits a similar pattern, with property taxes increasing steadily at 2% per year until the building is sold in 2003, at which point property taxes jump from $3,100 per year to $14,500 per year, a 368% increase. These very large increases in property taxes are above average in the sample, but demonstrate the extreme changes in property tax burden created by Proposition 13. The average increase in property taxes for sold versus unsold properties is shown in Figure 2. When a property is sold, property tax liability increases by 110% on average (represented by the dotted grey line). When a property is not sold, the average annual change in property taxes is approximately 2% (represented by the dashed grey line).

I identify sales in the property tax data by using a combination of 1) increases in taxable value that are significantly greater than 2%, 2) the date of the latest document filed for the property, and 3) changes in the owner's name and address. Using this method, I can separate true sales from other, less common types of taxable value reassessments.[11] Additionally, I use the property owner's address to link properties owned by the same landlord, to provide a measure of the landlord's size (for example, to identify 'mom-and-pop' versus corporate landlords). I am able to link property tax data and unit-level rent data by parcel number and/or address.

Table 1 shows the number of buildings and units in the regression sample. The data contain 3,590 distinct buildings, of which 2,276 are ever sold in the sample. As some buildings are sold more than once, the data contain 5,147 sale observations. The buildings in the sample correspond to 17,367 distinct units, of which 9,874 are ever sold in the sample. Reassessments without a sale are much less frequent. Tenant spells refer to the length of time a tenant occupies a rental unit. I observe 97,017 tenant spells in total. During 15,019 of these spells, a sale occurred, which causes the identifying large change in property tax burden.

2.2 Rent

The Berkeley Rent Board collects data on all leases fully or partially covered by rent control protections in the city. However, since 1996, new tenants have not been subject to rent control

[11] Other types of reassessment can occur under some circumstances, such as 'like-new' remodeling, construction of additions, and certain types of inheritance transfer. See Santa Clara County Assessor's Office 1, 2.

due to the phased implementation of vacancy decontrol under the statewide Costa-Hawkins Rental Housing Act of 1995. **This paper uses only new-tenant rent observations from 1996 onward, which are freely set by the landlord with no restrictions.**

Rent Board data cover 19,000–26,000 rental units over the period 1980–2022, with the number increasing as more units were built and/or registered with the Rent Board (see Figure A3). The data include each unit's parcel number, address, number of bedrooms, initial lease amount, lawful rent ceiling, and the start date of the tenancy. This dataset has not yet been used, to my knowledge, and is unique in its granularity.

Berkeley, California, located in the San Francisco Bay Area, has an active rental housing market with vacancy rates typically around 5%, among the lowest in the country.[12] Berkeley is a historically progressive city, and one of the first to enact post-WWII rent control in the United States. Rent control passed in Berkeley in 1980, limiting annual rent increases to a rate less than inflation (typically <2%). Interestingly, popular support for rent control came in part from renters feeling that the passage of Proposition 13 had not significantly helped reduce their rent burden.[13] In order to encourage new construction, buildings built after 1980 were exempt from rent control. Many of these units are still observed in the data, however, as they are still subject to Rent Board-enforced eviction protections.

Despite strict rent control laws in Berkeley, I observe unrestricted rents in the majority of Berkeley rentals after the passage of the Costa-Hawkins Rental Housing Act (1995). This statewide bill weakened rent control by mandating "vacancy decontrol," which allows landlords to set rents freely for new tenants. Thus, post-1996 new-tenant rents are freely set by the landlord and face no rent control restrictions.[14] The data also include new tenancies in many non-rent-controlled units. Figure A2 compares the evolution of rent over time for 1) new tenants in rent-controlled buildings (unrestricted rents), 2) continuing tenants in rent-controlled buildings (restricted rents), and 3) new tenants in non-rent-controlled buildings (unrestricted rents).

The empirical analysis in this paper uses only unrestricted new-tenant rent observations, from 1996 to present. In the regression sample, in addition to excluding pre-1996 rent observations, I exclude rent observation outliers including units with more than five bedrooms, and rent observations that deviate significantly from the average unrestricted rent for units with the same number of bedrooms in the same year.[15]

[12] Housing Vacancies and Homeownership (CPS/HVS), U.S. Census Bureau.

[13] "History of the Rent Control Debate in California," No Place Like Home, UC Santa Cruz.

[14] Full vacancy decontrol took effect on 1/1/1999, but landlords were allowed two unconstrained rent increases between 1996 and 1999.

[15] I calculate the percentage change from the rent observation to year-bedroom average rent, and drop

2.3 Building Permits

I obtain publicly available building permit data from the City of Berkeley. Every time a construction project is undertaken, the landlord is required to file appropriate building permits or else risk a fine. These permits help to identify rent-increasing improvements (i.e., kitchen remodels, bathroom remodels, new flooring) that can and should affect a unit's rent. Each building permit entry contains the building/unit address, a short description of the project, the date of filing with the city, and the date of completion.

Figure 3 shows a word cloud of the short permit descriptions available with each issued permit. Words such as *replace*, *new*, *install*, *remodel*, *remove*, *roofing*, *kitchen*, *repairs*, and *bathroom* are frequently found. These permits provide crucial information on changes in a unit's quality that could potentially confound a rent response due to a change in property taxes. I test for this in Section 4.

3 Empirical Results

3.1 Event Study

First, I conduct a simple event study to demonstrate the effect of a sale on both rent and property taxes. Figure 4 shows an event study of log taxable value around a sale, using the specification:

$$\ln[TaxableValue_{it}] = \sum_{j \in [-5,5]} \gamma_j \cdot D_{i,t+j} + \epsilon_{it},$$

where $D_{i,t+j}$ is a dummy variable equal to one if property i is $t+j$ years away from a sale. The coefficient of interest is γ_j, representing the change in log taxable value associated with being $t+j$ years away from a sale. The error term is captured by ϵ_{it}.

In Figure 4, the event study shows that taxable value increases by a small amount (approximately 2% per year) before a sale, and jumps discontinuously upward when a sale occurs, increasing by 55%. Taxable value continues to increase slightly each year after the sale, reflecting the mechanical 2% per year increase.

observations in the top and bottom percentile (1st and 99th percentiles).

Figure 5 shows log new-tenant rent before and after a sale, using the specification:

$$\ln[Rent_{it}] = \sum_{j\in[-5,5]} \gamma_j \cdot D_{i,t+j} + \lambda_{g,t_i} + \alpha_i + \gamma_{m_{t_i}} + \epsilon_{it},$$

where $D_{i,t+j}$ is again a dummy variable equal to one if property i is $t+j$ years away from a sale. The coefficient of interest is γ_j, now representing the change in log rent associated with being $t+j$ years away from a sale. A year times census tract fixed effect is captured by λ_{g,t_i} in this specification, since the price level and neighborhood have obvious effects on rent.[16] Unit fixed effects α_i and month fixed effects $\gamma_{m_{t_i}}$ are also included, to control for stable unit attributes and seasonal rent premiums. The error term is captured by ϵ_{it}. I exclude rent observations that occur within one month of a sale, since it is unclear which landlord posted those rents. For observations in the sale year more than one month before (after) the sale, I assign them to the -1 year (1 year) category. This panel is unbalanced, as it includes only new-tenant (market-level) rents, which happen at irregular year intervals.

Figure 5 shows that there are no pre-trends in rent before a sale. This helps rule out the possibility that units are in poor condition before a sale, with subsequent rent increases attributable to the new landlord making necessary repairs. No pre-trends also rules out a scenario in which the previous landlord improves the building before a sale, leading to higher rents both at and after the transaction. Figure 5 shows that after a sale, there is a discontinuous jump up in rent prices, an approximate 6% increase. The increase in rent persists over the next four years.

Notably, this specification utilizes only one source of variation—sale timing—and does not leverage the amount of the change in property tax, which also varies among properties.

3.2 Pass-Through Specification

In order to utilize the variation in the change in tax burden around a sale, I employ a specification resembling a typical pass-through estimation with an additional difference-in-difference component. The specification compares rents in similar buildings that were either sold between new-tenant rent observations (treated) or not sold (control), and if sold, received varying 'doses' of treatment in terms of how much change in property taxes occurred. I use only new-tenant rent observations as these are freely set by the landlord and not subject to

[16] I do not include fixed effects in the property tax specification, since changes in property taxes are 1) purely mechanical outside of a sale, and 2) a function of the sale price when sold, meaning that current price levels and neighborhood amenities should be reflected in the sale price.

rent control. Thus, each observation in the sample will include a rent pair and a property tax pair, with the first observation in each pair coming from the start of a tenant spell, and the second observation in each pair coming from the end of a tenant spell. I illustrate an example of this in Figure 6, using a sample unit from each property used in Figure 1. Each box represents one data point in the sample, which will relate the change in new-tenant rent and the change in property tax liability over a tenant spell. Using the change in rent over a tenant spell is necessary because landlords can freely set rent only upon a change in tenant.

Using tenant spells also helps to address a potential reverse causality problem. One might suspect that high rents would cause landlords to sell their buildings, making the timing of the sale highly relevant to rent-setting. However, per Berkeley eviction protections, tenants cannot be evicted due to a sale. New landlords retain a building's current tenants until the tenants decide to vacate, which is typically 2-3 years later.[17] This means that the timing of the sale is somewhat unrelated to the time at which the new landlord can first set an unrestricted rent.

The key source of quasi-random variation in this specification is the magnitude of the change in property taxes. The longer a property was held by the previous owner before the current sale, the greater the difference between its market value and its taxable value, and the greater the increase in property tax burden upon sale. Again, this is because the market value of a property typically increases much faster than 2% per year, while the taxable value increases by a maximum of 2% per year. The identifying assumption is that, after controlling for a number of potential confounders, the length of time the property was held by the previous owner is close to random, yielding a random increase in the property tax burden upon sale.

The baseline specification is as follows: for unit i with j tenant spells, with a new tenant in periods $t_{ij} - k_{ij}$ and t_{ij}, in Census tract g, with rent R and unit taxable value TV:

$$\begin{aligned} \Delta \ln[R_{i,g,t_{ij},t_{ij}-k_{ij}}] = {} & \beta_1 \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}] + \beta_2 \mathbb{1}\{Sale_{t_{ij}-k_{ij},t_{ij}}\} \\ & + \beta_3 \mathbb{1}\{Sale_{t_{ij}-k_{ij},t_{ij}}\} \cdot \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}] \\ & + \lambda_{g,t_{ij},t_{ij}-k_{ij}} + \alpha_i + \gamma_{m_{t_{ij}},m_{t_{ij}-k_{ij}}} + \epsilon_{i,g,t_{ij},t_{ij}-k_{ij}}, \end{aligned} \tag{1}$$

where $\Delta \ln[R_{i,g,t_{ij},t_{ij}-k_{ij}}]$ is the change in new-tenant rent from time t_{ij} to time $t_{ij} - k_{ij}$, which controls for any unit-specific unobservables reflected in pre-sale rent values, and $\Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$ is the change in taxes over the same period. The second term is an

[17] See Table A4 for average pre- and post-sale tenant spell lengths, which verify that tenants are not pressured out post-sale.

indicator for a sale occurring at any time between the two new-tenant rent observations in t_{ij} and $t_{ij} - k_{ij}$. The coefficient of interest is β_3, representing the effect on rent of the interaction between sale and the change in taxable value due to the sale. Tract $\times$ $\text{Year}_{t_{ij}} \times \text{Year}_{t_{ij}-k_{ij}}$ fixed effects are denoted by $\lambda_{g,t_{ij},t_{ij}-k_{ij}}$ and control for time-varying trends in neighborhood desirability. Unit fixed effects, denoted by α_i, control for stable unit attributes that might make the unit more or less desirable.[18] Month by month fixed effects, denoted by $\gamma_{m_{t_{ij}},m_{t_{ij}-k_{ij}}}$, control for a premium on rents set in different seasons—rents set in summer tend to be higher than those set in off-peak seasons.[19] Standard errors are clustered by building to account for any within-building error correlation. This specification resembles a difference-in-difference specification, where sold properties are 'treated' with a tax shock, but the dosage of the shock varies. The controls allow for a comparison of rents in equivalent units in the same tract-years with different property tax shocks.

The results of Equation (1) are shown in Column 3 of Table 2. Columns 1 and 2 of Table 2 present observational specifications for comparison with Equation (1). Column 1 presents an observational specification in which only the change in taxable value is used, without distinguishing between sold and unsold properties. The coefficient on taxable value is equal to 0.05 and is positive and significant. Column 2 adds a variable for sale, indicating if the building was sold in $[t_{ij} - k_{ij}, t_{ij}]$. The coefficient on sale is positive and significant, and reduces the magnitude of the coefficient on taxable value significantly. This coefficient, as in the event study from Section 3.1, captures one source of variation in property taxes (sale status) but ignores a second important source of variation, which is the amount of the property tax shock. Column 3 presents the results from Equation (1), which utilizes both sources of variation with the addition of two interaction effects. First, the interaction effect of sale and taxable value separates changes in taxable value due to sale from those simply due to the mechanical 2% annual increase. The coefficient on this interaction effect is significant at 0.048, similar to the coefficient in Column 1. Second, I include an indicator variable for non-sale reassessments in $[t_{ij} - k_{ij}, t_{ij}]$, which should be treated differently than sales. I also interact this reassessment dummy with the change in taxable value. I find the interaction coefficient to be positive but insignificant.[20] Using Column 3, the observed elasticity of rent

[18]For instance, amenities such as above-average square footage or a top floor unit.

[19]Seasonal premiums are shown to be significant in Baker and Wroblewski (2024). Table A1 shows the main specification with the addition of each fixed effect, with tract by year fixed effects and unit fixed effects being the most significant.

[20]Non-sale reassessments typically reflect large-scale taxable improvements or certain types of inheritance transfer. Including these variables is weakly helpful in disentangling the effects of taxable improvements from sale-triggered changes in taxable value. See Table A5 for the Column 3 specification without reassessment coefficients. The results are also not sensitive to the exclusion of these observations.

to property taxes is equal to 0.048. With an average value of $\frac{\text{Monthly Rent}}{\text{Monthly Per-Unit Tax Liability}} = 11$ for sold buildings, this equates to a pass-through rate of \$0.53 per \$1. Interestingly, the coefficient of interest on $\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times \Delta$ Log Taxable $\text{Value}_{t_{ij}-k_{ij},t_{ij}}$ in Column 3 does not differ much from the coefficient in the observational specification in Column 1. The similarity of these coefficients allows me to utilize an observational specification in levels (dollars) to validate the estimate of \$0.53 per \$1 of pass-through. Table A2 provides a validating pass-through estimate of \$0.55 per \$1.

Further, the pass-through estimate is not sensitive to the use of a never-treated control group, but the use of this specification reduces the sample by half. See Table A3, which compares the baseline results (Column 1) with the pure control specification (Column 2).

3.3 IV Specification

I validate the pass-through estimate from Section 3.2 using an instrumental variables approach, in order to address potentially confounding events around a sale. The threat to identification is this: Suppose there is some property-specific amenity change that affects only one property in a Census tract, and as such this amenity change would not be captured by tract fixed effects. This amenity change would simultaneously increase both a property's purchase price upon sale (and, thus, its post-sale property tax burden) and potential future rents, confounding the pass-through of property taxes to rents.

To address this potential confound, I instrument for the change in taxable value around a sale using the number of years since the property was last sold, since this variation is not affected by property-specific amenity changes. Recall that a key source of random variation in the main specification is the magnitude of the change in property taxes due to a sale. This variation is determined by the market value of the home at the current and previous sale dates. This can be considered semi-random because two buildings sold in the same year will have very different *changes* in property tax liability if the year in which they were previously sold differs. Under Proposition 13, a building sold twenty years ago and today will face a much larger change in property tax liability than a building sold two years ago and today. Thus, the change in property taxes will be highly dependent on the length of time between sales.[21]

The exclusion restriction in this IV specification is that the number of years since a property was last sold affects changes in rent only through changes in property taxes. However, while this specification addresses potential problems around property-specific amenity

[21] See Figure A5 for a visual representation.

shocks, Section 5.2 provides evidence on how the exclusion restriction might be violated.

3.3.1 IV Specification in Log-Changes

First, I employ the IV specification as in Equation 1, using log-changes in rent and taxes. Figure 7 shows the change in log per-unit property tax liability binned by the number of years since the last sale for sold units. There is a positive, significant relationship between the change in log taxable value and the number of years since the last sale. This means that the longer between two sales, the larger the change in property tax due to a sale.

This relationship motivates the specification below. I exploit the variation in the change in property taxes due to the number of years since last sale for sold buildings, by instrumenting for the magnitude of a sale-triggered change in property tax burden with the number of years since the last sale. The instrument, $Yrs_{i,g,t}$, is equivalent to the current sale year minus the most recent previous sale year for a sold property. I utilize this instrument in the following specification, where Equation (2) denotes the first stage, and Equation (3) denotes the structural equation:

$$\begin{aligned} 1[Sale_{t_{ij}-k_{ij},t_{ij}}] \cdot \Delta \ln[TV_{i,g,t_{ij}-k_{ij},t_{ij}}] = {} & \pi_1 1[Sale_{t_{ij}-k_{ij},t_{ij}}] \cdot Yrs_{i,t} \\ & + \pi_2 1[Sale_{t_{ij}-k_{ij},t_{ij}}] \\ & + \lambda_{g,t_{ij},t_{ij}-k_{ij}} + \alpha_i + \gamma_{m_{t_{ij}},m_{t_{ij}-k_{ij}}} + \epsilon_{i,g,t_{ij},t_{ij}-k_{ij}} \end{aligned} \tag{2}$$

$$\begin{aligned} \Delta \ln[R_{i,g,t,t-k}] = {} & \gamma_1 1[Sale_{t_{ij}-k_{ij},t_{ij}}] \cdot \Delta \ln[TV_{i,g,t_{ij}-k_{ij},t_{ij}}] \\ & + \gamma_2 1[Sale_{t_{ij}-k_{ij},t_{ij}}] \\ & + \lambda_{g,t_{ij},t_{ij}-k_{ij}} + \alpha_i + \gamma_{m_{t_{ij}},m_{t_{ij}-k_{ij}}} + v_{i,g,t_{ij},t_{ij}-k_{ij}} \end{aligned} \tag{3}$$

Results are presented in Table 3. Column 1 shows Equation (1) for comparison, restricted to the sample for which I observe or can impute previous sale dates.[22] Column 2 shows Equation (2), the first stage. An indicator for sale in $[t_{ij} - k_{ij}, t_{ij}]$ is a strong predictor of the interaction mechanically, but years since last sale is also positive and highly significant, with an F-statistic of 46. Column 3 shows the 2SLS results. The coefficient of interest is 0.081, implying a pass-through rate of \$0.89 per \$1. This estimate is larger than that produced by

[22] I impute some sale dates using the earliest 'latest document date' recorded in the data. Spot checks using sites such as Redfin have shown that these typically do represent sales. I am planning on acquiring new data that will help verify these dates.

the OLS specification, \$0.49 per \$1, though not statistically distinguishable.

3.3.2 IV Specification in Levels

Second, I employ the IV specification in levels, using monthly per-unit values for both rent and property taxes instead of log-changes.[23] In levels terms, property tax liability varies widely among otherwise similar properties. This variation in property taxes is caused by differences in the most recent date of reassessment (typically a sale). This can be considered semi-random, because two identical buildings last sold in different years will have very different property tax liability. A building sold this year, and thus recently reassessed at market value, will face much higher property taxes than a building last sold and reassessed twenty years ago. Thus, the level of property tax liability for a landlord will be highly dependent on the number of years since the last sale. Figure 8 shows per-unit property tax liability in levels plotted against the number of years since the last sale. The per-unit property tax burden is calculated by dividing the building tax burden by the number of units at the address, and converted to a monthly payment to compare with monthly rent. Figure 8 shows a significant and negative relationship between the per-unit tax and the number of years since the last sale. The longer a property has gone without being sold (and thus reassessed), the smaller the per-unit property tax burden. I utilize this instrument in the following specification, where Equation (4) represents the first stage and Equation (5) represents the structural equation. For unit i with j new-tenant rent observations:

$$TV_{i,g,t_{ij}} = \pi_1 Yrs_{i,g,t_{ij}} + \lambda_{g,t_{ij}} + \alpha_i + \gamma_{m_{t_{ij}}} + \epsilon_{i,g,t_{ij}}; \tag{4}$$

$$R_{i,g,t_{ij}} = \gamma_1 TV_{i,g,t_{ij}} + \lambda_{g,t_{ij}} + \alpha_i + \gamma_{m_{t_{ij}}} + v_{i,g,t_{ij}}, \tag{5}$$

where $R_{i,g,t_{ij}}$ is the rent of unit i in Census tract g with a new tenant in period t_{ij}, with monthly per-unit taxable value $TV_{i,g,t_{ij}}$ and years since the last sale $Yrs_{i,g,t_{ij}}$. Again, the specification includes Tract×Year$_{t_{ij}}$ fixed effects, unit fixed effects, and Month$_{t_{ij}}$ fixed effects.

