

Five Facts About (Rental) Prices: Landlord Heterogeneity and the Dynamics of Shelter Inflation*

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Abstract

Housing is the largest component of the CPI, yet how landlords adjust contract rents remains poorly understood. Using 25 years of administrative data from Berkeley, California and the nationally representative American Housing Survey, we document five facts about rental price dynamics. First, new-tenant rents exhibit state-dependent downward nominal rigidity: although 13% of leases reset at exactly the previous tenant's rent, the missing mass of rent cuts arises only in expansions and largely disappears in downturns. Second, both the frequency and size of rent changes move with market conditions, unlike most non-housing CPI components. Third, rents display strong seasonality comparable to the home purchase market. Fourth, rents cluster at round numbers and just below them, reflecting coarse pricing, left-digit bias, and misoptimization by landlords. Round-number clustering intensifies when rent growth is unpredictable, revealing a novel cognitive cost of inflation. Fifth, larger landlords adjust rents more aggressively in response to the business cycle, with implications for shelter inflation volatility. Our estimates provide new moments for sticky-price models and highlight the role of behavioral frictions and firm heterogeneity in inflation dynamics.

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1 Introduction

Housing is the largest cost of living expense for most U.S. households, making shelter prices central to understanding household budgets and economic well-being. Shelter accounts for 35% of total expenditures in the Consumer Price Index (CPI), about the same as all goods combined. These costs also play a key role in shaping aggregate inflation dynamics over the business cycle. From 1990-2019, core (non-shelter) CPI remained stable, while the rental component covaried strongly with the business cycle (see Figure 1). Similarly, during the post-Covid inflation period of 2021, the non-shelter components of CPI peaked at around 6%, while rental price inflation peaked at nearly 9%.

Despite the central role of rental housing in shaping both aggregate inflation and household budgets, price-setting in rental markets remains poorly understood. Much of what we know about price-setting in goods markets comes from retail scanner data, which links transactions to clearly defined products. No equivalent dataset exists for rental housing. Recent studies have used advertised rents from multiple listing services or platforms like Craigslist, but these data cover only selected segments of the market, are limited to recent years, and track posted, rather than transacted, rents. The composition of listings also shifts over time, complicating inference about broader market dynamics.

We use a unique administrative dataset covering the universe of contract rents in Berkeley, California, a city located in the San Francisco Bay Area and part of one of the nation’s most important rental markets. This dataset allows us to provide new evidence on rental price setting over the last 25 years. Our dataset allows us to follow contract rents for new tenants at the unit level. Our setting is ideal for several reasons. First, Berkeley has experienced significant variation in rental prices over the last few decades. Thus, we can study rental price setting in normal times, as well as in periods when rental prices are falling or rising rapidly. Our sample period includes multiple years when new tenant rents fell by more than 3%, as well as multiple years when rents increased by more than 10%. As a result, we avoid having to use only periods of moderate inflation to understand dynamics in high- or low-inflation periods (Nakamura et al., 2018; Montag and Villar, 2023; Gagliardone et al., 2025).

Second, the unit-level detail in our administrative dataset allows us to control carefully for housing quality when analyzing price setting and rental inflation. Specifically, our setting allows us to examine how price-setting behavior varies for the exact same unit at different points in the business cycle, thus ensuring that our results are not driven by differences in the types of units that are transacted over the business cycle (Nakamura and Steinsson, 2010;

Orchard, 2025).

Finally, the institutional context of our setting closely resembles a Calvo (1983)-style pricing friction. In Berkeley, rents are tightly regulated once a tenant occupies a unit, and tenant protections are strong. However, landlords are free to set rents without restriction when a tenant vacates.¹ While Calvo pricing is often used as a modeling device for price stickiness, few real-world settings so closely mirror its assumptions. Our data allow us to observe how landlords set prices under these frictions, and our estimates offer novel empirical moments for calibrating Calvo models. Moreover, because 1) landlords cannot adjust rents once a tenant is in place, 2) tenancies often last many years, and 3) high rent growth is typical in the Berkeley market, landlords have strong incentives to set prices optimally when new tenants enter a unit.

Although much of our analysis uses granular administrative data from Berkeley, California, we reproduce the key empirical facts in a nationally representative panel of U.S. rental units for new tenants.² This alignment indicates that the mechanisms we identify extend well beyond the San Francisco Bay Area. At the same time, because Berkeley has experienced greater cyclical and seasonal variation than most U.S. rental markets, it provides a rich setting to study how aggregate shocks influence rent-setting behavior. We use these novel data to document five new facts about the dynamics of rental housing prices.