One advantage of this specification is that it utilizes variation in property taxes among all units, sold and unsold, instead of inherently grouping all unsold units together. Additionally, evidence suggests that incomplete pass-through in log-changes might mask complete pass-through in levels (Nakamura and Zerom (2010), Sangani (2023)). The results of Equations

[23] I calculate per-unit property taxes by dividing per-building property taxes by the number of units in the building.

(4) and (5) are shown in Table 4. In this table, the coefficients can be directly interpreted as pass-through of property taxes in cents per \$1. Column 1 shows Equation (1) restricted to the sample for which I can observe or impute previous sale dates, for comparison with the results in Section 3.2.[24] The coefficient of interest on the monthly per-unit property tax implies a pass-through rate of \$0.62 per \$1, larger than the rate of \$0.53 per \$1 from Section 3.2. I control for the number of properties owned by the landlord as a robustness check, and find a positive and significant relationship (this is discussed further in Section 4). Column 2 presents the results of Equation (4), which regresses monthly per-unit taxable value on the number of years since the most recent sale. I observe a coefficient of −3.12 with an F-statistic of 122. This implies a decrease of \$3.12 in monthly per-unit taxable value per additional year since the most recent sale. Column 3 presents the results of Equation (5). The property tax coefficient is equal to 0.88, which is equivalent to a pass-through of \$0.88 per \$1. This pass-through rate is nearly identical to the pass-through rate found using Equation (3) in Table 3. Notably, the pass-through rate is again higher than that of the corresponding OLS specification (Table 4, Column 1; Table 3, Column 1), though again these estimates are not statistically distinguishable.

4 Robustness Checks

4.1 Landlord Size Effects

One might be concerned that a post-sale rent increase is driven by a change in landlord type, for example, if a mom-and-pop landlord sells their property to a large, sophisticated landlord who substantially raises the rent. To test for this, I augment the specification in Equation (1) with the change in landlord size around a sale. I calculate landlord size by linking all Berkeley units owned under the same mailing address in the county's property tax records.[25] I show summary statistics for landlord size in Table 5. The first row shows the average number of units owned for all landlords in the sample, with the median landlord owning 12 units.[26] Landlords engaging in sales (rows 2–3) are slightly larger, with the median landlord in this group owning 18 units. Row 4 shows that the majority of building sales occur between

[24] I impute some sale dates using the earliest 'latest document date' recorded in the data. Spot checks using sites such as Redfin have shown that these typically do represent sales.

[25] My data contain unit counts for Berkeley and building counts for Alameda County, but the number of buildings owned is a less precise measure of market power than the number of units owned, as buildings vary widely in size.

[26] The median building contains 1 unit, and the 75th percentile of building size is 3 units.

similarly sized landlords, with half of sales occurring between landlords who differ in size by four units at most.

I present two specifications to test for landlord size effects. The first specification, presented in Equation (6), investigates exactly the case mentioned above, in which small landlords sell to larger landlords or vice versa. Sales are divided into groups based on the size quartile of the old landlord and the size quartile of the new landlord. I define Q1 landlords as those who own p25=6 units or fewer, Q2 landlords as those who own more than p25=6 units but fewer than p50=18 units, and so on. I combine all transactions occurring between landlords of the same size into one group, meaning that $Q1 \rightarrow Q1$, $Q2 \rightarrow Q2$, $Q3 \rightarrow Q3$, and $Q4 \rightarrow Q4$ transactions are all combined into one group. Indicator variables for each group are added to Equation (1) for $A, B \in [1, 4]$, yielding:

$$\begin{aligned} \Delta \ln[R_{i,g,t_{ij},t_{ij}-k_{ij}}] = {} & \beta_1 \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}] + \beta_2 1[Sale_{t_{ij}-k_{ij},t_{ij}}] \\ & + \beta_3 1[Sale_{t_{ij}-k_{ij},t_{ij}}] \cdot \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}] \\ & + \boldsymbol{\beta_{QA \rightarrow QB}} 1[Sale_{t_{ij}-k_{ij},t_{ij}}] \cdot 1[Landlord\ QA \rightarrow Landlord\ QB] \\ & + \lambda_{g,t_{ij},t_{ij}-k_{ij}} + \alpha_i + \gamma_{m_{t_{ij}},m_{t_{ij}-k_{ij}}} + \epsilon_{i,g,t_{ij},t_{ij}-k_{ij}}, \end{aligned} \tag{6}$$

where the fourth term represents the added indicator variables. As an example, a sale from a landlord in the smallest size quartile to a landlord in the largest size quartile would yield the term $\beta_{Q1 \rightarrow Q4} 1[Sale_{t_{ij}-k_{ij},t_{ij}}] \cdot 1[Landlord\ Q1 \rightarrow Landlord\ Q4]$.

The results of Equation (6) are presented in Column 2 of Table 6, with the omitted group being sales for which the original landlord and new landlord are in the same size quartile. Equation (1) is presented in Column 1 for comparison. Very few additional coefficients in Column (2) are significant (3 out of 12). There is some statistically significant evidence that being purchased by a very large (Q4) landlord does cause a large rent increase. An increase in landlord size to the highest quartile (Q4) leads to statistically significant rent increases in units previously held by Q2 and Q3 landlords, with coefficients ranging from 0.048 to 0.054. Interestingly, the coefficients on an increase in landlord size from Q1 to any other quartile are very small and insignificant, and a decrease in landlord size from Q2 to Q1 is associated with a statistically significant *increase* in rent (the wrong direction). This suggests that smaller landlords do not unilaterally set lower rents than larger landlords.

Further, the coefficients in Column 2 show that a change in landlord size from one quartile to another does not produce symmetric rent increases and decreases—for example, $\beta_{Q1 \rightarrow Q4} \neq -\beta_{Q4 \rightarrow Q1}$. Some pairs of coefficients weakly support a sticky rents theory, meaning that an increase in landlord size causes a larger increase in rent than a reduction in landlord size causes a reduction in rent.[27]

Given that most coefficients in Column 2 of Table 6 are insignificant, a simpler, alternative specification is presented below. Equation (7) is equivalent to Equation (1) with the addition of a variable equal to the number of units owned by the new landlord minus the number of units owned by the previous landlord for sold properties. This specification captures the effect of the change in landlord size on rent-setting, while masking some of the nuance captured by Equation (6):

$$\begin{aligned}\Delta \ln[R_{i,g,t_{ij},t_{ij}-k_{ij}}] = {} & \beta_1 \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}] + \beta_2 1[Sale_{t_{ij}-k_{ij},t_{ij}}] \\ & + \beta_3 1[Sale_{t_{ij}-k_{ij},t_{ij}}] \cdot \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}] \\ & + \beta_4 1[Sale_{t_{ij}-k_{ij},t_{ij}}] \cdot \Delta \text{ Num. Units Owned by Landlord} \\ & + \lambda_{g,t_{ij},t_{ij}-k_{ij}} + \alpha_i + \gamma_{m_{t_{ij}},m_{t_{ij}-k_{ij}}} + \epsilon_{i,g,t_{ij},t_{ij}-k_{ij}},\end{aligned} \tag{7}$$

Column 3 of Table 6 presents the results from Equation (7). The coefficient of interest on change in landlord size is small but highly significant, supporting the results suggested by the few significant coefficients in Column 2. Notably, including landlord size has minimal effects on the coefficient of interest on Sale $\cdot \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$ from Column 1. The coefficient remains stable at 0.046, compared with the original coefficient of 0.048.

Further, the pass-through coefficient is robust to other definitions of landlord size, as shown in Table A9. Column 1 of Table A9 again presents the results of Equation (1) for comparison. The additional columns present results similar to those of Equation (7), with the fourth term replaced by corporate landlord status[28] (Column 2), landlord business-ownership status[29] (Column 3), and the change in the number of county buildings owned by the landlord (Column 4). The pass-through estimate remains stable at \$0.50 per \$1 in each specification.

4.2 Renovations

Landlords sometimes renovate or make improvements to their units, and these renovations/improvements should allow landlords to charge higher rents. If landlords are most likely to renovate their units during the time period around a sale, this could bias the es-

[27]This is demonstrated visually in Figure A6.

[28]Corporate landlord status is determined by whether the owner's name recorded in the property tax records contains 'LLC', 'Corp', 'Inc', or other words that would indicate the building is corporate-owned.

[29]Business ownership is determined by whether the owner's name recorded in the property tax records can be matched to a business ownership record in the state of California, using California Business Search.

timate of pass-through upward. Notably, improvements should affect rent, but not pre-sale property taxes.[30] They do, however, affect post-sale property taxes if such improvements are incorporated into a property's purchase price.

Evidence from the owner-occupied housing market shows that households increase spending on home improvements around a sale (Benmelech et al. (2023)). I document a similar pattern using building permit data obtained from the City of Berkeley. Figure 9 shows that, similar to owner-occupied homeowners, landlords are more likely to obtain permits to renovate in the year following a sale, with the probability of obtaining a permit increasing from 4.7% at baseline to 9.5% in the year following a sale. This result highlights the importance of controlling for permitted renovations when estimating pass-through.

Next, I utilize the permit data to control for rent-increasing improvements in Equation (1). Each publicly available permit summary contains the building address, date the permit was received, date the permit closed, and a brief description of the project. The permit is assigned to a tenant spell based on the date the permit was received by the city. If that date falls in $[t_{ij} - k_{ij}, t_{ij}]$, it is assigned to that tenant spell. I assign permits to the relevant unit if a specific unit or apartment is mentioned in the description, otherwise I assign the permit to the entire building. I use a natural language processing (NLP) algorithm to score each permit. Specifically, I employ a regularized Lasso regression of change in rent on all frequently observed words in the permit description. This yields the specification:

$$\begin{aligned} \Delta \ln[R_{i,g,t_{ij},t_{ij}-k_{ij}}] &= \beta_1 \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}] + \beta_2 1[Sale_{t_{ij}-k_{ij},t_{ij}}] \\ &+ \beta_3 1[Sale_{t_{ij}-k_{ij},t_{ij}}] \cdot \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}] \\ &+ \beta_4 Num.\ Permits_{t_{ij}-k_{ij},t_{ij}} + \beta_5 NLP\ Permit\ Score_{t_{ij}-k_{ij},t_{ij}} \\ &+ \lambda_{g,t_{ij},t_{ij}-k_{ij}} + \alpha_i + \gamma_{m_{t_{ij}},m_{t_{ij}-k_{ij}}} + \epsilon_{i,g,t_{ij},t_{ij}-k_{ij}}, \end{aligned} \tag{8}$$

where the fourth term is the number of permits accrued over a tenant spell (i.e., between new-tenant rent observations), and the fifth term is the sum of the NLP permit scores for all permits accrued over a tenant spell.

Table 7 presents the results of Equation (8). Equation (1) is presented in Column 1 for comparison, with Equation (8) presented in Column 2. The coefficient on the number of permits is negative and significant at $\beta_5 = -0.003$, which is puzzling, but it is dwarfed in magnitude by the coefficient on the NLP permit score. The coefficient on the NLP permit

[30] Very few improvements incur additional property taxes in California. Those that do are major renovations, for example, increasing the property's square footage or a 'like new' renovation ("New Construction and Property Taxes," SCC Assessor).

score is very large and highly significant, at $\beta_6 = 0.27$. By construction, unit improvements/renovations have a large and positive effect on rent. The coefficient of interest on Sale $\cdot\, \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$ decreases somewhat from 0.048 in Column 1 to 0.044 in Column 2, with a corresponding reduction in the pass-through rate of \$0.53 to \$0.49 per \$1. This suggests that there is some effect of building improvements on the realized sale price, which biases the estimate in Column 1 upward. However, the reduction in magnitude is small (∼8%), suggesting that the pass-through result is largely robust to unit quality improvements.[31] Further, even if some landlords ignore permit requirements when renovating, a back-of-the-envelope calculation suggests that the permit data would have to miss about 90% of all renovations for β_3 to become insignificant. This is unlikely, given that I observe permits in the majority of buildings. Finally, the inclusion of building permits reduces the size of the coefficients on reassessment, because reassessment is typically related to a very large change in property quality (such as an increase in square footage, or a like-new renovation) that should be captured in building permits.

4.3 Sensitivity to Purchase Price

As noted, property tax liability and the purchase price of the home are highly related. This means that the landlord's monthly mortgage payment and property tax burden are typically linked one-for-one, so if either one is being used in a landlord's rent-setting calculation, it is difficult to disentangle the effects of the two.[32]

The IV specification in Section 3.3.1, Equation (3), attempts to address this, using the variation in property taxes due to the variation in years between sales, not the specific purchase prices (current and previous). I find larger effects of taxable value on rent using this specification than in the baseline specification represented by Equation (1), suggesting that the results are robust to specific purchase prices (current and previous). If I include an additional control for the most recent sale price for sold buildings in Equation (3), this specification then compares two homes sold most recently for the same dollar amount, but previously sold in different years. The results are presented in Table A7, and are nearly identical to the results in Table 3. I repeat this exercise for Equation (1), with results presented in Table A8. The coefficient of interest on $Sale_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$ is reduced slightly, but is generally robust to the inclusion of purchase price.

Finally, the public discussion around the passage of Proposition 13 points towards tax

[31] The results are also robust to dropping all tenant spells with any permitted renovations, see Table A10.

[32] As is briefly mentioned in Giacoletti and Parsons (2022).

costs playing some role in rent-setting.[33] And, regardless of which type of cost, this does not diminish the evidence of cost pass-through to renters.

5 Theoretical Framework

Classical linear profit-maximization cannot rationalize the pricing behavior documented in Section 3. As the property tax is a fixed cost, it does not enter into the first order condition of the standard profit maximization formula.[34] Other potential explanations for high rates of pass-through—such as search frictions and reference-dependent preferences—also fail to produce satisfactory results.[35,36] As a result, I propose an explanatory model of heterogeneity in landlord sophistication that can rationalize the positive relationship between rent and property taxes, as well as explain why below-market taxes lead to below-market rents. This model is empirically motivated by evidence of incumbent landlords' inattention to market-rate rents, which creates an opportunity for high-sophistication landlords to purchase properties from landlords charging below-market rents. Thus, below-market rents increase the likelihood of a sale, which causes an increase in both property taxes and rents.

5.1 Neoclassical Benchmark

First, following Giacoletti and Parsons (2022), I present a fully rational agent's rent-setting strategy to serve as a benchmark. Consider a model of rent-setting in which the landlord faces a trade-off between the rent price and the amount of time it takes to find a tenant. Also assume that the probability of finding a tenant is negatively related to rent. Let R denote the rent set by the landlord. Let $\alpha(R)$ be the probability of filling a vacancy. The landlord's utility is equivalent to $u(R, C) = R - C$, where C represents the landlord's per-unit costs, which include the per-unit property tax burden. The landlord faces the maximization

[33]See Figure A1.

[34]See Section 5.1.

[35]See Appendices B and C for further discussion. A simple Diamond-Mortensen-Pissarides (DMP) model predicts a positive relationship between pass-through and the vacancy rate, which I show is not empirically supported. Reference dependence can rationalize high pass-through, but the predictions depend somewhat on the particular functional form of landlord utility.

[36]Basu and Emerson (2003) suggest that in markets with tenancy rent control (such as in Berkeley), landlords with monopoly power set below-market rates to be able to select better-quality (shorter-staying) tenants, called 'efficiency rents'. However, this would not explain the difference in rent-setting behavior between new and incumbent landlords, and I find that lower rents increase tenure. See Table A11.

problem:

$$\max_R \ \alpha(R)(R - C) + (1 - \alpha(R))(0 - C),$$

where the first term represents the landlord's utility if the apartment rents, and the second term represents the landlord's utility if the apartment remains vacant. This yields the first order condition:

$$0 = \alpha'(R^*)R^* + \alpha(R^*)$$
$$\implies R^* = \frac{-\alpha(R^*)}{\alpha'(R^*)},$$

which does not depend on C. To build intuition, allow $\alpha(R) = \alpha_0 - \alpha_1 R$, a simple form of downward-sloping demand. This yields:

$$R^* = \frac{\alpha_0}{2\alpha_1}.$$

In the neoclassical benchmark case, landlords obey the law of one price and all units are priced identically. The amount of property taxes owed on the unit, included in per-unit costs C, does not enter into the equation for optimal rent R^*. This runs contrary to the results presented in Section 3, which show that units with higher per-unit costs command higher rents.

5.2 Entry-Exit Framework

Next, I propose an explanatory model of heterogeneity in landlord sophistication that can rationalize the positive relationship between rent and property taxes documented in Section 3, as well as explain why below-market taxes lead to below-market rents. This model is empirically motivated by evidence of incumbent landlords' inattention to market-rate rents, which creates an opportunity for high-sophistication landlords to purchase properties from landlords charging below-market rents. Thus, below-market rents increase the likelihood of a sale, which causes an increase in both property taxes and rents.

5.2.1 Motivation: Inattention

The results presented in Section 3 show that new landlords raise rents upon acquiring a new building, suggesting that the previous landlord did not charge the maximum possible rent. This would occur if incumbent landlords are missing skills and/or information possessed by newer landlords. A new landlord should be knowledgeable about rental market dynamics, since she just purchased a rental property for a price that accurately reflects its revenue potential. Thus, I will assume the new landlord sets an initial rent 'correctly' at the rational benchmark $R^* = \frac{\alpha_0}{2\alpha_1}$, which covers all per-unit costs.[37] Afterwards, a small annual cost increase (e.g., the 2% annual tax increase) calls attention to the need for a small annual rent increase, but the incumbent landlord is otherwise inattentive to market dynamics. This causes the incumbent landlord's rent to deviate more and more from the market rate rent over time. This framework rationalizes the relationship observed in the data—the longer a property has been held by an incumbent landlord before a sale, the larger the increase in rent around a sale. The incumbent landlord was pricing incorrectly, while the new landlord corrects to the rational benchmark but will herself become inattentive over time.

This relationship can be summarized as follows:

$$R^* = \begin{cases} R^*_{i,t} & \text{if new landlord} \\ \theta R^*_{i,t} + (1-\theta) R^*_{i,t-k=1} & \text{if incumbent landlord} \end{cases} \tag{9}$$

Equation (9) says that a new landlord sets rent correctly at the market rate for unit i in time t, $R^*_{i,t}$. An incumbent landlord uses a weighted average of new landlord rent $R^*_{i,t}$ and the initial rent she set for unit i in period $t-k=1$, $R^*_{i,t-k=1}$, which was the market-rate rent in period $t-k=1$. The weight θ denotes the degree of attentiveness: a high value of θ implies that the landlord is very attentive to market conditions and will set rent closer to the market rate. Equivalently, a high-θ landlord is less anchored to her initial rent price.[38]

This can be directly tested in the data in a number of ways. First, Figure 10 shows a coefficient plot of the new-incumbent landlord monthly rent gap for new leases. The x-axis denotes the number of years since a market-rate rent was first set for apartment i by a distinct landlord, or equivalently the number of years since the landlord was 'new'. The gap is equal to the difference in new-tenant rent set by an incumbent landlord versus a new landlord in time t.[39] The coefficients increase linearly, with the gap in monthly rent increasing by \$8.70 per year of landlord tenure, equivalent to an annual profit gap between new and incumbent landlords of \$104 per unit per year of landlord tenure. This suggests increased deviation from market-rate rents over time—and consequently, increased deviation from profit maximization—by incumbent landlords.

[37] As with any fixed cost, if the tax burden was not less than the market-rate rent, the new landlord would not have entered the market.

[38] Basic inattention frameworks like these, and more complex variations, are discussed in Gabaix (2019).

[39] New landlord rent is predicted by a hedonic rent equation of new-tenant rent on year × census tract and number of bedrooms for units that were sold between two rent observations.

Table 8 directly tests Equation (9), which regresses log new-tenant rent in time t on the market-rate rent set by new landlords in time t, the initial rent for unit i by the current landlord, and the landlord's size. The coefficient on market rent, Log New Landlord $\mathrm{R}^*_{g,t,beds}$, is equivalent to θ from Equation (9). This specification finds $\theta = 0.23$, with $1 - \theta$, the coefficient on Log $\mathrm{R}^*_{i,t-k}$, equal to 0.77. The results suggest that when rent-setting, incumbent landlords weight a unit's initial rent three times more than the current market-rate rent. Landlords thus seem to be over-indexing on a unit's initial rent, and only partially updating to market-rate rents, demonstrating inattention to market-rate rent.

Figure 11, reproduced from Baker and Wroblewski (2024), provides another potential source of rent under-pricing. Figure 11 shows the density of nominal dollar rent changes for new tenants. Significant bunching at zero denotes rent stickiness, in that many landlords choose not to raise rent even for a brand new tenant. Figure 11 also demonstrates the bunching of rent changes at multiples of \$50 and \$100, suggesting that landlords follow a heuristic in rent-setting that allows them to inattentively increase rents without capturing the maximum possible (market-rate) rent.

5.2.2 Theory: Entry and Exit of Landlords

Section 5.2.1 provides evidence that landlords are pricing inattentively, causing older, incumbent landlords to price their units below the market rate. Next, I will demonstrate both theoretically and empirically how below-market rents create an opportunity for more sophisticated landlords to enter the rental market, driving up both rents and property taxes.

Recall that in the neoclassical benchmark, optimal rent depended on the relationship between vacancy-filling and rent level, represented by $\alpha(R)$:

$$R^* = \frac{-\alpha(R^*)}{\alpha'(R^*)} = \frac{\alpha_0}{2\alpha_1}$$

for $\alpha(R) = \alpha_0 - \alpha_1 R$, a simple form of downward-sloping demand.

Consider the same model with the addition of a sophistication parameter s_i. In this model, the probability of filling a vacancy depends negatively on R, but now also positively on landlord sophistication s_i such that $\alpha(R) = \alpha_0 s_i - \alpha_1 R$. Sophistication s_i can also be considered the sensitivity of landlord i to the market rate rent. The landlord faces the same maximization problem as in the rational benchmark:

$$\max_{R_i} \ \alpha(R_i)(R_i - T_i) + (1 - \alpha(R_i))(0 - T_i).$$

This yields the first order condition:

$$0 = \alpha'(R_i^*)R_i^* + \alpha(R_i^*),$$

which implies

$$R_i^* = \frac{\alpha_0 s_i}{2\alpha_1}.$$

Rent now depends on both market demand parameters α_0, α_1 and landlord sophistication s_i. A more sophisticated landlord will thus charge a higher rent than a less sophisticated landlord for an identical apartment.

Each landlord receives per-period profit $\pi_{it} = R_{it}^* - T_{it}$. Landlords meet in pairs and consider a potential transaction. Landlord j decides whether to make an offer on incumbent landlord i's unit. Landlord j will bid if there are potential gains to surplus, such that:

$$\begin{aligned} \pi_{jt} &> \pi_{it} \\ R_{jt}^* - T_{jt} &> R_{it}^* - T_{it} \\ R_{jt}^* - R_{it}^* &> T_{jt} - T_{it}. \end{aligned}$$

Meaning that landlord j will bid if the gains to potential rent are large enough to offset the higher tax cost she will face after the sale.

Importantly, the relationship between the rent gap and the tax gap suggested above can be directly tied to my empirical specification. Rearranging:

$$\begin{aligned} R_{jt}^* - R_{it}^* &> T_{jt} - T_{it} \\ \frac{R_{jt}^* - R_{it}^*}{R_{it}^*} &> \frac{T_{jt} - T_{it}}{T_{it}} \times \frac{T_{it}}{R_{it}^*} \\ \implies \Delta \ln[R] &> \Delta \ln[TV] \times \frac{T_{it}}{R_{it}^*}. \end{aligned}$$

With a median value of $\frac{T_{it}}{R_{it}^*} = \frac{1}{22} = 0.045$ for unsold properties, this equation implies sales occur only if $\Delta \ln[R] > \Delta \ln[TV] \times 0.045$. This squares neatly with my empirical results: I find an average rate of pass-through of 0.048 for sales that occur, which is just larger than 0.045. This implies that sales are in fact occurring only if the rent gap exceeds the tax gap.

Finally, to close the model, note that the potential tax cost for landlord j depends on her purchase price bid p_j, such that $T_j = \lambda p_j$. The total surplus created by the match is

$\pi_j - \pi_i$. Employing Nash bargaining, the bid offered by j solves:

$$
\begin{aligned}
p_j &= argmax_{p_j}(\pi_j - p_j)^\beta (p_j - \pi_i)^{1-\beta} \\
p_j &= argmax_{p_j}((R_j^* - \lambda p_j) - p_j)^\beta (p_j - (R_i^* - \lambda p_i))^{1-\beta} \\
\implies p_j &= \frac{1-\beta}{1+\lambda} R_j^* + \beta(R_i^* - \lambda p_i),
\end{aligned}
$$

which demonstrates a positive relationship between the rent of the new landlord j and her property taxes λp_j, as shown empirically in Section 3.

5.2.3 Simulation: Entry and Exit of Landlords

Next, I run a simulation to provide theoretical evidence that sales from inattentive landlords to high-sophistication landlords (in other words, landlord entry and exit) can generate a positive and significant relationship between rent and property taxes. Consider n identical units of equivalent value, each owned by a different incumbent landlord i. Each unit was purchased in year $t-k$, where $k \in [0, 30]$, for price p_i. Taxes are directly related to purchase price, and taxable value increases by 2% per year such that $T_{it} = \lambda p_i \times 1.02^k$. Landlord sophistication is normally distributed such that $s_i \sim N(a, b)$. As in the rational benchmark, the probability of filling a vacancy depends negatively on R, but now also positively on landlord sophistication s_i such that $\alpha(R) = \alpha_0 s_i - \alpha_1 R$. Landlord i receives per-period profit $\pi_{it} = R_{it}^* - T_{it}$. If a building is sold to a new owner, taxes reset to market value, s.t. $T_{j \neq i,t} > T_{it}$.

Figure 12 provides an illustration of the relationship between rent and property taxes over time simulated by the entry-exit framework above. Each dot represents a distinct property, with darker shades of red indicating higher levels of landlord sophistication. In Period 0, shown in Panel (a), there is no relationship between tax burden and rent ($\beta = -0.027(0.19)$). Over the course of the next twenty periods, high sophistication landlords purchase properties for which they can profit given their sophistication level. Panel (b) shows that, by Period 20, high-sophistication landlords have consolidated a majority of rental properties. The entry and exit dynamics lead to the positive and significant relationship shown between rent and taxes in Panel (b) ($\beta = 0.75(0.032)$). Sales are particularly likely to occur for properties in the southeast corner of Panel (a), where the rent gap is high (below-market rents) and the tax gap is low (near-market taxes). Sales are much less likely to occur in the northwest corner, where the tax gap is high and the rent gap is low.

Thus, the entry and exit of landlords can generate the positive relationship between rent and taxes around a sale that is documented in Section 3.

5.2.4 Testable Prediction of Sale Likelihood

In the simulation, a large percentage of units are sold each period. In the data, transactions are less common,[40] but this is likely due to transaction costs or other frictions that reduce the frequency of sales. However, the theoretical framework predicts that sales are more likely to occur when 1) potential gains to rent are high ($R^*_{jt} - R^*_{it}$ is large) and 2) the change in taxes is low ($T_{jt} - T_{it}$ is small), which is a testable prediction.

Table 9 indirectly tests for the effect of the rent gap, $R^*_{jt} - R^*_{it}$, and the effect of the tax gap, $T_{jt} - T_{it}$, on the probability of sale. According to the theoretical framework, sales are *less* likely to occur if the rent gap between the new and incumbent landlord is *low*, and the tax gap between the new and incumbent landlord is *high*. Table 9 shows exactly this pattern, testing for the effect of residualized rent decile and the number of years since sale on the probability of sale. Rent decile is a (negative) proxy for the rent gap—the higher the rent decile, the lower the rent gap. The coefficient on rent decile is significant and negative, equal to -0.066. This implies that an increase of one rent decile decreases the probability of sale by 6.6%. The number of years since a sale, or equivalently the number of years off market, is a proxy for the tax gap. The greater the number of years since sale, the larger the tax gap. The coefficient on years since sale is significant and negative, equal to -0.027. This implies that one additional year off-market decreases the probability of sale by 2.7%. Notably, these two measures are likely related,[41] but they separately influence the probability of sale.

5.2.5 Summary of Theoretical Mechanism

In this explanatory framework, inattention causes incumbent landlords to set below-market rents. I demonstrate that this holds in the data, with Figure 10 showing that incumbent landlords become less attached to the market-rate rent over time. Additionally, Table 8 confirms that landlords only partially update to the market-rate rent when rent-setting. These below-market rents create an opportunity for high-sophistication landlords to purchase properties from low-sophistication (inattentive) landlords, increasing both property taxes and rents. The theory predicts that sales are more likely to occur when potential gains to rent are large and potential increases in tax costs are low. I verify this in the data, and show that high-rent and low-tax properties are less likely to sell (Table 9). Notably, this theoretical

[40] About 7% of rental units are sold each year. See Figure A9.
[41] See section 5.2.1.

framework matches the data better than the rational benchmark, a simple model of search frictions, and reference-dependent landlord preferences.

5.3 Policy Implications

The empirical results from Section 3 and the explanatory framework proposed above have a number of important policy implications. First, Proposition 13 does provide rent rebates to tenants with incumbent landlords, who seem to price their units at a below-market rate. However, this is a blunt policy instrument, and likely inefficient, since it is unclear who receives this form of rental assistance.

Both the empirical results and my explanatory model suggest that an increase in property taxes due to the repeal of Proposition 13 (or a similar property tax cap) would lead to rent increases. This is through two channels: first, increasing taxes would increase the probability that a building is sold from an inattentive landlord to a high-sophistication landlord, which would lead to a rent increase. This is shown in Section 5.2.4. Second, it is likely that increasing taxes might force inattentive landlords to update their rent prices, increasing rents. Still, an efficient policy instrument could be created in this scenario, if increased state tax revenue was used to provide targeted rental assistance to low-income renters.

6 Conclusion

This paper contributes to a growing literature on irrational pricing behavior in the housing market—and a sparser literature on our understanding of the rental market—in a number of ways. First, I use a novel dataset of near-universal unit-level rents, which is an improvement over traditionally used survey data or incomplete samples of a given market. In particular, I am able to provide novel pass-through estimates using within-property variation in property tax costs. Second, I utilize a novel quasi-experimental empirical design to determine the elasticity of rent to a property tax shock. I find an elasticity of 0.04–0.08, which equates to tax shifting of \$0.50–\$0.89 per \$1 increase in property tax burden. This result shows a violation of the law of one price, suggesting a departure from a perfectly competitive housing market benchmark.

The results are robust to the inclusion of possible confounding variables, such as differential rent-setting behavior by landlord size, unit-level renovations, and a property's specific purchase price. I find that a change in landlord size upon sale weakly impacts rents, with larger landlords charging slightly higher rents than their smaller counterparts in newly acquired buildings. This is an interesting finding in and of itself, as one might expect larger landlords to price much more aggressively than their smaller counterparts, but I do not find evidence of substantially different rent-setting strategies among landlords of different sizes. Further, I use building permit data to investigate the channel of rent increases due to building- or unit-level improvements, and find that such improvements do not account for much of the rent increase attributable to a property tax shock. Finally, I show that the baseline results are robust to the inclusion of a property's specific purchase price.

I propose a theoretical framework of landlord pricing behavior to compare the rational benchmark—the law of one price for landlords with heterogeneous tax costs—with a model of heterogeneity in landlord sophistication. I provide evidence that landlords become inattentive to market-rate rents over time, possibly due to a lack of informative tax cost shocks, putting them at risk of sale to a more sophisticated landlord. The entry and exit of landlords via sales generates a positive relationship between rent and taxes and explains why landlords with below-market tax costs set below-market rents, which matches the empirical results.

This paper provides novel evidence on behavioral pricing in the rental market, demonstrating that rental prices reflect heterogeneous cost shocks to landlords. My findings suggest that variation in property tax burdens due to property tax caps such as Proposition 13 can have unexpected distortionary effects on the rental market, providing rebates to some (but not all) renters. Since many states have adopted some version of property tax curtailment, these distortionary effects are applicable well beyond the California rental market.

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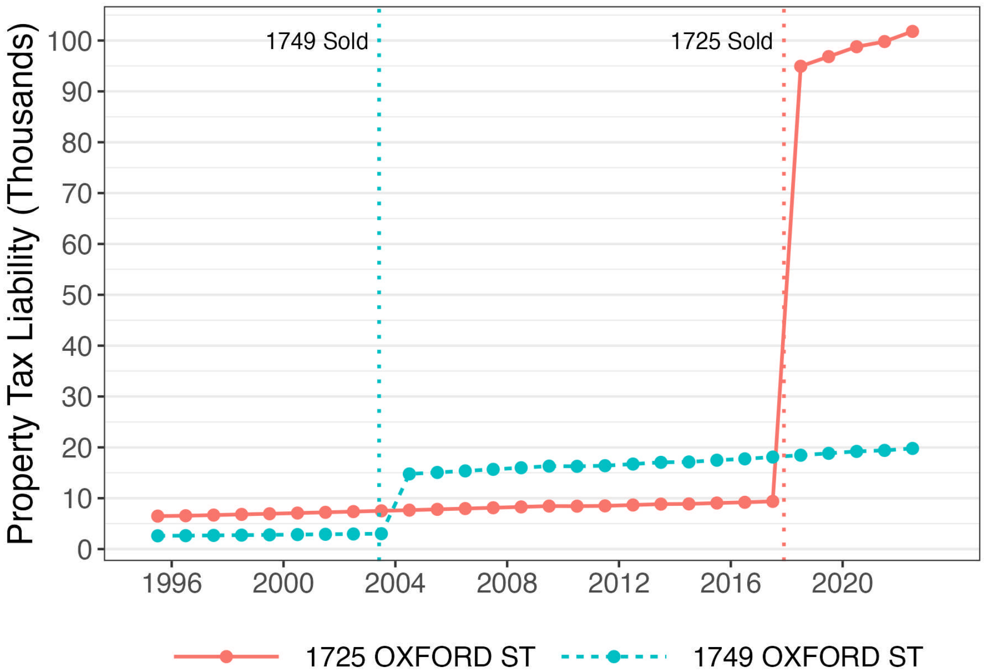
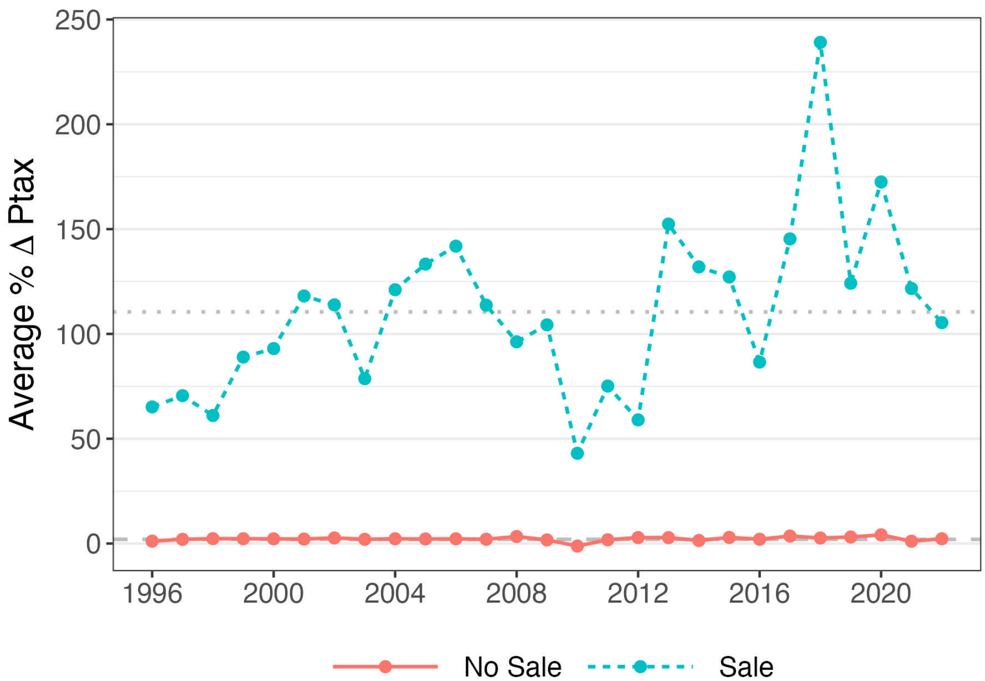
Figure 1: Property Tax Liability for Two Berkeley Buildings



Note: Under Proposition 13 in California, property taxes increase at approximately 2% per year until sold, at which point property taxes jump discretely by varying amounts. The figure shows annual property tax liability in thousands of dollars for two multi-unit properties in Berkeley. Vertical dotted lines represent sale dates.

Figure 2: Average Percent Change in Property Taxes, Sale vs. No Sale

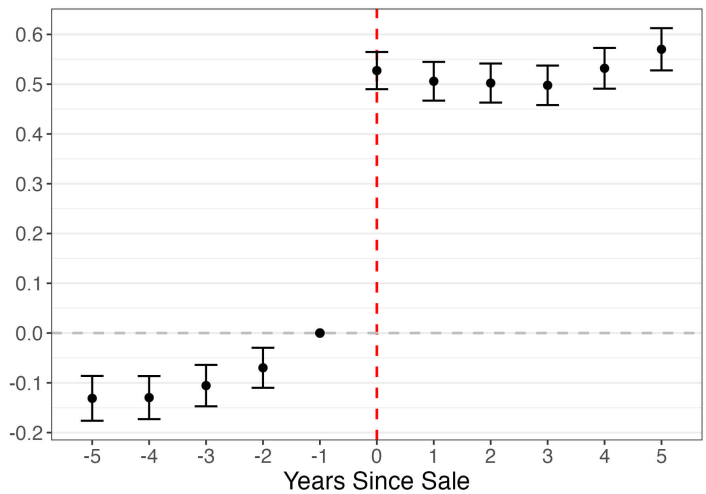


Note: Property taxes increase by over 100% on average upon sale and by 2% per year if unsold. The figure shows the average percent change in property tax liability for two categories of properties: those that were sold in the previous year (blue dashed line) and those that were not sold in the previous year (red solid line). The dotted gray line denotes the average change in property tax for sold properties, and the dashed gray line denotes the average change in property tax for unsold properties. The sample consists of all properties in Berkeley in the county property tax records.

Figure 3: Word Cloud of Permit Descriptions

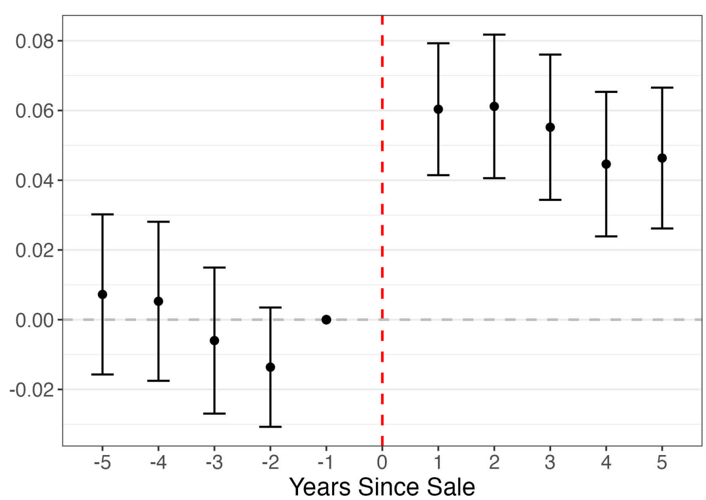
Note: Text data from building permits capture rent-increasing renovations. The figure shows a word cloud of all words found in the descriptions of approved construction/building permits. The size of the word denotes its frequency, with larger words being more common. The sample consists of all permits for buildings with units registered with the Berkeley Rent Board from 1996 to 2022.

Figure 4: Log Property Taxes Before and After Sale



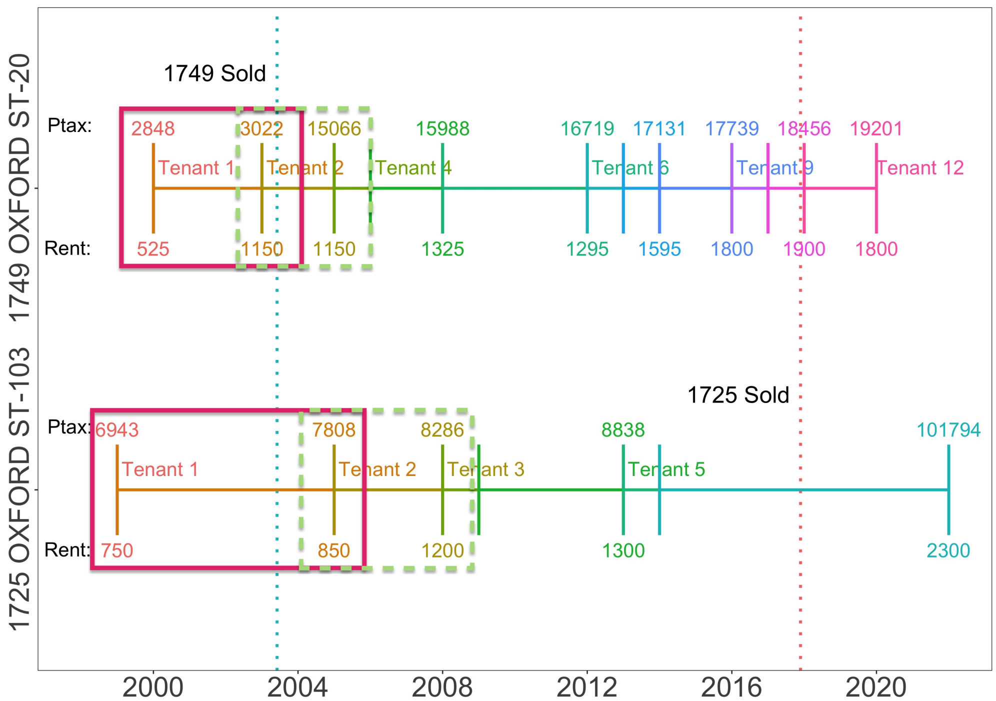
Note: Property taxes increase by 55% on average after a sale. The figure plots the coefficients of an event study of log property taxes regressed on years since sale, using no controls since property tax calculation is purely mechanical. The event study is unbalanced, as not all properties have property tax observations for each $t \in [-5, 5]$. A balanced version showing similar results is presented in Figure A4. The sample consists of all buildings that were sold exactly once between 1996 and 2022 containing units registered with the Berkeley Rent Board that are able to be matched to county property tax data and have fewer than six bedrooms.