First, we provide evidence of nominal rent rigidity for new tenants. The distribution of rent changes shows a pronounced spike at exactly \$0: 13% of tenant spells begin with the same rent as the previous initial contract for that unit. These patterns surprisingly arise in a setting where (1) average rent growth is strong, (2) a new landlord-tenant match eliminates relational contracting concerns, (3) the landlord is already incurring the menu costs of vacancy posting, and (4) landlords have strong incentives to price optimally, due to rent control for continuing tenants. We also find evidence of downward nominal rent rigidity: there is a large mass of rent changes just above \$0 and a missing mass just below.

However, we also find evidence that the strength of these nominal rigidities responds to both economic incentives and the business cycle. The likelihood of a zero rent change strongly correlates with the time between leases, a proxy for the difference between the current price and the optimal reset price. About 25% of rents that reset within one year remain unchanged, compared with 5% after a five-year gap. Thus, landlords are more likely to reoptimize when the economic incentives to do so are stronger. Second, nominal rigidity

¹Throughout our analysis of the Berkeley dataset, we only study (unrestricted) rents for new tenants.

²We proxy for new tenancies by only including observations where the tenants have changed between American Housing Survey survey waves.

is asymmetric over the cycle: Downward nominal rent rigidity is present during expansions, but not recessions. Downward nominal *wage* rigidity is understood to be important for business cycles, as an unwillingness to cut wages can lead to unemployment. In contrast, since downward nominal rent rigidity is only present in expansions, our results suggest that rent rigidity does not prevent the efficient reallocation of rental units over the business cycle.

Second, we document how landlords adjust rents over the business cycle. [Nakamura and Steinsson \(2008\)](#) show that for the non-shelter components of the CPI, only the frequency of price increases rises with inflation. In contrast, the frequency of price decreases and the size of both price increases and decreases remain stable—patterns consistent with a benchmark menu-cost model.

We find strikingly different behavior for the shelter component of CPI. We find that the frequency *and* size of rent increases and decreases responds strongly to the business cycle. We estimate notably similar sensitivities of the frequency and size of price changes to the rental price index in the broader sample of U.S. rental units.³ These new moments strengthen our understanding of rent-setting behavior, revealing that pricing is highly state-dependent and shifts over the business cycle. Our first two facts provide evidence that is hard to reconcile with a pure [Calvo \(1983\)](#) pricing model. Instead, our results suggest the need for hybrid models where time-dependent resets are combined with fixed costs to actively reoptimize.

Third, we show that predictable seasonal variation in rental demand has large price effects. In both Berkeley and the broader U.S. market, a large share of new leases begin during the summer months (May–August). We find that these predictable, seasonal effects have large effects on rental prices. However, most of the variation in pricing over the seasonal cycle is driven by differences on the extensive margin: new leases that start in these peak periods are less likely to feature rent cuts or \$0 price changes. Rental market seasonality is comparable, perhaps surprisingly, to that found in the home-purchase market.⁴

Fourth, we provide evidence of significant rounding and bunching in the rental price distribution that covaries strongly with both the business cycle and proxies for landlord sophistication. In Berkeley, 35% of new contract rents are exact multiples of \$100, and nearly 60% are multiples of \$50. We find similarly large bunching in the broader U.S. rental

³Our baseline regressions in both the Berkeley and broader U.S. sample include unit fixed effects, and thus our results are not driven by shifts in the quality of units transacted over the business cycle.

⁴[Ngai and Tenreyro \(2014\)](#) document similarly strong seasonality in the home-purchase market and argue that it is inconsistent with standard housing models, suggesting instead that thick-market effects that raise match quality amplify seasonal moving patterns. Finding comparable (or even larger) seasonality in the rental market, despite shorter contract durations and weaker incentives to maximize match quality, suggests that other forces are necessary to explain seasonality across both rental and owner-occupied markets.

market, indicating that price clustering is a widespread feature of housing markets, not unique to Berkeley, CA.⁵⁶

We also document pronounced left-digit pricing, with 15% of rents set at prices exactly \$5 below multiples of \$100. Both rounding and left-digit pricing vary systematically with proxies for landlord sophistication: large, corporate landlords rely less on round-number pricing but more frequently employ left-digit pricing. We interpret this pattern as evidence that smaller landlords, who exhibit more coarse pricing, are more prone to behavioral “pricing mistakes.” The persistence of such mistakes suggests that market power and search frictions permit substantial heterogeneity in pricing behavior. Overall, these results indicate that behavioral frictions on the seller side play a meaningful role in rental price-setting, even in a high-stakes environment where prices may remain fixed for many years.