Figure 5: Log Rent Before and After Sale



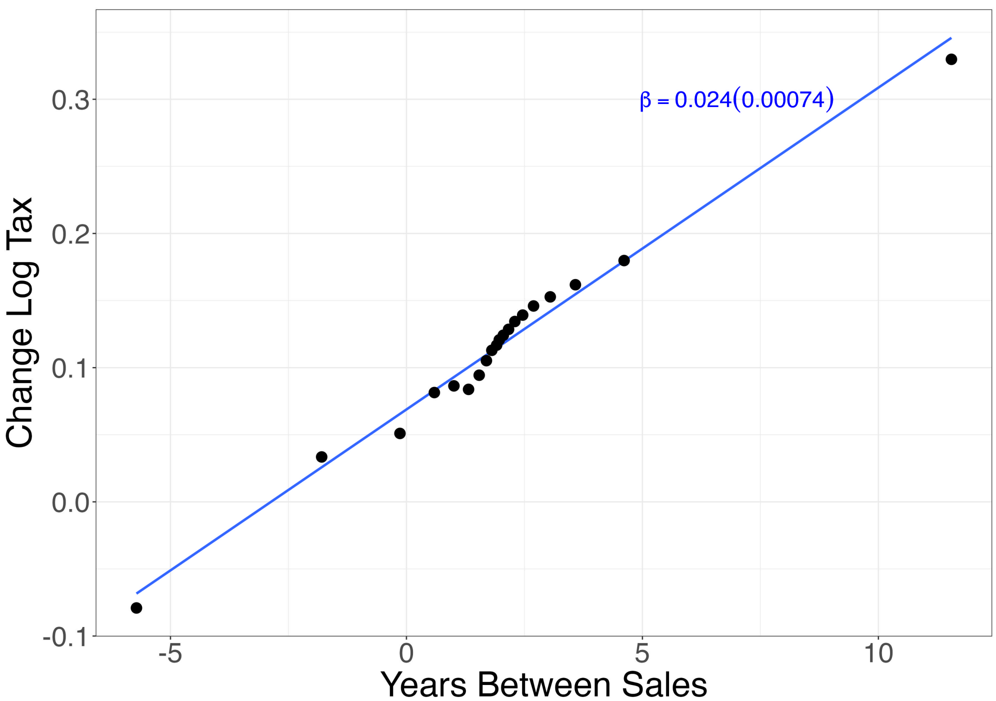
Note: Rents increase by 6% on average after a sale. The figure plots the coefficients of an event study of log new-tenant rent regressed on years since sale, using the same controls as in Table 2. The event study is unbalanced, as not all properties have rent observations for each $t \in [-5, 5]$. The sample consists of all buildings that were sold at least once between 1996 and 2022 containing units registered with the Berkeley Rent Board that are able to be matched to county property tax data and have fewer than six bedrooms and positive rent values. Standard errors are clustered by building.

Figure 6: Sample Data Pairs



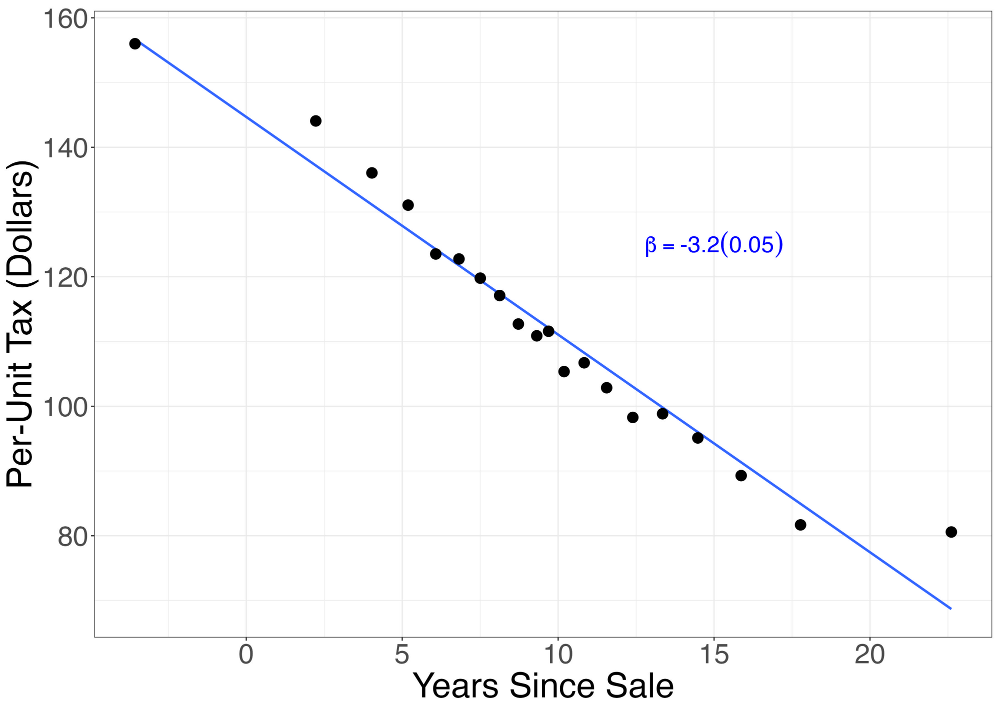
Note: In my main specification, I compare changes in rents over a tenant spell to changes in property taxes over a tenant spell, such that each box (pink solid and green dashed) represents one data point in the specification shown in Equation 1. The figure shows a timeline of tenant spells for one unit in each Oxford Street property referenced in Section 2.1. Each tenant spell is denoted in a different color. The numbers at the top of each tenant timeline denote the property tax liability of the building at the time of the tenant's entry. The numbers at the bottom of each timeline denote the tenant's rent value upon entry. The vertical dotted lines represent sale dates for each building.

Figure 7: Change in Log Per-Unit Property Tax by Years Since Sale Bins



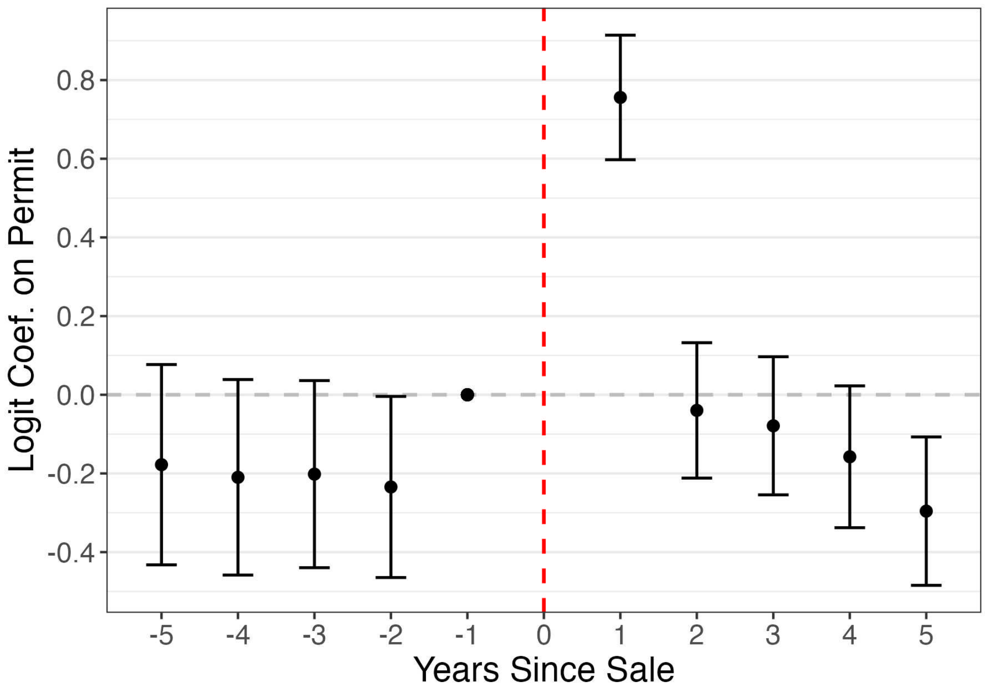
Note: Years between sales, or the number of years since a property was last sold, is significantly and positively related to the change in log tax at (current) sale. The longer a property was held by its previous owner, the lower its tax burden, and thus the larger the change in property taxes upon sale. The figure shows a binned scatter plot of the relationship between change in log taxable value and years between sales, using an equivalent specification to the first stage represented by Equation (2). The regression line is shown in blue. The sample consists of all units registered with the Berkeley Rent Board from 1996 to 2022 that are able to be matched to county property tax data and have fewer than six bedrooms.

Figure 8: Per-Unit Property Tax by Years Since Sale Bins



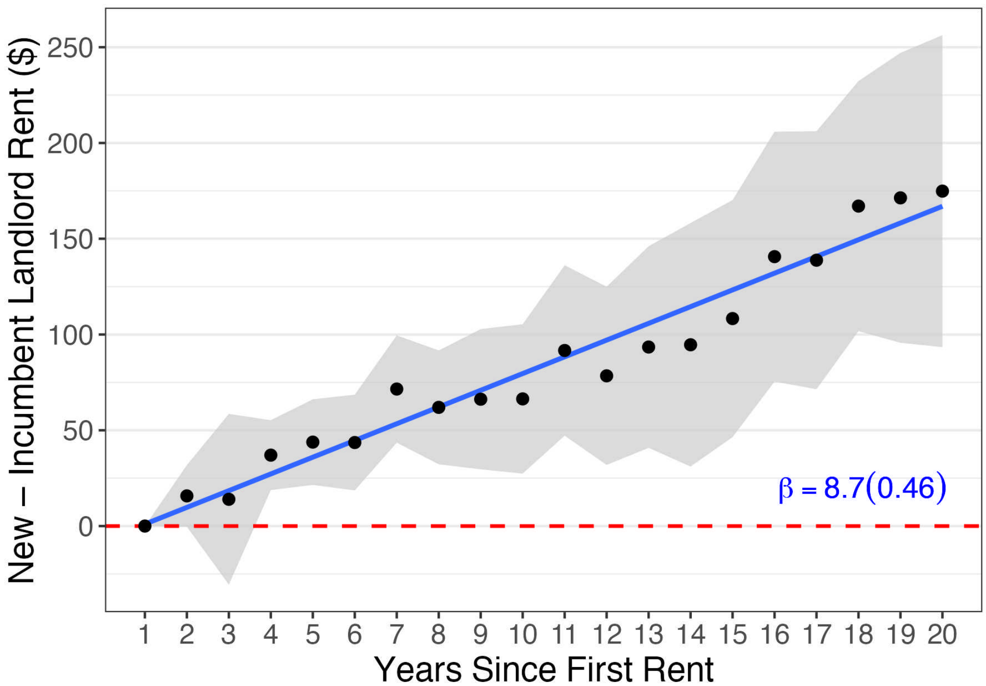
Note: The number of years since a property was last sold is significantly and negatively related to a property's current tax liability in dollars. The longer a property has been held, the lower its tax burden. The figure shows a binned scatter plot of the relationship between per-unit taxable value and years since last sale, using an equivalent specification to the first stage represented by Equation (4). The regression line is shown in blue. The sample consists of all units registered with the Berkeley Rent Board from 1996 to 2022 that are able to be matched to county property tax data and have fewer than six bedrooms.

Figure 9: Log-Likelihood of Permits Around a Sale



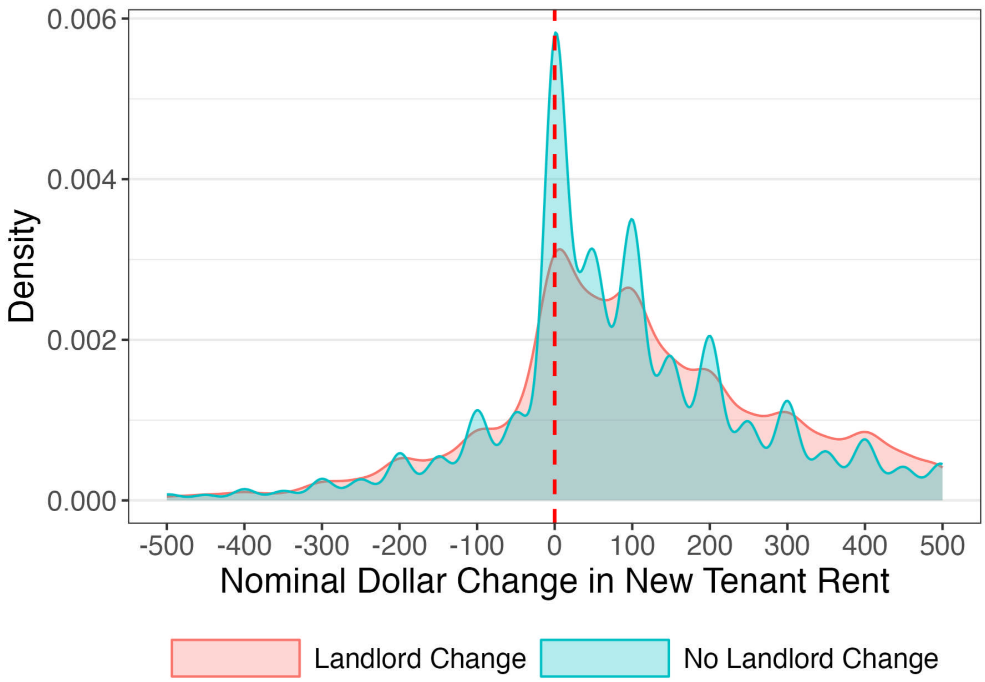
Note: Building permits (i.e., renovations) are more likely to occur just after a sale. The figure plots event study coefficients of building permit presence regressed on years since sale, with reference group $t = -1$. The sample consists of all buildings that were sold at least once between 1996 and 2022 containing units registered with the Berkeley Rent Board that are able to be matched to county property tax data and have fewer than six bedrooms and positive rent values. The same event study with an alternative reference group ($t = -2$) is presented in Figure A8, with similar results.

Figure 10: New-Tenant Rent Gap by Landlord Tenure



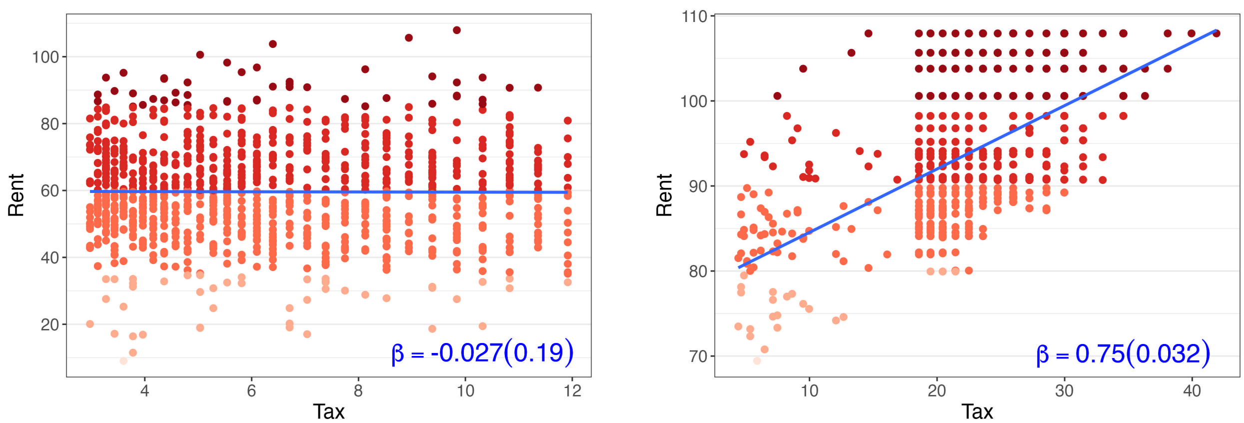
Note: New landlords set higher rents than incumbent landlords, with the difference increasing in the tenure of the incumbent landlord. The plot shows the coefficients of the new-tenant rent gap—the gap between market-rate rent (new landlord rent) and incumbent landlord rent—regressed on the number of years since the landlord was new, at the unit-new lease level. The specification controls for landlord size, year-tract and unit fixed effects. Standard errors are clustered by building and denoted by the gray shading. A regression line and the corresponding β are shown in blue. The sample consists of units registered with the Berkeley Rent Board from 1996 to 2022 that have positive recorded rents and fewer than six bedrooms.

Figure 11: Nominal Rent Changes for Berkeley Apartments, 1–2 Years Between New Tenants



Note: Nominal rent changes bunch at zero and multiples of 50 and 100, suggesting landlord inattention and/or heuristic usage when rent setting. The figure shows kernel density of nominal rent changes in dollars for new tenants. The sample consists of units registered with the Berkeley Rent Board from 1996 to 2022 that have positive recorded rents and fewer than six bedrooms. Reproduced from Baker and Wroblewski (2024).

Figure 12: Simulated Per-Unit Rent vs. Taxes



(a) Period 0

(b) Period 20

Note: Entry of high-sophistication landlords and exit of low-sophistication landlords can produce a positive, significant relationship between rent and property tax burden. The plot shows simulated data for the entry-exit model presented in Section 5.2. Each dot represents one unit, and each color represents an individual landlord. Panel (a) shows the relationship between rent and taxes in Period 0, while Panel (b) shows the same relationship after twenty periods of landlord entry and exit. Regression lines and β coefficients are in blue. The parameters used are $n = 1000, a = 10, b = 3, \alpha_0 = 20, \alpha_1 = 1, \alpha_2 = 10, \lambda = 0.0125$ with unit market value growth of 7% per year.

Table 1: Sample Sales and Reassessments

	Buildings	Units	Tenant Spells
Sold	2276	9874	15019
Reassessed	442	1864	2008
Total	3590	17367	97017

Note: The main sample consists of 17,367 rental units in 3,590 buildings, with 63% of buildings and 57% of units sold over the course of the sample period. The first two rows of Columns 1 and 2 show the number of buildings/units that were ever sold or reassessed during the sample period of 1996–2022. The 'Total' row includes all buildings/units in the sample period, regardless of sale/reassessment status. Tenant spells refer to the length of time one tenant remained in the same apartment. Column 3 counts the number of tenant spells during which a sale or reassessment event occurred, with the total including tenant spells during which no event occurred. The sample consists of buildings/units registered with the Berkeley Rent Board from 1996 to 2022 that are able to be matched to county property tax data and have fewer than six bedrooms, trimmed on rent at the 1% level.

Table 2: Effect of Sale-Triggered Property Tax Changes on Rent

	Dependent variable:		
	$\Delta \ln[Rent_{t_{ij}-k_{ij},t_{ij}}]$		
	(1)	(2)	(3)
$\Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$	0.050***	0.036***	−0.004
	(0.005)	(0.005)	(0.009)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}}$		0.029***	0.017***
		(0.004)	(0.005)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$			0.048***
			(0.010)
$\text{Reassessed}_{t_{ij}-k_{ij},t_{ij}}$			0.012
			(0.009)
$\text{Reassessed}_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$			0.001
			(0.017)
$\text{Tract} \times \text{Year}_t \times \text{Year}_{t-k}$ FE	Y	Y	Y
$\text{Month}_t \times \text{Month}_{t-k}$ FE	Y	Y	Y
Unit FE	Y	Y	Y
Implied Pass-Through Per $1			$0.53
Observations	97,017	97,017	97,017
Adjusted R^2	0.698	0.699	0.699

*p<0.1; **p<0.05; ***p<0.01

Note: Sale-triggered property tax increases cause significant rent increases. The table reports fixed effect linear regressions using the change in log rent as the dependent variable. The sample consists of units registered with the Berkeley Rent Board from 1996 to 2022 that 1) have more than one recorded tenant spell and positive recorded rents, 2) are able to be matched to county property tax data, and 3) have fewer than six bedrooms, trimmed on rent at the 1% level. Regressions are at the unit-tenant spell level, and include tract-year-year, month-month, and unit fixed effects. Standard errors are clustered by building.

Table 3: IV: Effect of Sale-Triggered Property Tax Changes on Rent

	Dependent variable:		
	$\Delta \ln[Rent]$	Sale $\times$ $\Delta \ln[TV]$	$\Delta \ln[Rent]$
	(1)	(2)	(3)
$\Delta \ln[TV_{t_{ij}-k_{ij},t_{ij}}]$	-0.0003		
	(0.010)		
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}}$	0.018^{***}	0.398^{***}	-0.006
	(0.005)	(0.033)	(0.016)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{t_{ij}-k_{ij},t_{ij}}]$	0.045^{***}		0.081^{***}
	(0.011)		(0.022)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times$ Yrs Since Last Sale		0.021^{***}	
		(0.003)	
Specification	Original	First Stage	2SLS
Tract$\times$Year$_t$ $\times$ Year$_{t-k}$ FE	Y	Y	Y
Month$_t$ $\times$ Month$_{t-k}$ FE	Y	Y	Y
Unit FE	Y	Y	Y
Implied Pass-Through Per $1	$0.49		$0.89
F-statistic	39.5	46.62	49.43
Observations	95,414	95,414	95,414

*p<0.1; **p<0.05; ***p<0.01

Note: Sale-triggered property tax increases cause significant rent increases. This holds in OLS and when using the number of years since the property was last sold as an instrument for the change in taxable value after the current sale. Column (1) reports fixed effect linear regressions using the change in log rent as the dependent variable. Column (2) is the first stage of a two-stage least squares regression, using the number of years since the last sale as an instrument for the change in property tax upon sale. Column (3) is the two-stage least squares regression. The sample consists of units registered with the Berkeley Rent Board from 1996 to 2022 that 1) have more than one recorded tenant spell and positive recorded rents, 2) are able to be matched to county property tax data, 3) have fewer than six bedrooms, and 4) have a recorded sale date, trimmed on rent at the 1% level. Regressions are at the unit-tenant spell level, and include tract-year-year, month-month, and unit fixed effects. Standard errors are clustered by building.

Table 4: IV in Levels: Effect of Property Tax Burden (in Levels) on Rent

	Dependent variable:		
	Monthly Rent	Monthly Per-Unit TV	Monthly Rent
	(1)	(2)	(3)
Monthly Per-Unit Property Tax	0.617***		0.876***
	(0.109)		(0.246)
Years Since Sale		−3.116***	
		(0.282)	
Num. Units - Landlord	0.358***	0.080**	0.337***
	(0.063)	(0.031)	(0.072)
Specification	Original	First Stage	2SLS
Tract × Year FE	Y	Y	Y
Month FE	Y	Y	Y
Unit FE	Y	Y	Y
Implied Pass-Through Per $1	$0.62		$0.88
F-statistic	29.78	122.09	28.89
Observations	92,114	92,114	92,114
Adjusted R^2	0.646	0.810	0.645

*p<0.1; **p<0.05; ***p<0.01

Note: Higher property tax burdens (in levels/dollars) cause higher rents. This holds in OLS and when using the number of years since the property was last sold as an instrument for the property's current tax burden. Column (1) reports fixed effect linear regressions using monthly rent as the dependent variable. Column (2) is the first stage of a two-stage least squares regression, using the number of years since the last sale as an instrument for monthly per-unit property taxes. Column (3) is the two-stage least squares regression. The sample consists of units registered with the Berkeley Rent Board from 1996 to 2022 that 1) have more than one recorded tenant spell and positive recorded rents, 2) are able to be matched to county property tax data, 3) have fewer than six bedrooms, and 4) have a recorded sale date, trimmed on rent at the 1% level. Regressions are at the unit-tenant level, and include tract-year-year, month-month, and unit fixed effects. Standard errors are clustered by building.

Table 5: Landlord Summary Statistics

	Min	p25	p50	p75	Max
Units Owned (All)	1	4	12	39	786
Units Owned (Sold, Old Landlord)	1	6	18	49	786
Units Owned (Sold, New Landlord)	1	6	18	62	786
Change in Units Owned (Sold)	-757	-4	0	4	782

Note: Most landlords in Berkeley are relatively small, and most property sales occur between landlords of similar sizes. This table shows the distribution of landlord size (number of units owned) by a unit's recent sale status. The notation 'p25' denotes the 25th percentile. Row 1 shows the distribution of the number of units owned by all landlords. Row 2 shows the distribution of number of units owned for landlords who just sold a unit. Row 3 shows the distribution of number of units owned for landlords who just bought a unit. Row 4 shows the distribution of the change in the number of units owned by a landlord when a unit is sold from one landlord to another. The sample consists of units registered with the Berkeley Rent Board from 1996 to 2022 that 1) have more than one recorded tenant spell and positive recorded rents, 2) are able to be matched to county property tax data, and 3) have fewer than six bedrooms, trimmed on rent at the 1% level.

Table 6: Effect of Sale-Triggered Property Tax Changes on Rent by Landlord Size

	Dependent variable:		
	$\Delta \ln[Rent_{t_{ij}-k_{ij},t_{ij}}]$		
	(1)	(2)	(3)
$\Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$	−0.004	−0.003	−0.004
	(0.009)	(0.010)	(0.009)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}}$	0.017***	0.014***	0.018***
	(0.005)	(0.005)	(0.005)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$	0.048***	0.046***	0.046***
	(0.010)	(0.010)	(0.010)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times$ *Landlord Q1 → Landlord Q2*		0.009	
		(0.018)	
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times$ *Landlord Q1 → Landlord Q3*		0.003	
		(0.030)	
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times$ *Landlord Q1 → Landlord Q4*		0.004	
		(0.036)	
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times$ *Landlord Q2 → Landlord Q1*		0.043**	
		(0.018)	
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times$ *Landlord Q2 → Landlord Q3*		0.029	
		(0.023)	
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times$ *Landlord Q2 → Landlord Q4*		0.054**	
		(0.026)	
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times$ *Landlord Q3 → Landlord Q1*		−0.013	
		(0.020)	
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times$ *Landlord Q3 → Landlord Q2*		−0.015	
		(0.012)	
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times$ *Landlord Q3 → Landlord Q4*		0.048***	
		(0.017)	
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times$ *Landlord Q4 → Landlord Q1*		−0.023	
		(0.024)	
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times$ *Landlord Q4 → Landlord Q2*		−0.024	
		(0.018)	
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times$ *Landlord Q4 → Landlord Q3*		−0.021	
		(0.014)	
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times \Delta_{t_{ij}-k_{ij},t_{ij}}$ Number of Units			0.0001***
			(0.00002)
Implied Pass-Through Per $1	$0.53	$0.50	$0.51
Observations	97,017	97,017	97,017
Adjusted R^2	0.699	0.700	0.699

*p<0.1; **p<0.05; ***p<0.01

Note: Sale-triggered property tax increases cause significant rent increases, even when controlling for landlord size. The table reports fixed effect linear regressions using the change in log rent as the dependent variable. Column (1) presents Equation (1), Column (2) Equation (6), Column (3) Equation (7). The sample consists of units registered with the Berkeley Rent Board from 1996 to 2022 that 1) have more than one recorded tenant spell and positive recorded rents, 2) are able to be matched to county property tax data, and 3) have fewer than six bedrooms, trimmed on rent at the 1% level. Regressions are at the unit-tenant spell level, and include tract-year-year, month-month, and unit fixed effects. Standard errors are clustered by building.

Table 7: Effect of Sale-Triggered Property Tax Changes on Rent with Building Permits

	Dependent variable:	
	$\Delta \ln[Rent_{t_{ij}-k_{ij},t_{ij}}]$	
	(1)	(2)
$\Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$	-0.004	-0.004
	(0.009)	(0.009)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}}$	0.017^{***}	0.016^{***}
	(0.005)	(0.005)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$	0.048^{***}	0.044^{***}
	(0.010)	(0.009)
$\text{Reassessed}_{t_{ij}-k_{ij},t_{ij}}$	0.012	0.009
	(0.009)	(0.009)
$\text{Reassessed}_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$	0.001	0.00002
	(0.017)	(0.016)
Number of Permits		-0.003^{***}
		(0.001)
NLP Permit Score		0.273^{***}
		(0.020)
$\text{Tract}\times\text{Year}_t \times \text{Year}_{t-k}$ FE	Y	Y
$\text{Month}_t \times \text{Month}_{t-k}$ FE	Y	Y
Unit FE	Y	Y
Implied Pass-Through Per $1	$0.53	$0.49
Observations	97,017	97,017
Adjusted R^2	0.699	0.702

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: Sale-triggered property tax increases cause significant rent increases, even when controlling for permitted unit upgrades. The table reports fixed effect linear regressions using the change in log rent as the dependent variable. Column (1) presents Equation (1), and Column (2) presents Equation (8). The sample consists of units registered with the Berkeley Rent Board from 1996 to 2022 that 1) have more than one recorded tenant spell and positive recorded rents, 2) are able to be matched to county property tax data, and 3) have fewer than six bedrooms, trimmed on rent at the 1% level. Regressions are at the unit-tenant spell level, and include tract-year-year, month-month, and unit fixed effects. Standard errors are clustered by building.

Table 8: Test of Inattention Model

	Dependent variable:
	Log Rent_t
Log New Landlord $R^*_{g,t,beds}$	0.227***
	(0.013)
Log $R^*_{i,g,t-k=1}$	0.769***
	(0.023)
Num. Units Owned by Landlord	0.0001**
	(0.00002)
$\text{Year}_t \times \text{Year}_1 \times \text{Tract}$	Y
Observations	80,073
Adjusted R^2	0.909

*p<0.1; **p<0.05; ***p<0.01

Note: Incumbent landlords only partially update to market-level (new landlord) rents, demonstrating inattention to the maximum rent they could charge. The table reports the results of Equation (9). The sample consists of units registered with the Berkeley Rent Board from 1996 to 2022 that 1) have positive recorded rents, 2) are able to be matched to county property tax data, and 3) have fewer than six bedrooms. Regressions are at the unit-new lease level, and include $\text{Year}_t \times \text{Year}_1 \times \text{Tract}$ fixed effects. Standard errors are clustered by building.

Table 9: Effect of Rent and Tax Gaps on Probability of Building Sale

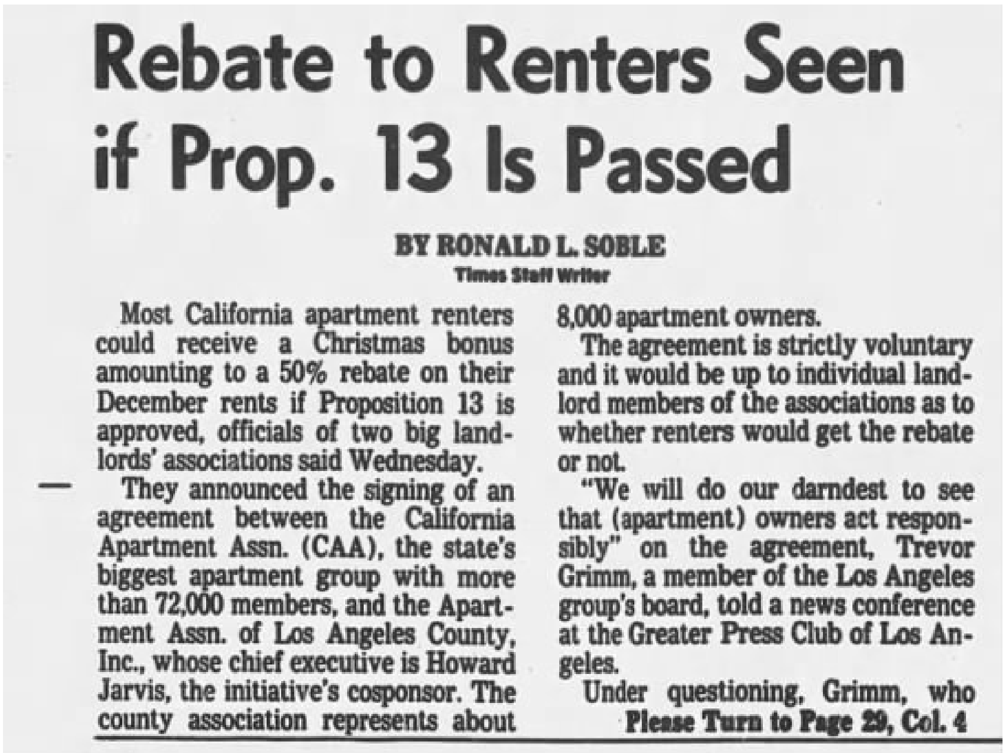
	Dependent variable:
	Probability of Sale_t
Rent Decile_{t-1}	-0.066^{***}
	(0.006)
Years Since Sale_{t-1}	-0.027^{***}
	(0.002)
Tract×Year_t FE	Y
Observations	75,489

*p<0.1; **p<0.05; ***p<0.01

Note: Sales are less attractive when the incumbent landlord sets high rents and faces a low tax burden. The table reports fixed effect linear regressions using the probability of sale at the building-year level as the dependent variable. Rent decile is equivalent to the per-year decile of a building's most recent new-tenant rent observation residualized on tract by year and unit fixed effects, with a higher rent decile denoting higher current rents. Years since sale serves as a proxy for the size of the tax increase upon sale, with a higher value of years since sale implying a larger tax increase upon sale. The sample consists of buildings in Berkeley that contain units registered with the Berkeley Rent Board from 1996 to 2022 that have positive recorded rents and are able to be matched to county property tax data. Observations are at the building-year level, and the regression includes tract by year fixed effects.

A Appendix Figures and Tables

Figure A1: Article from the *Los Angeles Times*, May 1978



Rebate to Renters Seen if Prop. 13 Is Passed

BY RONALD L. SOBLE
Times Staff Writer

Most California apartment renters could receive a Christmas bonus amounting to a 50% rebate on their December rents if Proposition 13 is approved, officials of two big landlords' associations said Wednesday.

They announced the signing of an agreement between the California Apartment Assn. (CAA), the state's biggest apartment group with more than 72,000 members, and the Apartment Assn. of Los Angeles County, Inc., whose chief executive is Howard Jarvis, the initiative's cosponsor. The county association represents about 8,000 apartment owners.

The agreement is strictly voluntary and it would be up to individual landlord members of the associations as to whether renters would get the rebate or not.

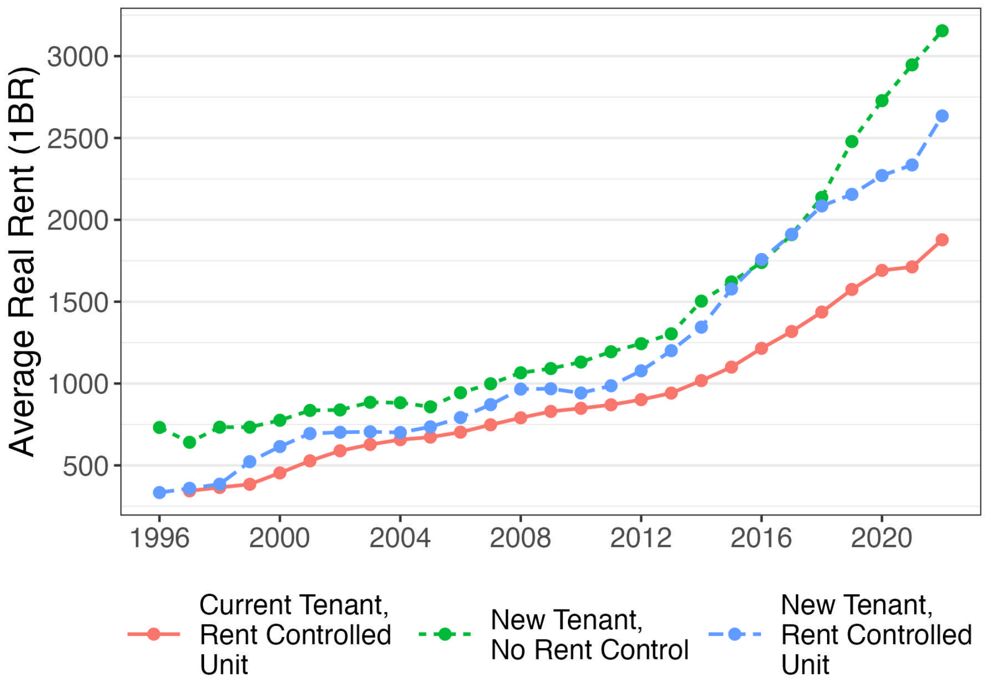
"We will do our darndest to see that (apartment) owners act responsibly" on the agreement, Trevor Grimm, a member of the Los Angeles group's board, told a news conference at the Greater Press Club of Los Angeles.

Under questioning, Grimm, who

Please Turn to Page 29, Col. 4

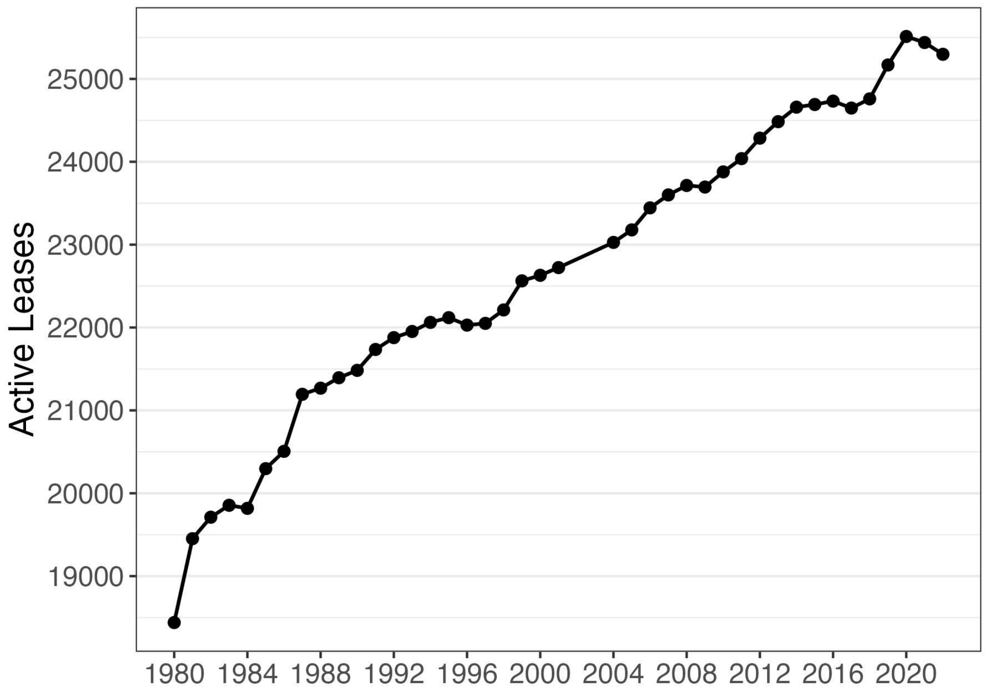
Note: Property owners publicly pledge to keep rents low if Proposition 13 passes. The figure shows an article from the *Los Angeles Times* that ran in May 1978, with Proposition 13 on the ballot in the November 1978 election.

Figure A2: Average Real Rent in Berkeley by Rent-Control Status



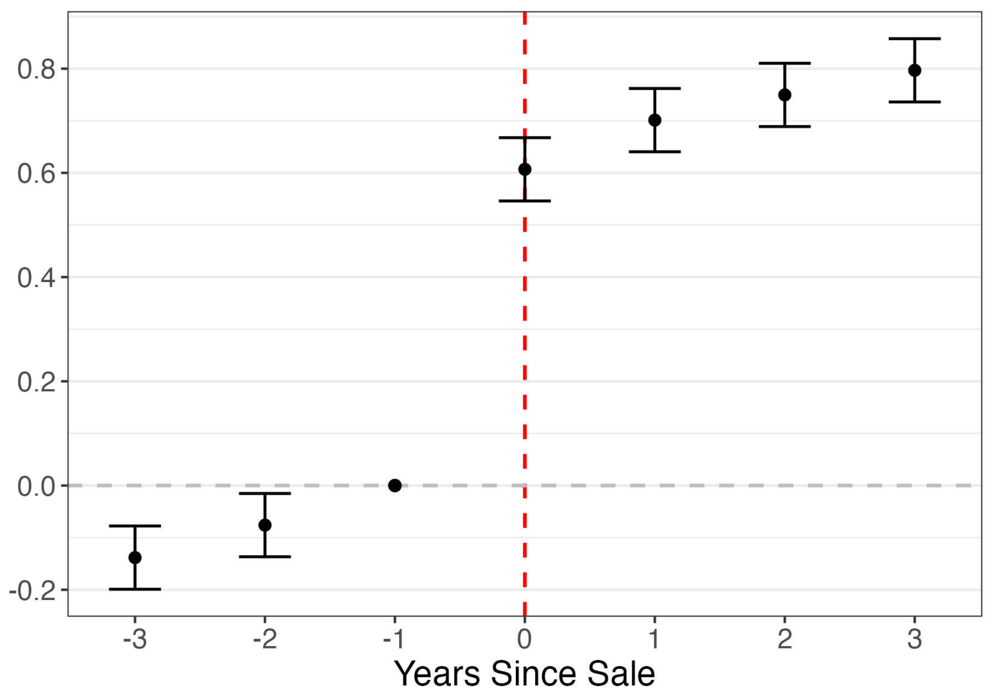
Note: New tenants in non-rent-controlled buildings (built after 1980) pay only slightly higher rents than new tenants in rent-controlled buildings (built before 1980; recall that rents are unrestricted for new tenants). The figure shows average CPI-adjusted rent in Berkeley for one bedroom units over the period 1996–2022. The red line represents average rent for continuing tenants in rent-controlled units. The blue long-dashed line represents average rent for new tenants in rent-controlled units. The green short-dashed line represents average rent for new tenants in non-rent-controlled units. The sample consists of all one bedroom units registered with the Berkeley Rent Board from 1996 to 2022.