Further, these behavioral pricing patterns are state-dependent. When annual rent inflation departs from its median, landlords shift toward round-number pricing (multiples of \$50/\$100) and away from left-digit pricing, consistent with the idea that unusual nominal adjustments raise cognitive demands and reduce pricing precision. These effects are especially pronounced among small landlords and appear in both the Berkeley data and a broader U.S. sample.

Similarly, we find that when landlords reset prices after long tenancies—implying a larger optimal price change—they utilize more coarse pricing and less left-digit pricing. These results point to a novel cost of inflation omitted from standard New Keynesian models: as inflation becomes more volatile, the complexity of price setting increases, leading to less precise pricing.

Fifth, we show that landlord heterogeneity is crucial for understanding rent dynamics over the business cycle. We find that large landlords adjust prices more aggressively in response to cyclical variation: they are more likely to cut rents during recessions and raise rents, and by larger amounts, during expansions. Our results suggest that firm heterogeneity is a critical driver of changes in inflation over time, implying that as more large landlords enter the rental housing market, rental price inflation will become more volatile and cyclical.

Taken together, our facts provide new evidence that can discipline static and dynamic models of housing markets. Our results also speak to a wide range of crucial policy issues, including the role of housing in the evolution of inflation dynamics over the business cycle

⁵⁶These magnitudes substantially exceed prior U.S. estimates from [Genesove \(2003\)](#), which relied on survey data from the 1970s and 1980s.

⁶Our results thus parallel recent findings from [Dube, Manning and Naidu \(2025\)](#), who find comparable bunching in the wage distribution and show it reflects a combination of monopsony power and employer misoptimization.

and cost-of-living pressures over time. Our work also has implications for recent policy and academic debates about the welfare impacts of the growing influence of larger, corporate landlords.

1.1 Literature

Our work contributes to three main strands of the literature. First, we build on foundational research documenting price-setting behavior for non-housing components of the CPI. Studies such as [Hosken and Reiffen \(2004\)](#), [Bils and Klenow \(2004\)](#), [Nakamura and Steinsson \(2008\)](#), [Klenow and Kryvtsov \(2008\)](#), and [Klenow and Malin \(2010\)](#) establish empirical facts that have shaped how economists model pricing frictions. In contrast, we present new statistics on shelter prices—the largest component of household expenditure and a key driver of recent inflation dynamics. Our institutional setting closely resembles the staggered pricing friction introduced by [Calvo \(1983\)](#). While Calvo pricing is often invoked for tractability, few real-world environments closely match its structure. [Bils and Klenow \(2004\)](#) and [Nakamura and Steinsson \(2008\)](#) show that many observed facts are more consistent with menu-cost models. In contrast, we offer new moments that describe firm behavior under Calvo-style timing frictions. Our results also point to inattentiveness or cognitive costs of reoptimizing that lead to patterns that deviate from these standard time-dependent models. We also document state-dependent pricing in the rental market, contributing to recent work on how price-setting behavior evolves in high- and low-inflation environments ([Golosov and Lucas Jr., 2007](#); [Nakamura et al., 2018](#); [Montag and Villar, 2023](#); [Gagliardone et al., 2025](#)). We document the effects of seasonality in the rental market, contributing to a broader literature that leverages seasonal patterns to study economic behavior ([Barsky and Miron, 1989](#)). Our work on how rents vary over the business cycle can also inform recent papers examining the optimal policy response to housing price inflation ([Bianchi, McKay and Mehrotra, 2024](#)).

Second, we contribute to the literature on rental price dynamics. Prior work has documented nominal rent stickiness using household surveys ([Genesove, 2003](#); [Hoffmann and Kurz-Kim, 2006](#); [Shimizu, Nishimura and Watanabe, 2010](#); [Aysoy, Aysoy and Tumen, 2014](#); [Gallin and Verbrugge, 2019](#)), but such data often suffer from recall error and limited coverage. In contrast, we leverage an administrative dataset based on legally reported contract rents submitted by landlords. We also study rent setting over decades, which allows us to analyze how rental-price setting is affected by cyclical variation. We provide evidence of how contract rental prices respond to the business and seasonal cycle. We also show that nominal rigidity and coarse pricing are endogenous responses to inflation, the timing of lease

resets, and landlord characteristics. Our results highlight behavioral frictions as key drivers of sticky rent-setting behavior.