Figure A3: Active Leases Subject to Rent Board, 1980–2022



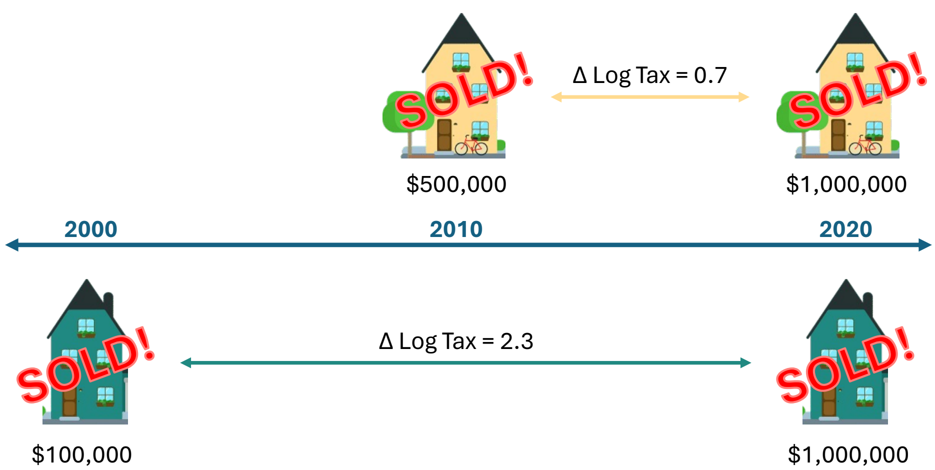
Note: The number of active leases reported to the Berkeley Rent Board has grown over time, as more units have become subject to tenant protections. The black line shows the number of active leases subject to tenant protections from 1980 to 2022. The sample consists of all units registered with the Berkeley Rent Board from 1980 to 2022.

Figure A4: Log Property Taxes Before and After Sale, Balanced Sample



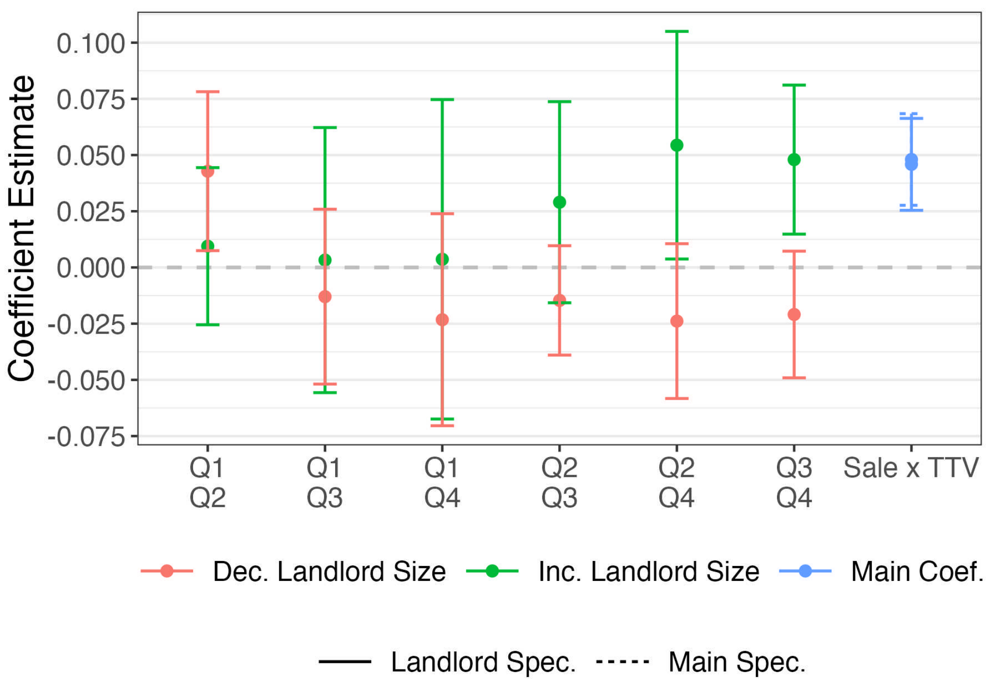
Note: Property taxes increase by 60% on average after a sale. The figure plots the coefficients of an event study of log property taxes regressed on years since sale, using no controls since property tax calculation is purely mechanical. The sample consists of all buildings that were sold exactly once between 1996 and 2022 for which I observe $t \in [-3, 3]$ that contain units registered with the Berkeley Rent Board that are able to be matched to county property tax data and have fewer than six bedrooms.

Figure A5: Motivation for IV Specification



Note: The change in property tax burden at sale is highly dependent on the length of time since the property was previously sold. The IV specification presented in Table 3 uses the length of time since a property was previously sold as an instrument for the property tax change at the current sale. The IV specification presented in Table A7 uses the same instrument, but controls for current sale price to compare properties of the same quality (current sale price) that differ only in the length of time since previously sold.

Figure A6: Coefficients on Landlord Size



Note: This figure plots the coefficients and standard errors from Columns 1 and 2 of Table 6. The coefficients on the change in landlord size around a sale are mostly insignificant and not perfectly symmetric. The main coefficient is unchanged by the inclusion of landlord size.

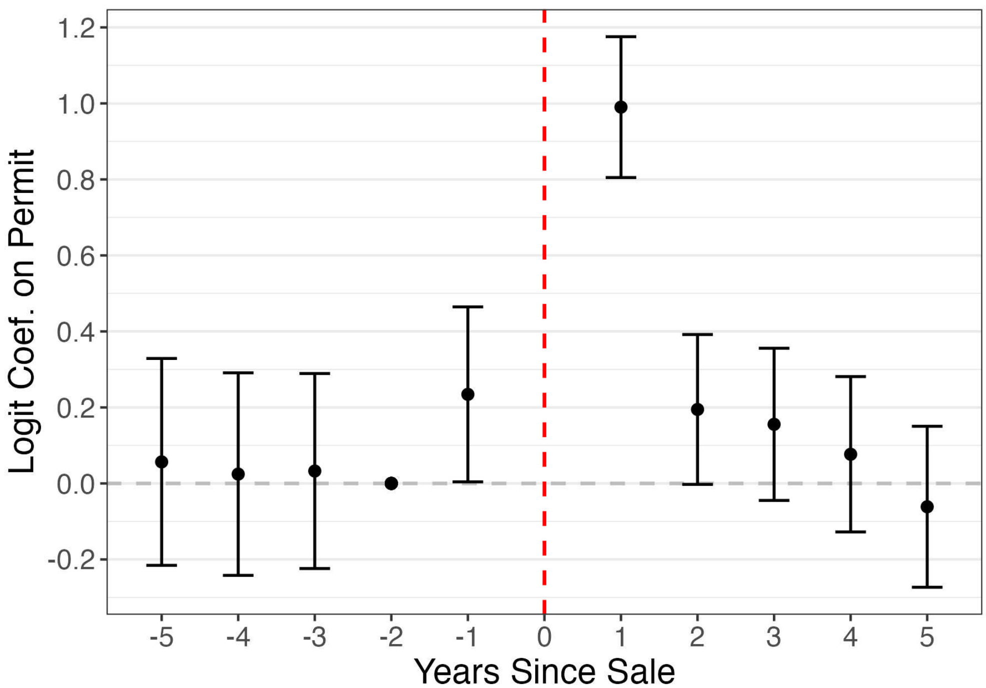
Figure A7: Oxford Street Apartment Quality

(a) Kitchen of 1725 Oxford Street in 2024

(b) Kitchen of 1749 Oxford Street in 2024

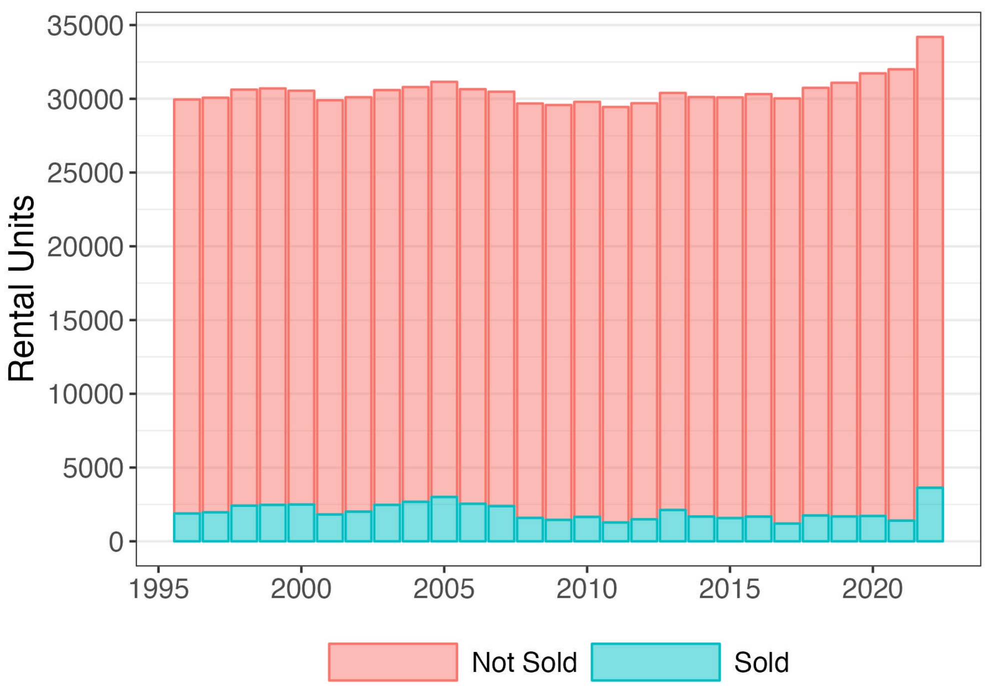
Note: The figure shows the kitchens of two representative units in the Oxford Street buildings mentioned throughout this paper. The quality appears similar and suggests that these units have not been updated for approximately 30 years ("90s kitchens").

Figure A8: Log-Likelihood of Permits Around a Sale, $t = -2$



Note: Building permits (i.e., renovations) are more likely to occur just before and after a sale. The figure plots event study coefficients of building permit presence regressed on years since sale, with reference group $t = -2$. The sample consists of all buildings that were sold at least once between 1996 and 2022 containing units registered with the Berkeley Rent Board that are able to be matched to county property tax data and have fewer than six bedrooms and positive rent values.

Figure A9: Annual Units Sold



Note: About 2,100 units, or 7% of all units in Berkeley, are sold each year. This graph shows a histogram of all rental units registered with the Berkeley Rent Board in a given year, with shading representing if the units were sold (blue) or not sold (red) in a given year.

Table A1: Effect of Sale-Triggered Property Tax Changes on Rent, With and Without FEs

	Dependent variable:			
	$\Delta \ln[Rent_{t_{ij}-k_{ij},t_{ij}}]$			
	(1)	(2)	(3)	(4)
$\Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$	0.564***	0.003	0.003	−0.004
	(0.055)	(0.008)	(0.008)	(0.009)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}}$	0.133***	0.018***	0.018***	0.017***
	(0.010)	(0.005)	(0.005)	(0.005)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$	−0.392***	0.043***	0.044***	0.048***
	(0.056)	(0.009)	(0.009)	(0.010)
$\text{Reassessed}_{t_{ij}-k_{ij},t_{ij}}$	0.032**	0.011	0.011	0.012
	(0.015)	(0.008)	(0.008)	(0.009)
$\text{Reassessed}_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$	−0.218***	0.005	0.005	0.001
	(0.050)	(0.014)	(0.014)	(0.017)
Tract×Year_t × Year_{t-k} FE	N	Y	Y	Y
Month_t × Month_{t-k} FE	N	N	Y	Y
Unit FE	N	N	N	Y
Observations	97,017	97,017	97,017	97,017
Adjusted R^2	0.197	0.686	0.693	0.699

*p<0.1; **p<0.05; ***p<0.01

Note: The inclusion of fixed effects is crucial to identifying pass-through of sale-triggered property tax changes to rent. The table reports fixed effect linear regressions using the change in log rent as the dependent variable, progressively adding different fixed effects. The sample consists of units registered with the Berkeley Rent Board from 1996 to 2022 that 1) have more than one recorded tenant spell and positive recorded rents, 2) are able to be matched to county property tax data, and 3) have fewer than six bedrooms, trimmed on rent at the 1% level. Regressions are at the unit-tenant spell level, and include tract-year-year, month-month, and unit fixed effects. Standard errors are clustered by building.

Table A2: Effects of Sale-Triggered Property Tax Changes on Rent

	Dependent variable:	
	$\Delta \ln[Rent_{t_{ij}-k_{ij},t_{ij}}]$	Monthly Rent
	(1)	(2)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$	0.048^{***}	
	(0.010)	
Monthly Per-Unit Property Tax		0.553^{***}
		(0.104)
Implied Pass-Through Per $1	$0.53	$0.55
Observations	97,017	121,398
Adjusted R^2	0.699	0.669
Note:	*p<0.1; **p<0.05; ***p<0.01	

Note: The estimate of pass-through from the baseline specification presented in Column 1 is confirmed by the estimate of pass-through in levels presented in Column 2. Column 1 reports the fixed effect linear regression from Column 3 of Table 2 (the baseline specification). Column 2 reports the coefficient of a fixed effect linear regression of monthly rent in dollars on monthly per-unit property tax burden in dollars. Monthly per-unit property tax burden is calculated by dividing annual property tax burden by 12, and then by the number of units in the building. Both specifications include tract-year, month, and unit fixed effects. Standard errors are clustered by building.

Table A3: Effects of Sale-Triggered Property Tax Changes on Rent

	Dependent variable:	
	$\Delta \ln[Rent_{t_{ij}-k_{ij},t_{ij}}]$	
	(1)	(2)
$\Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$	-0.004	-0.008
	(0.009)	(0.014)
$Sale_{t_{ij}-k_{ij},t_{ij}}$	0.017^{***}	0.009^{*}
	(0.005)	(0.005)
$Sale_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$	0.048^{***}	0.058^{***}
	(0.010)	(0.014)
Implied Pass-Through Per $1	$0.53	$0.64
Observations	97,017	43,850
Adjusted R^2	0.699	0.727
Note:	*p<0.1; **p<0.05; ***p<0.01	

Note: Using a never-treated control group (Column 2) *increases* the pass-through estimate over that provided by the baseline specification (Column 1), but halves the size of the sample. The table reports fixed effect linear regressions using the change in log rent as the dependent variable. The sample consists of units registered with the Berkeley Rent Board from 1996 to 2022 that 1) have more than one recorded tenant spell and positive recorded rents, 2) are able to be matched to county property tax data, and 3) have fewer than six bedrooms, trimmed on rent at the 1% level. Regressions are at the unit-tenant spell level, and include tract-year-year, month-month, and unit fixed effects. Standard errors are clustered by building.

Table A4: Tenant Spell Length by Sold/Unsold Status

	Average Spell Length (Years)		
Spell Year End	Not Sold	Sold	Post-Sale
1999-2004	2.1	2.9	1.8
2005-2009	2.3	3.9	2.2
2010-2014	2.5	5.1	2.7
2015-2022	2.9	6.0	3.0

Note: Tenants are not pressured out after a sale. Tenants remain in the same building post-sale for 2–3 years on average. The table shows tenant spell lengths grouped by move-out year for sold versus unsold buildings. The sample consists of units registered with the Berkeley Rent Board from 1996 to 2022 that 1) have more than one recorded tenant spell and positive recorded rents, 2) are able to be matched to county property tax data, and 3) have fewer than six bedrooms, trimmed on rent at the 1% level.

Table A5: Effects of Sale-Triggered Property Tax Changes on Rent: Reassessments

	Dependent variable:		
	$\Delta \ln[Rent_{t_{ij}-k_{ij},t_{ij}}]$		
	(1)	(2)	(3)
$\Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$	−0.004	−0.001	0.001
	(0.009)	(0.009)	(0.010)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}}$	0.017***	0.018***	0.019***
	(0.005)	(0.005)	(0.005)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$	0.048***	0.046***	0.042***
	(0.010)	(0.010)	(0.011)
$\text{Reassessed}_{t_{ij}-k_{ij},t_{ij}}$	0.012		
	(0.009)		
$\text{Reassessed}_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$	0.001		
	(0.017)		
Specification	Main	Exclude Reass. Variables	Exclude Reass. Observations
Tract×$\text{Year}_t \times \text{Year}_{t-k}$ FE	Y	Y	Y
$\text{Month}_t \times \text{Month}_{t-k}$ FE	Y	Y	Y
Unit FE	Y	Y	Y
Implied Pass-Through Per $1	$0.53	$0.50	$0.47
Observations	97,017	97,017	95,009
Adjusted R^2	0.699	0.699	0.703
Note:			*p<0.1; **p<0.05; ***p<0.01

Note: The inclusion or exclusion of reassessment indicators or reassessment observations have little effect on the main pass-through estimate. The table reports fixed effect linear regressions using the change in log rent as the dependent variable. The sample consists of units registered with the Berkeley Rent Board from 1996 to 2022 that 1) have more than one recorded tenant spell and positive recorded rents, 2) are able to be matched to county property tax data, and 3) have fewer than six bedrooms, trimmed on rent at the 1% level. Regressions are at the unit-tenant spell level, and include tract-year-year, month-month, and unit fixed effects. Standard errors are clustered by building.

Table A6: IV: Effects of Sale-Triggered Property Tax Changes on Rent, Split Sample

	Dependent variable:		
	$\Delta \ln[Rent_{t_{ij}-k_{ij},t_{ij}}]$		
	(1)	(2)	(3)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}}$	−0.006	0.004	−0.039
	(0.016)	(0.032)	(0.028)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{t_{ij}-k_{ij},t_{ij}}]$	0.081^{***}	0.070	0.116^{***}
	(0.022)	(0.064)	(0.034)
Specification	Full Sample	< Median Years	> Median Years
$\text{Tract}\times\text{Year}_t \times \text{Year}_{t-k}$ FE	Y	Y	Y
$\text{Month}_t \times \text{Month}_{t-k}$ FE	Y	Y	Y
Unit FE	Y	Y	Y
Implied Pass-Through Per $1	$0.89	$0.76	$1.28
F-statistic	49.43	12.44	28.06
Observations	95,414	87,985	88,006
Note:			*p<0.1; **p<0.05; ***p<0.01

Note: The larger IV coefficient (relative to OLS) presented in Column 3 of Table 3 is driven by sold properties with above-median years since last sale (i.e., by properties that were off-market for longer prior to the current sale). Column 1 reports the two-stage least squares regression for the whole sample, as reported in Column 3 of Table 3. Column 2 reports the two-stage least squares regression for properties with below-median years since last sale. Column 3 reports the two-stage least squares regression for properties with above-median years since last sale. The sample consists of units registered with the Berkeley Rent Board from 1996 to 2022 that 1) have more than one recorded tenant spell and positive recorded rents, 2) are able to be matched to county property tax data, 3) have fewer than six bedrooms, and 4) have a recorded sale date, trimmed on rent at the 1% level. Regressions are at the unit-tenant spell level, and include tract-year-year, month-month, and unit fixed effects. Standard errors are clustered by building.

Table A7: IV: Effects of Sale-Triggered Property Tax Changes on Rent with Sale Price Control

	Dependent variable:		
	$\Delta \ln[Rent]$	Sale $\times$ $\Delta \ln[TV]$	$\Delta \ln[Rent]$
	(1)	(2)	(3)
$\Delta \ln[TV_{t_{ij}-k_{ij},t_{ij}}]$	-0.003		
	(0.010)		
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}}$	0.021^{***}	-2.908^{***}	-0.067
	(0.006)	(0.269)	(0.078)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}}$ $\times$ Current Sale Price		0.242^{***}	0.005
		(0.020)	(0.007)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{t_{ij}-k_{ij},t_{ij}}]$	0.047^{***}		0.071^{***}
	(0.011)		(0.021)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}}$ $\times$ Yrs Since Last Sale		0.023^{***}	
		(0.003)	
Specification	Original	First Stage	2SLS
Tract$\times$$\text{Year}_t$ $\times$ Year_{t-k} FE	Y	Y	Y
Month_t $\times$ Month_{t-k} FE	Y	Y	Y
Unit FE	Y	Y	Y
Implied Pass-Through Per $1	$0.51		$0.78
F-statistic	44.14	77.65	41.63
Observations	96,646	96,646	96,646
Note:			*p<0.1; **p<0.05; ***p<0.01

Note: Sale-triggered property tax increases cause significant rent increases, even when controlling for current purchase price. Column 1 reports fixed effect linear regressions using the change in log rent as the dependent variable. Column 2 is the first stage of a two-stage least squares regression, using the number of years since the last sale as an instrument for the change in property tax upon sale. Column 3 is the two-stage least squares regression. The sample consists of units registered with the Berkeley Rent Board from 1996 to 2022 that 1) have more than one recorded tenant spell and positive recorded rents, 2) are able to be matched to county property tax data, 3) have fewer than six bedrooms, and 4) have a recorded sale date, trimmed on rent at the 1% level. Regressions are at the unit-tenant spell level, and include tract-year-year, month-month, and unit fixed effects. Standard errors are clustered by building.