While our analysis focuses on rents for new tenants, we complement recent work by [Adams et al. \(2024\)](#), who emphasizes the differences between pricing for new and continuing tenants.⁷ [Calder-Wang and Kim \(2024\)](#) study how the adoption of AI pricing tools affects asking rents using a large sample of multi-unit buildings. Our work also relates to [Genesove and Mayer \(2001\)](#), who document how behavioral frictions influence home sale and purchase decisions. [Baker \(2024\)](#) uses the same Berkeley dataset as we do to study pass-through of property taxes to rents, and finds results consistent with non-standard, behavioral pricing patterns. Finally, our work complements a significant recent literature on the effects of large, institutional landlords ([Lambie-Hanson, Li and Slonkosky, 2022](#); [Gurun et al., 2022](#); [Neroli, 2022](#); [Hanson, 2024](#); [Barbieri and Dobbels, 2025](#); [Chang, 2025](#); [Coven, 2025](#); [Gorback, Qian and Zhu, 2025](#); [Raymond, 2025](#)).

Finally, our findings relate to a growing literature on behavioral frictions in firm decision-making ([Matějka, 2016](#); [DellaVigna and Gentzkow, 2019](#); [Stevens, 2020](#); [Strulov-Shlain, 2022, 2024](#)). We show that behavioral considerations, including heuristic pricing and inattention, are first-order in the rental housing market, and that their influence varies systematically with the identity of the seller and the business cycle. [Repetto and Solís \(2019\)](#) document left-digit pricing in the U.S. home purchase market. [Yang \(2022\)](#) shows that firms with greater product scope are more informed about inflation, while [Bhattarai and Schoenle \(2014\)](#) and [Yang \(2022\)](#) show that multiproduct firms adjust prices more regularly. [Amiti, Itskhoki and Konings \(2019\)](#) provide evidence that the degree of strategic complementarities varies across firms. In contrast to this focus on strategic complementarities, we provide evidence consistent with larger landlords having better information and being more responsive, conditional on a price reset, to business cycle conditions. In related, contemporaneous work, [Park \(2024\)](#) finds heterogeneity in how frequently landlords update listed rents for vacant units. Consistent with [Dube, Manning and Naidu \(2025\)](#), who interpret round-number bunching in wages as a joint outcome of firm misoptimization and market power, we document pronounced bunching in the rent distribution and interpret it as reflecting a combination of landlord misoptimization and pricing power.

⁷[Ball and Koh \(2025\)](#) also study the discrepancy between new-tenant rents and rents for continuing tenants.

2 Setting & Data

2.1 Berkeley Rent Registry

We use administrative data from the Berkeley Rent Board covering 1980–2022. The Rent Board collects detailed information on rental units subject to rent control or eviction protections, including unit characteristics, initial rent, and lease start dates. Our primary sample focuses on new-tenant rents from 1999 onward, after the adoption of vacancy decontrol under the Costa-Hawkins Rental Housing Act of 1995. Landlords in Berkeley who are partially or fully covered by rent control required to register any new leases with the Rent Board. These new-tenant rents are freely set by landlords and not subject to rent control restrictions. Our sample excludes many single-family homes and condos which are not subject to rent control, and thus were not required to report starting rents until very recent years.

We exclude the small number of units with more than five bedrooms, which tend to either be very large homes for students (frat houses) or are the very richest segment of the rental market. The dataset covers 19,000–26,000 units annually, with the number increasing as more units were built and/or registered with the Rent Board.

We link Rent Board records to property tax data from the Alameda County Assessor’s Office, which provides owner names and mailing addresses. Corporate landlords are identified by terms like LLC, Corp, or Company in the owner name ([Harwood, Gould Ellen and O’Regan, 2025](#)). We group properties by owner mailing address to construct a proxy for landlord size.

Table 1, Panel (A) presents summary statistics from the Berkeley sample. The vast majority of units in our data are relatively small units (studios to two bedroom units). The median observation sample is for a one-bedroom apartment in a twelve-unit building, owned by a landlord who owns 28 units in Berkeley. The median tenant spell in our sample lasts two years, but with significant dispersion: the 90th percentile time between new leases in our sample lasts almost 6 years. This highlights the strong incentives landlords have in our sample to set prices correctly: on average, a landlord will not be legally allowed to update their price for almost 3 years.

2.2 Berkeley Rental Market

Berkeley, California, is part of the San Francisco Bay Area, one of the most competitive rental markets in the U.S., with persistently low vacancy rates around 5%.⁸ Consistent with this, rents in our Berkeley data are quite high. The median nominal rent in our main sample period is \$1,495 per month. Figure A.1 plots a repeat-rent index for new-tenant rents in Berkeley since 1999. The index includes unit fixed effects, capturing within-unit price changes over time and adjusting for time-invariant quality. Quality-adjusted rents rose by around 80% during our sample period, though growth was uneven. Rents declined after the 2001 and 2008 recessions and were flat from 2018 to 2021.

Our setting closely mirrors the pricing friction introduced by [Calvo \(1983\)](#). Landlords can freely set rents when a tenant exits, but cannot raise rents during an ongoing tenancy in a rent-controlled unit.⁹ Strong tenant protections in Berkeley further limit evictions and, in some cases, restrict rent increases following an eviction.¹⁰ Because landlords reset prices precisely when they must already re-list the unit and match with a new tenant, frictions such as menu costs or buyer-seller relationships are minimal. This makes our setting a clean environment in which to study price-setting behavior under Calvo frictions.

2.3 American Housing Survey

We use the American Housing Survey (AHS) to test whether our findings generalize to the broader American rental market. The AHS is a longitudinal panel survey conducted by the Census Bureau that tracks individual housing units over time.¹¹ We focus on the 1985 panel, which follows the same houses every other year from 1985 to 2013.¹²

Despite its broader scope, the AHS has several critical limitations that led us to use the Berkeley registry as our primary data source. First, the AHS does not capture all new contracts, even for sampled units, because the survey is conducted biennially. Second, the AHS does not have a separate identifier that can be used to differentiate between new tenant contracts and continuing tenant contracts, a distinction crucial for analysis as these

⁸[Housing Vacancies and Homeownership \(CPS/HVS\)](#), U.S. Census Bureau.

⁹We also show in Section 3.2 that the number of new tenant contracts does not vary with the business cycle.

¹⁰In many cases, rent control laws prevent landlords from raising rents after an eviction.

¹¹New homes are added to the sample as they are constructed.

¹²We do not use data from the 2015 panel onwards because many crucial variables are either suppressed for confidentiality or rounded, making it impossible to study questions related to coarse pricing, left-digit pricing, or sticky rents.

contract types may differ systematically (Adams et al., 2024).¹³ Third, the AHS provides less business cycle variation in rents because the aggregate U.S. rental market is less volatile than the San Francisco Bay Area, observations occur only biennially, and the AHS lacks detailed geographic information to precisely locate properties. Fourth, the AHS contains no data on landlord characteristics, which our Berkeley analysis reveals as a significant driver of pricing behavior. Finally, as a survey completed by tenants, the AHS may suffer from non-response bias and imprecise recall of rental contract details.

To construct our main sample, we use AHS data from 1985 to 2013, focusing exclusively on rental properties and excluding mobile homes to enhance comparability with the Berkeley sample. We restrict our analysis to metropolitan areas, including center cities and urban suburbs, while excluding households in rural areas. We link units longitudinally to measure changes in rents over time. To better approximate our new tenant sample, we only include observations where the current household differs from the one interviewed in the previous survey wave. All observations are weighted using the Census Bureau’s sampling weights.

Table 1, Panel (B) presents summary statistics from the AHS sample. Given the earlier time period (beginning in the 1980s), and the cooler market in the rest of the United States, the median rental price in this sample is much lower, at around \$550. The median unit in the broader sample is a 2-bedroom unit, in a building with 6 units.

3 How Often and How Much Do Rents Change

3.1 Fact 1: Downward Nominal Rent Rigidity

For our first fact, we document that rents exhibit pronounced nominal rigidity. Figure 2, Panel (A) plots the distribution of rent changes for new tenants at each nominal dollar value.¹⁴ A large spike appears at exactly zero: in our main sample, 13% of new-tenant leases have rents that are identical to those paid by the previous tenant. This is the same share reported by Genesove (2003), despite their study using a different dataset and a sample period two decades earlier.