Table A8: Effects of Sale-Triggered Property Tax Changes on Rent with Sale Price Control

	Dependent variable:	
	$\Delta \ln[Rent]$	
	(1)	(2)
$\Delta \ln[TV_{t_{ij}-k_{ij},t_{ij}}]$	-0.004	-0.004
	(0.009)	(0.010)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}}$	0.017^{***}	-0.092^{*}
	(0.005)	(0.052)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{t_{ij}-k_{ij},t_{ij}}]$	0.048^{***}	0.044^{***}
	(0.010)	(0.011)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times$ Current Sale Price		0.008^{**}
		(0.004)
Tract$\times$Year$_t$ $\times$ Year$_{t-k}$ FE	Y	Y
Month$_t$ $\times$ Month$_{t-k}$ FE	Y	Y
Unit FE	Y	Y
Implied Pass-Through Per $1	$0.53	$0.48
Observations	97,017	97,017
Adjusted R^2	0.699	0.699
Note:	*p<0.1; **p<0.05; ***p<0.01	

Note: Sale-triggered property tax increases cause significant rent increases, even when controlling for current purchase price. The inclusion of current purchase price has little effect on the pass-through estimate provided by the baseline specification (Column 1). The table reports fixed effect linear regressions using the change in log rent as the dependent variable. The sample consists of units registered with the Berkeley Rent Board from 1996 to 2022 that 1) have more than one recorded tenant spell and positive recorded rents, 2) are able to be matched to county property tax data, and 3) have fewer than six bedrooms, trimmed on rent at the 1% level. Regressions are at the unit-tenant spell level, and include tract-year-year, month-month, and unit fixed effects. Standard errors are clustered by building.

Table A9: Effect of Sale-Triggered Property Tax Changes on Rent by Landlord Characteristics

	Dependent variable:			
	$\Delta \ln[Rent_{t_{ij}-k_{ij},t_{ij}}]$			
	(1)	(2)	(3)	(4)
$\Delta \ln[TV_{t_{ij}-k_{ij},t_{ij}}]$	-0.004	-0.003	-0.005	-0.004
	(0.009)	(0.010)	(0.010)	(0.010)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}}$	0.017^{***}	0.010^{*}	0.013^{**}	0.020^{***}
	(0.005)	(0.005)	(0.005)	(0.006)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{t_{ij}-k_{ij},t_{ij}}]$	0.048^{***}	0.046^{***}	0.048^{***}	0.048^{***}
	(0.010)	(0.011)	(0.011)	(0.012)
Corporate		-0.003		
		(0.004)		
Business Owner			-0.004	
			(0.004)	
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times$ Corporate		0.028^{***}		
		(0.008)		
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times$ Business Owner			0.022^{**}	
			(0.009)	
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times \Delta$ County Buildings				0.0003^{**}
				(0.0001)
Implied Pass-Through Per $1	$0.53	$0.50	$0.53	$0.53
Observations	97,017	97,017	96,744	79,464
Adjusted R^2	0.699	0.699	0.699	0.650

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: The baseline pass-through estimate presented in Column 1 is robust to the inclusion of different definitions of landlord size. The table reports fixed effect linear regressions using the change in log rent as the dependent variable. Column 1 shows results for the main sample, Column 2 shows results controlling for landlord LLC status, Column 3 shows results controlling for if the landlord is registered as a business owner in California, and Column 4 shows results controlling for how many buildings the landlord owns in the county. The sample consists of units registered with the Berkeley Rent Board from 1996 to 2022 that 1) have more than one recorded tenant spell and positive recorded rents, 2) are able to be matched to county property tax data, and 3) have fewer than six bedrooms, trimmed on rent at the 1% level. Regressions are at the unit-tenant spell level, and include tract-year-year, month-month, and unit fixed effects. Standard errors are clustered by building.

Table A10: Effect of Sale-Triggered Property Tax Changes on Rent with Improvements

	Dependent variable:		
	$\Delta \ln[Rent_{t_{ij}-k_{ij},t_{ij}}]$		
	(1)	(2)	(3)
$\Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$	-0.004	-0.004	-0.029^{***}
	(0.009)	(0.009)	(0.010)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}}$	0.017^{***}	0.016^{***}	0.009^{*}
	(0.005)	(0.005)	(0.005)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$	0.048^{***}	0.044^{***}	0.060^{***}
	(0.010)	(0.009)	(0.012)
$\text{Reassessed}_{t_{ij}-k_{ij},t_{ij}}$	0.012	0.009	-0.003
	(0.009)	(0.009)	(0.011)
$\text{Reassessed}_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$	0.001	0.00002	0.031
	(0.017)	(0.016)	(0.024)
Number of Permits		-0.003^{***}	
		(0.001)	
NLP Permit Score		0.273^{***}	
		(0.020)	
Tract$\times$Year$_t$ $\times$ Year$_{t-k}$ FE	Y	Y	Y
Month$_t$ $\times$ Month$_{t-k}$ FE	Y	Y	Y
Unit FE	Y	Y	Y
Implied Pass-Through Per $1	$0.53	$0.49	$0.66
Observations	97,017	97,017	64,879
Adjusted R^2	0.699	0.702	0.639

$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: The baseline pass-through estimate presented in Column 1 is robust to the inclusion of permitted renovations (Column 2) or dropping tenant spells that include permitted renovations (Column 3). Column 1 shows results for the main sample, Column 2 shows results for the same sample with added controls for permits, and Column 3 shows results for the main sample restricted to spells with no registered permits. The sample consists of units registered with the Berkeley Rent Board from 1996 to 2022 that 1) have more than one recorded tenant spell and positive recorded rents, 2) are able to be matched to county property tax data, and 3) have fewer than six bedrooms, trimmed on rent at the 1% level. Regressions are at the unit-tenant spell level, and include tract-year-year, month-month, and unit fixed effects. Standard errors are clustered by building.

Table A11: Test of Efficiency Rents

	Dependent variable:
	Tenure (Years)
Residualized $\text{Rent}_{i,g,t}$	-0.891^{***}
	(0.109)
Observations	97,017
Adjusted R^2	0.002

*p<0.1; **p<0.05; ***p<0.01

Note: Lower rents increase tenure, contrary to the model proposed in Basu and Emerson (2003). The table reports the result of a regression of tenant tenure in years on residualized rent. Rent is residualized on taxable value, landlord size, and year-tract, month, and unit fixed effects. The sample consists of units registered with the Berkeley Rent Board from 1996 to 2022 that 1) have positive recorded rents, 2) are able to be matched to county property tax data, 3) have fewer than six bedrooms, 4) whose tenancies have ended. Regressions are at the unit-new lease level. Standard errors are clustered by building.

B Search and Matching Framework

Consider a simple search and matching model (adapted from David Card's lecture notes):

- L potential renters: uL looking for apts, vL vacant apts
- match function $M(uL, vL)$ with CRS so $M(uL, vL) = vL \cdot M(\frac{u}{v}, 1)$
- $\theta \equiv v/u$
- $q \equiv M/vL = M(\frac{u}{v}, 1) = M(\frac{1}{\theta}, 1) = q(\theta) =$ vacancy filling rate
- $\theta q(\theta) = M/uL =$ rate that searchers find an apartment (exit hazard)
- $q(\theta) \to \infty$ as $\theta \to 0$ and $q(\theta) \to 0$ at as $\theta \to \infty$
- $\theta q(\theta) \to 0$ as $\theta \to 0$ and $\theta q(\theta) \to \infty$ as $\theta \to \infty$

B.1 Beveridge Curve

Let tenancy exit $= \delta(1-u)L$ and the new openings rate $= \theta q(\theta) \times uL$. Equating the two:

$$u = \frac{\delta}{\delta + \theta q(\theta)} = \frac{\delta}{\delta + (v/u)q(v/u)}.$$

B.2 Vacancy Creation

Given $V =$ value of unfilled vacancy and $J =$ value of a filled vacancy:

$$rV = -c + q(\theta)(J - V),$$

assuming $V = 0$:

$$J = c/q(\theta) = \text{cost per period } \times \text{expected time to fill.}$$

With rent R, maintenance cost m, and tenant exit rate δ, interest rate r:

$$J = \frac{R - m}{r + \delta},$$

so in equilibrium:

$$R = m + (r + \delta)c/q(\theta).$$

B.3 Rents Conditional on Tightness

A representative potential tenant has flow value of searching U and value $V(R)$ of an apartment with rent R:

$$
\begin{aligned}
rU &= -h + \theta q(\theta)(V(R) - U) \\
rV(R) &= S - R + \delta(U - V(R)),
\end{aligned}
$$

where h is the cost of temporary accommodation while searching, and S is the dollar value of the flow utility from an apartment (i.e., $S - R$ is the net value after paying rent). The second equation implies:

$$V(R) = \frac{S - R}{r + \delta} + \frac{\delta}{r + \delta} U.$$

Using this plus the equation for rU:

$$rU = \frac{-(r + \delta)}{r + \delta + \theta q(\theta)} h + \frac{\theta q(\theta)}{r + \delta + \theta q(\theta)} (S - R),$$

which is a weighted average of $-h$ and $S - R$. The gain to a worker of having an apartment versus searching is $V(R) - U$, which implies:

$$V(R) - U = \frac{S - R - rU}{r + \delta}.$$

Match surplus is given by:

$$
\begin{aligned}
\Gamma &= V(R) - U + J \\
&= \frac{S - R - rU}{r + \delta} + \frac{R - m}{r + \delta} \\
&= \frac{S - m - rU}{r + \delta},
\end{aligned}
$$

which does not depend on R. Nash bargaining gives:

$$R = argmax_R (\frac{S - R - rU}{r + \delta})^{\beta} (\frac{R - m}{r + \delta})^{1-\beta}.$$

The solution gives a share $(1-\beta)$ of the surplus to the landlord:

$$R - m = (1-\beta)(S - m - rU)$$
$$\Rightarrow R = \beta m + (1-\beta)(S - rU).$$

Combining:

$$R = \frac{(1-\beta)(r+\delta)}{r+\delta+\beta\theta q(\theta)}(S+h) + \frac{\beta(r+\delta)+\beta\theta q(\theta)}{r+\delta+\beta\theta q(\theta)}m.$$

The equation shows that the rent is a weighted average of $S+h$ (the total value of the property to the tenant, taking account of the cost of living while searching) and the owner's maintenance cost m, with weights that depend on θ :

$$R = (1-A(\theta))(S+h) + A(\theta)m$$
$$A(\theta) = \frac{\beta(r+\delta)+\beta\theta q(\theta)}{r+\delta+\beta\theta q(\theta)}.$$

B.4 Implications of the Model

- $A(\theta) = 1$ when $\theta q(\theta) \to \infty$. This is a tight market, with many open apartments and few searchers (i.e., a bad market for landlords). Rent is only maintenance costs:

  $$R = m.$$

  When the vacancy rate is high, rent is low and pass-through of taxes (which are included in m) is high.

- $A(\theta) = \beta$ when $\theta q(\theta) \to 0$. This is a loose market, with no open apartments and many searchers (i.e., a good market for landlords). Rent is a weighted average of apartment value and maintenance cost:

  $$R = (1-\beta)(S+h) + \beta m.$$

  When the vacancy rate is low, rent is high and pass-through of taxes (which are included in m) is low.

B.5 Testing the Implications

Table A12 shows Equation (1) controlling for changes in the vacancy rate, provided quarterly by the Census Bureau from 2005-present for large metro areas.[42] Column (1) presents Equation (1) for comparison. Column (2) shows that as the vacancy rate increases, rent decreases and property tax pass-through decreases. This is in contrast to the DMP-style model, which predicts that an increase in the vacancy rate will decrease rents and *increase* property tax pass-through.

[42] Census Bureau data.

Table A12: Test of DMP Model

	Dependent variable:	
	$\Delta \ln[Rent_{t_{ij}-k_{ij},t_{ij}}]$	
	(1)	(2)
$\Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$	-0.004	-0.005
	(0.009)	(0.011)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}}$	0.017^{***}	0.029^{***}
	(0.005)	(0.007)
$\text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$	0.048^{***}	0.050^{***}
	(0.010)	(0.013)
$\Delta\text{Vacancy Rate}_{t_{ij}-k_{ij},t_{ij}}$		-0.395^{***}
		(0.067)
$\Delta\text{Vacancy Rate}_{t_{ij}-k_{ij},t_{ij}} \times \text{Sale}_{t_{ij}-k_{ij},t_{ij}} \times \Delta \ln[TV_{i,g,t_{ij},t_{ij}-k_{ij}}]$		-0.382^{*}
		(0.218)
$\text{Tract}\times\text{Year}_t \times \text{Year}_{t-k}$ FE	Y	Y
$\text{Month}_t \times \text{Month}_{t-k}$ FE	Y	Y
Unit FE	Y	Y
Implied Pass-Through Per $1	$0.53	$0.55
Observations	97,017	62,450
Adjusted R^2	0.699	0.632

*p<0.1; **p<0.05; ***p<0.01

Note: The table reports fixed effect linear regressions using the change in log rent as the dependent variable. The sample consists of units registered with the Berkeley Rent Board from 1996 to 2022 that 1) have more than one recorded tenant spell and positive recorded rents, 2) are able to be matched to county property tax data, and 3) have fewer than six bedrooms, trimmed on rent at the 1% level. Column (2) restricts to observations from 2005-present, due to vacancy rate data limitations. Regressions are at the unit-tenant spell level, and include tract-year-year, month-month, and unit fixed effects. Standard errors are clustered by building.

C Reference Dependence Framework

Reference dependence can rationalize the high pass-through rates documented in Section 3, and the existence of reference dependence in the housing market is supported in the literature.[43] It is easy to imagine that landlords consider their per-unit costs, and the changes in those costs, as a reference point for setting rent.

C.1 Rational Benchmark

Consider a model of rent-setting in which the landlord faces a trade-off between the rent price and the amount of time it takes to find a tenant. Also assume that the probability of finding a tenant is negatively related to rent, in other words, the demand for housing is downward sloping.[44] Let R denote the rent set by the landlord. Let $\alpha(R)$ be the probability of filling a vacancy. The landlord's utility is equivalent to $u(R, T) = R - T$, where T represents the landlord's per-unit costs, which includes the per-unit property tax burden. The landlord faces the maximization problem:

$$\max_R \ \alpha(R)(R - T) + (1 - \alpha(R))(0 - T),$$

where the first term represents the landlord's utility if the apartment rents, and the second term represents the landlord's utility if the apartment remains vacant. This yields the first order condition:

$$0 = \alpha'(R^*)R^* + \alpha(R^*),$$

which does not depend on T. To build intuition, allow $\alpha(R) = \alpha_0 - \alpha_1 R$, a simple form of downward-sloping demand. This yields:

$$R^* = \frac{\alpha_0}{2\alpha_1}.$$

In the rational benchmark case, landlords obey the law of one price and all units are priced identically. The amount of property taxes owed on the unit, included in per-unit costs T, does not enter into the equation for optimal rent R^*. This runs contrary to the results presented in Section 3, which showed that units with higher per-unit costs charge higher rents.

[43] Andersen et al. (2022), Giacoletti and Parsons (2022).

[44] As in Giacoletti and Parsons (2022), Andersen et al. (2022), and Watson and Ziv (2024).

C.2 Loss-Averse/Reference-Dependent Preferences

Following Giacoletti and Parsons (2022) and Andersen et al. (2022), consider the same model with the addition of reference-dependent and loss-averse preferences. Then, the landlord's utility function is a step-wise function that allows for steeper decreases in utility when in the loss domain. Given $g(x)$ as utility in the gain domain, s.t. $g'(x) > 0$ and $g''(x) \leq 0$, and $l(x)$ as loss domain utility, s.t. $l'(x) > g'(x) > 0$ and $l''(x) \geq 0$, her utility given that the apartment rents is:

$$u(R,T) = \begin{cases} g(R-T) & R > T \\ l(R-T) & R \leq T. \end{cases}$$

However, the landlord again faces a trade-off between rent and probability of renting, so the landlord maximizes per-unit profit:

$$\max_R \ \alpha(R)u(R-T) + (1-\alpha(R))l(0-T),$$

where the first term represents the landlord's utility if the apartment rents (with probability $\alpha(R)$), and the second term represents the landlord's utility if the apartment fails to rent. There are two cases to consider, depending on whether the landlord sets rent in the gain domain ($R^* > T$) or the loss domain ($R^* < T$). In both cases, if the apartment does not rent, the landlord incurs a loss because she receives no rent but still must pay the per-unit cost T. The maximization problem then becomes:

$$\max_R \begin{cases} \alpha(R)g(R-T) + (1-\alpha(R))l(0-T) & R^* > T \\ \alpha(R)l(R-T) + (1-\alpha(R))l(0-T) & R^* \leq T, \end{cases}$$

where the first line denotes the case in which rent is set above per-unit costs. The first term represents the case in which the apartment rents at $R^* > T$, and the second term represents the case in which the apartment fails to rent at $R^* > T$. The terms in the second line can be defined similarly, except rent is set such that $R^* \leq T$.

The maximization problem yields two FOCs:

$$0 = \begin{cases} \alpha(R^*)g'(R^*-T) + \alpha'(R^*)g(R^*-T) - \alpha'(R^*)l(-T) & R^* > T \\ \alpha(R^*)l'(R^*-T) + \alpha'(R^*)l(R^*-T) - \alpha'(R^*)l(-T) & R^* \leq T, \end{cases}$$

where, while it is not trivial to solve these conditions generally, the optimal rent will balance the increase in utility from capturing a high rent with the degree of utility loss if the unit fails to rent.

C.2.1 Linear–Non-Linear Case

Following Giacoletti and Parsons (2022) and Andersen et al. (2022), consider the model above with the addition of reference-dependent and loss-averse preferences. Then, the landlord's utility function is a step-wise function that allows for steeper decreases in utility when in the loss domain. Given $g(x)$ as utility in the gain domain, s.t. $g'(x) > 0$ and $g''(x) \leq 0$, and $l(x)$ as loss domain utility, s.t. $l'(x) > g'(x) > 0$ and $l''(x) \geq 0$, her utility given that the apartment rents is:

$$u(R, C) = \begin{cases} g(R - C) & R > C \\ l(R - C) & R \leq C. \end{cases}$$

However, the landlord again faces a trade-off between rent and probability of renting, so the landlord maximizes per-unit profit:

$$\max_R \; \alpha(R)u(R - C) + (1 - \alpha(R))l(0 - C),$$

where the first term represents the landlord's utility if the apartment rents (with probability $\alpha(R)$), and the second term represents the landlord's utility if the apartment fails to rent. There are two cases to consider, depending on whether the landlord sets rent in the gain domain ($R^* > C$) or the loss domain ($R^* < C$). In both cases, if the apartment does not rent, the landlord incurs a loss because she receives no rent but still must pay the per-unit cost C. The maximization problem then becomes:

$$\max_R \begin{cases} \alpha(R)g(R - C) + (1 - \alpha(R))l(0 - C) & R^* > C \\ \alpha(R)l(R - C) + (1 - \alpha(R))l(0 - C) & R^* \leq C, \end{cases}$$

where the first line denotes the case in which rent is set above per-unit costs. The first term represents the case in which the apartment rents at $R^* > C$, and the second term represents the case in which the apartment fails to rent at $R^* > C$. The terms in the second line can be defined similarly, except rent is set such that $R^* \leq C$.

The maximization problem yields two FOCs:

$$0 = \begin{cases} \alpha(R^*)g'(R^* - C) + \alpha'(R^*)g(R^* - C) - \alpha'(R^*)l(-C) & R^* > C \\ \alpha(R^*)l'(R^* - C) + \alpha'(R^*)l(R^* - C) - \alpha'(R^*)l(-C) & R^* \leq C, \end{cases}$$

where, while it is not trivial to solve these conditions generally, the optimal rent will balance the increase in utility from capturing a high rent with the degree of utility loss if the unit fails to rent.

Concavity in the utility function on the gain side generates the results closest to the empirical results presented in Section 3. As a simple example, consider:

$$u(R,C) = \begin{cases} 2\log[1+(R-C)] & R > C \\ 2\times(R-C) & R \leq C. \end{cases}$$

Figure A10 shows this simple example of a utility function that meets the conditions of reference dependence and loss aversion stated above. The red (blue) line again applies to landlords setting rent in the gain (loss) domain. This landlord dislikes losses linearly, but dislikes losses much more than she appreciates equivalent gains. With these functions, the FOCs become:

$$0 = \begin{cases} \alpha(R)\frac{2}{1+R-C} + \alpha'(R)\log(1+R-C) - \alpha'(R)(-2C) & R > C \\ 2\alpha(R) + \alpha'(R)2(R-C) - \alpha'(R)(-2C) & R \leq C. \end{cases}$$

Assuming again linear downward-sloping demand such that $\alpha(R) = \alpha_0 - \alpha_1 R$:

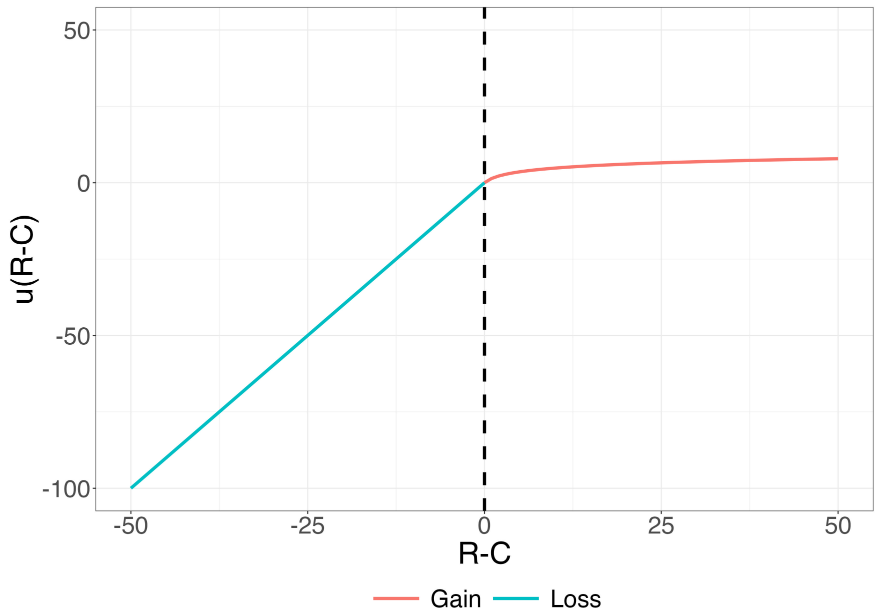
$$0 = \begin{cases} (\alpha_0 - \alpha_1 R)\frac{2}{1+R-C} - \alpha_1\log(1+R-C) - 2\alpha_1 C & R > C \\ 2(\alpha_0 - \alpha_1 R) - 2\alpha_1(R-C) - 2\alpha_1 C & R \leq C. \end{cases}$$

The step-wise utility function from Figure A10 and the solution for R^* above yields the relationship between rent R and the per-unit cost reference point C depicted in Figure A11. In the gain domain, rent depends positively on C as $C \rightarrow \hat{C}$. In the loss domain, rent is always set at the rational benchmark, and is always higher than the rent set in the gain domain. This behavior can be justified as follows. This landlord values small gains over the reference point, and thus for values of C that are sufficiently low ($C < \hat{C}$), she always sets rent just higher than her tax cost in the hopes of making at least a small profit. For high values of C such that $C > \hat{C}$, she sets rent at the rational benchmark, which she believes to be the highest the market will bear, in order to minimize her losses.

In sum, non-linearity in utility over gains produces a positive relationship between rent and per-unit costs, which is consistent with the empirical results from Section 3.[45]

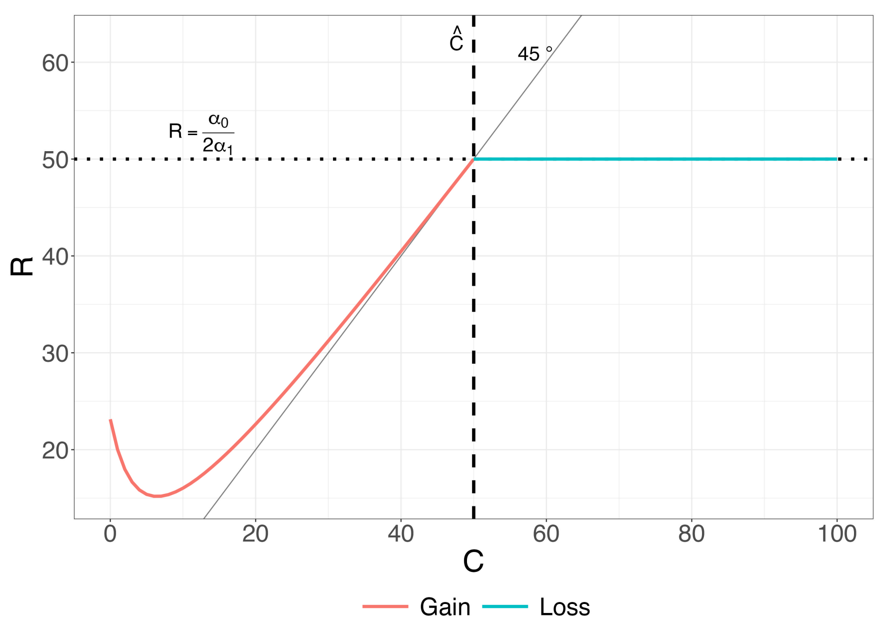
[45]See sections C.2.2 and C.2.3 for a discussion of other functional forms.

Figure A10: Utility Function for Reference-Dependent/Loss-Averse Landlord



Note: The figure plots a utility function for a loss-averse landlord with non-linear preferences in the gain domain (red line) and linear preferences in the loss domain (blue line) of rent relative to tax costs.

Figure A11: Relationship Between Rent and Tax Reference Point



Note: The figure plots the relationship between rent and taxes for a landlord with the utility function presented in Figure A10. The red line represents landlords in the gain domain, while the blue line represents landlords in the loss domain of rent relative to tax costs.

C.2.2 Linear Case

To build intuition, first I examine linear prospect theory preferences such that, for $b < c$:

$$u(R,T) = \begin{cases} b \times (R-T) & R^* > T \\ c \times (R-T) & R^* \leq T. \end{cases}$$

Figure A12 shows this simple example of a utility function that meets the conditions of reference dependence and loss aversion.[46] Namely, these conditions are 1) small losses cause larger reductions in utility than equivalently small gains increase utility, and 2) the landlord experiences an additional utility bump from income exceeding her reference point ($g'(x) > 1$). The red (blue) line applies to landlords setting rent in the gain (loss) domain. Landlords in the gain domain have set rent such that rent fully offsets their per-unit costs. In the loss domain, landlords have set rent below their per-unit costs, such that they are in a negative cash-flow state. Assuming again linear, downward-sloping demand such that $\alpha(R) = \alpha_0 - \alpha_1 R$, the FOCs become:

$$0 = \begin{cases} (\alpha_0 - \alpha_1 R)b - \alpha_1 b(R-T) - \alpha_1 cT & R > T \\ (\alpha_0 - \alpha_1 R)c - \alpha_1 c(R-T) - \alpha_1 cT & R \leq T, \end{cases}$$

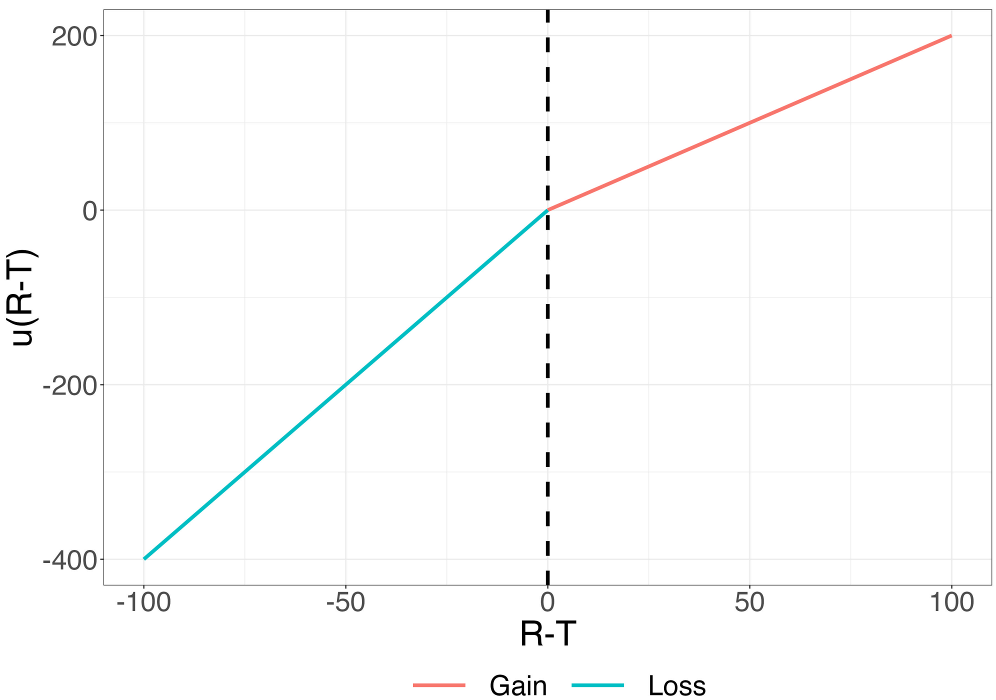
which implies:

$$R^* = \begin{cases} \frac{\alpha_0}{2\alpha_1} + \frac{1}{2}T - \frac{c}{2b}T & T < \hat{T} \\ \frac{\alpha_0}{2\alpha_1} & T \geq \hat{T}, \end{cases}$$

where $\hat{T}$ is the threshold value for which $T < \hat{T} \implies R^* > T$ in equilibrium. $\hat{T}$ is defined by $\alpha(\hat{T})g'(0) + \alpha'(\hat{T})g(0) - \alpha'(\hat{T})l(-\hat{T}) = 0$. The step-wise utility function from Figure A12 and the solution for R^* above yields the relationship between rent R and the per-unit cost reference point T depicted in Figure A13. The red (blue) line applies to landlords setting rent using the gain (loss) FOC. The vertical dashed line marks $\hat{T}$. Above the 45-degree line shown, landlords are profitable. The horizontal dotted line denotes optimal rent in the rational benchmark case, $R = \frac{\alpha_0}{2\alpha_1}$. A few interesting facts emerge. First, landlords with high reference points (e.g., high tax burdens) always set rent at the rational benchmark. Second, landlords with low reference points (e.g., low tax burdens) always set rent below the rational benchmark, and thus below that of landlords in the loss domain. This is the key observation supported by the empirical results presented in Section 3: landlords with high costs set rents significantly higher than those with low costs. Third, optimal rent depends negatively on T

[46] $g'(x) > 1, g''(x) \leq 0, l'(x) > 0, l''(x) > 0, g'(0) < l'(0)$.

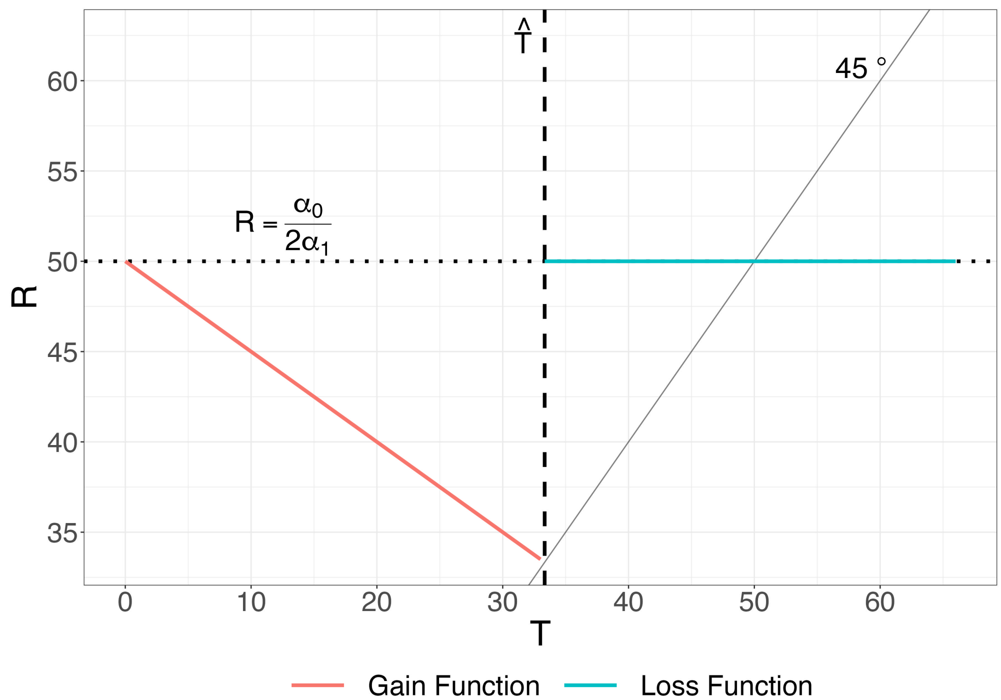
Figure A12: Utility Function for Reference-Dependent/Loss-Averse Landlord



for $T < \hat{T}$. This is justified theoretically by the fact that a reference-dependent landlord in the gain domain is less risk-seeking in gains, meaning much less willing to accept a vacancy, so rent is decreasing in T for $T < \hat{T}$. The discrete jump at $\hat{T}$ is justified theoretically by the fact that, in the loss domain, the landlord is more willing to gamble on setting a high rent—and thus risking a vacancy—for T near $\hat{T}$, to minimize dreaded small losses.

Notably, some landlords in the loss domain with $T >> \hat{T}$ are not profitable immediately. However, as the rational benchmark rent (e.g. market-rate rent) shifts up over time and per-unit costs remain relatively constant, the profitability region expands, eventually allowing even landlords with the highest cost burdens to become profitable.

Figure A13: Relationship Between Rent and Tax Reference Point



C.2.3 Non-Linear Case

As a more complex non-linear example, I examine:

$$u(R,T) = \begin{cases} \log[1+2(R-T)] & R > T \\ -2 \times \log[1-(R-T)] & R \leq T. \end{cases}$$

Figure A14 shows this simple example of a utility function that meets the conditions of reference dependence and loss aversion stated above. The red (blue) line again applies to landlords setting rent in the gain (loss) domain. This landlord hates small losses, shown by the steep drop off in utility for values of $R-T$ just below zero. This landlord also loves small gains, shown by the steep increase in utility for values of $R-T$ just above zero. With these functions, the FOCs become:

$$0 = \begin{cases} \alpha(R)\frac{2}{1+2(R-T)} + \alpha'(R)\log(1+2(R-T)) - \alpha'(R) \times -2\log(1+T) & R > T \\ \alpha(R)\frac{2}{1-(R-T)} + \alpha'(R) \times -2\log(1-(R-T)) - \alpha'(R) \times -2\log(1+T) & R \leq T. \end{cases}$$

Figure A14: Utility Function for Reference-Dependent/Loss-Averse Landlord

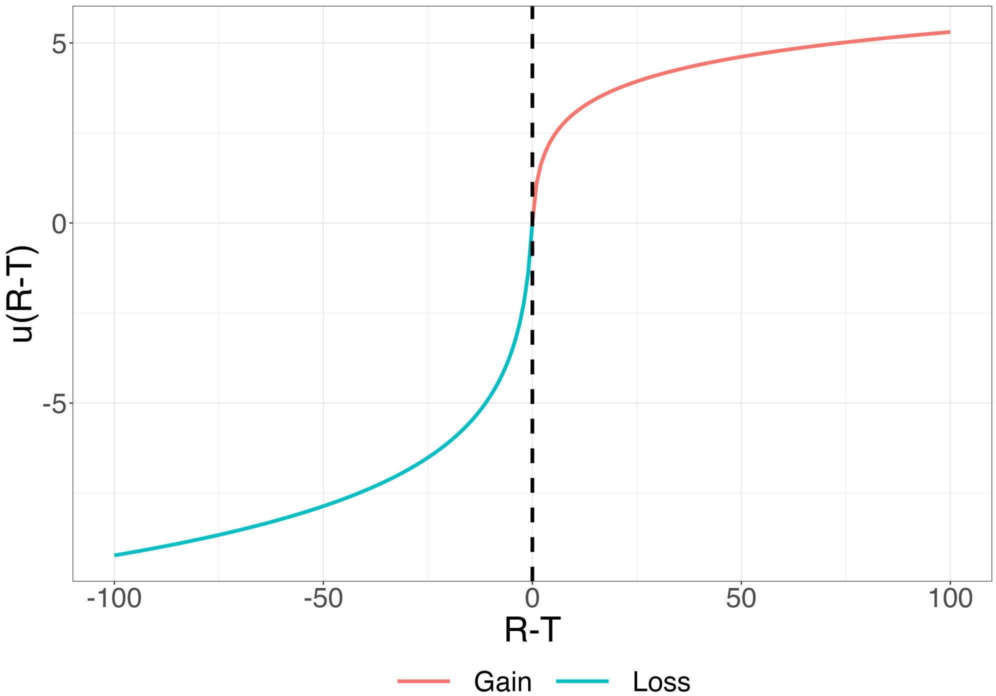
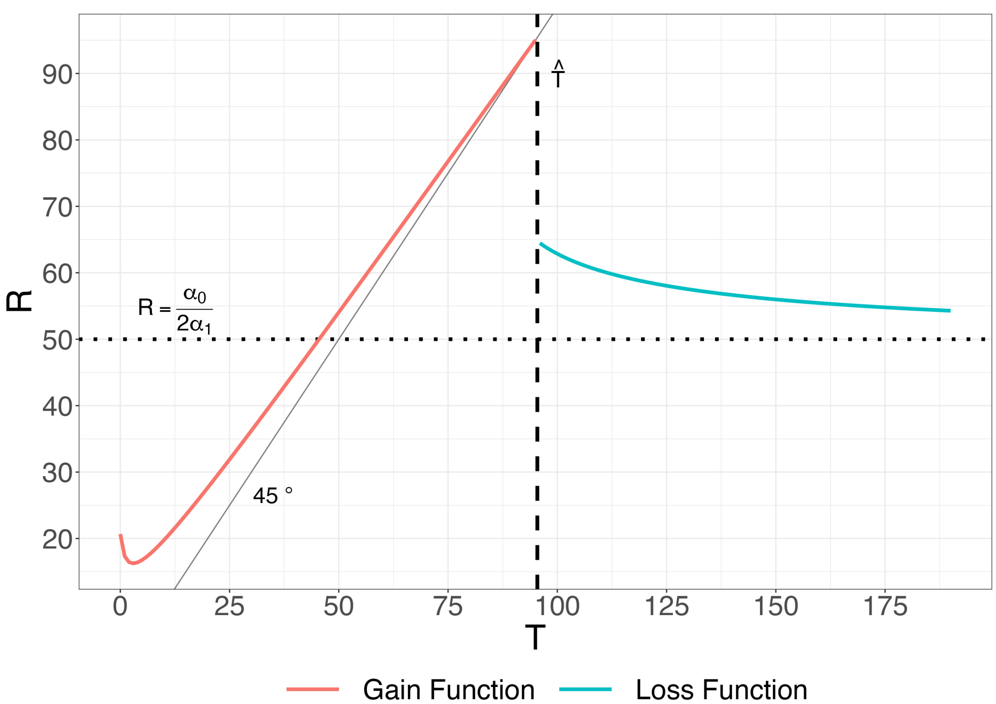


Figure A15: Relationship Between Rent and Tax Reference Point



Assuming again linear, downward-sloping demand such that $\alpha(R) = \alpha_0 - \alpha_1 R$:

$$0 = \begin{cases} (\alpha_0 - \alpha_1 R)\frac{2}{1+2(R-T)} - \alpha_1 \log(1 + 2(R-T)) - 2\alpha_1 \log(1+T) & R > T \\ (\alpha_0 - \alpha_1 R)\frac{2}{1-(R-T)} + 2\alpha_1 \log(1 - (R-T)) - 2\alpha_1 \log(1+T) & R \leq T. \end{cases}$$

The step-wise utility function from Figure A14 and the solution for R^* above yields the relationship between rent R and the per-unit cost reference point T depicted in Figure A15. This case exhibits similarities to and differences from the linear case. First, similar to the linear case, landlords with high reference points always set rent at or above the rational benchmark, and rent converges to the rational benchmark as $T \to \infty$. Second, contrary to the linear case, rent depends *positively* on T as $T \to \hat{T}$. Further, in the gain domain, rent is set below the rational benchmark for $T << \hat{T}$, but above the rational benchmark for $T \to \hat{T}$. Since the landlord loves small gains over the reference point and hates similar small losses, in this case she is risk-seeking in T near $\hat{T}$, and is thus willing to gamble on setting a higher rent than the rational benchmark for these values of T.

C.3 Takeaways

The particularities of $g(x)$ and $l(x)$ can generate a variety of rent-setting behavior for small changes in T—the model does not yield much insight for these small changes. However, this is the same result presented by Giacoletti and Parsons (2022) for the prospect theory preferences case and, as they do, I can rationalize the empirical findings from Section 3 with a reference dependence/loss aversion framework by comparing landlords with very low per-unit costs ($T << \hat{T}$) to those with very high per-unit costs ($T >> \hat{T}$). In terms of Figures A13, A15, and A11, this is equivalent to comparing landlords at the far left-hand side and the far right-hand side of the graph. In both cases, such a comparison yields a result consistent with the empirical results from Section 3—namely, that landlords with high per-unit costs set higher rents than those with low per-unit costs, even without additional assumptions on the functional forms of $g(x)$ and $l(x)$.