Figure 2, Panel (A) also provides initial evidence of downward nominal rent rigidity. The histogram of price changes features a striking asymmetry: there are many more rent changes right above zero than right below. For example, there are nearly 3.5 times more rent changes of exactly \$10 than there are rent changes that are -\$10. Panel (B) plots the distribution

¹³However, we impute these changes using differences in the households sampled across survey waves

¹⁴Rent changes are rounded to the nearest dollar.

of rent changes after removing new rental contracts where prices are unchanged. Panel (B) shows evidence that rents display the hallmarks of downward rigidity: rents increase much more often than they fall and “pile up” close to zero, as evidenced by the fact that there are far more very small rent increases than there are decreases. These patterns closely resemble those documented in wage-setting, where small increases are common and small decreases are rare (Hazell and Taksa, 2025). In the labor market, this asymmetry is often attributed to workers’ aversion to wage cuts (Davis and Krolkowski, 2025). However, in the rental market, that mechanism is absent, suggesting that downward nominal rigidity may also arise from firm-side frictions, such as cognitive constraints or inattention.

Figure 2, Panel (C) shows that rigidity responds to economic incentives. We exploit the fact that the cost of not updating rents rises with the time between leases, as market prices drift away from the previously set rent.¹⁵ Figure 2, Panel (C) shows, correspondingly, that the probability of the rent remaining fixed after a new tenant enters declines sharply with the time between leases. This relationship is estimated after residualizing on neighborhood-by-year and unit fixed effects, thereby controlling for unit-specific factors, the business cycle, and neighborhood trends. This pattern suggests that landlords face a cost of reoptimizing and are more willing to incur it as the potential pricing error grows. Because the landlord must pay the fixed cost of finding a new tenant, this reoptimization cost is distinct from the standard cost of posting a new vacancy. We estimate a semi-elasticity of -0.11, implying that a 50% increase in the length between leases lowers the probability of the landlord leaving the rent unchanged by about 4.5 percentage points.

We also find that rigidity responds to economic incentives that arise due to the business cycle. Figure 2, Panel (D) plots the kernel density of rent changes (excluding zeros) separately for different phases of the business cycle, as represented by the change in the new-tenant rental index. The asymmetry near zero—a concentration of mass just above zero and missing mass just below—is only present during expansions. In contractions, this asymmetry nearly disappears. This suggests that landlords’ reluctance to decrease rental prices is only present during periods of high and moderate rental price growth. During periods of low rent price growth, landlords are willing to set lower rents; indeed, there is very little asymmetry or missing mass in the rent change distribution for the lowest rent growth tercile. This form of state-dependent rigidity contrasts with evidence of downward nominal wage rigidity, where constraints appear binding and firms do not cut wages even in downturns (Hazell and Taksa,

¹⁵Appendix Figure A.2 illustrates this graphically by showing a binscatter plot of the relationship between the months since the previous lease began and the reset price. There is a tightly estimated positive slope, with an estimated elasticity of the reset price to the time between leases of 0.14.

2025).

Appendix Figure C.1 reproduces our core findings using the nationally representative AHS. Panel (A) plots nominal rent changes (rounded to the dollar) and reveals a pronounced spike at \$0, consistent with the Berkeley evidence. In the AHS, roughly 8% of rents are unchanged, versus 13% in Berkeley.¹⁶ The smaller zero mass likely reflects measurement frequency: the AHS observes rents biennially, which means we do not observe many rent changes that occur after the shortest leases, which we show contributes disproportionately to bunching at \$0.¹⁷

Figure C.1 Panel (B) reports the kernel density of nominal rent changes excluding zeros. Mirroring the Berkeley results, Panels (A) and (B) display signatures of downward nominal rigidity: missing mass just below zero and excess mass just above. Panel (C) documents state dependence: rigidity strengthens in periods of rapid national rent growth and weakens in moderate or low-growth periods. The AHS patterns are attenuated relative to Berkeley, plausibly due to lower volatility in the national rental market. Taken together, the AHS corroborates that our findings extend beyond a single market while underscoring the informational value of the granular Berkeley data and its elevated volatility as useful identifying variation for studying landlords' rent-setting over the business cycle.

3.2 Fact 2: How Rents Adjust to the Business Cycle

For our second fact, we examine the cyclical behavior of the rental housing market. [Nakamura and Steinsson \(2008\)](#) document that, for non-housing CPI components, the frequency of price increases comoves with inflation, whereas the magnitude of increases—and both the frequency and magnitude of decreases—remain largely unresponsive. These patterns align with the predictions of canonical menu-cost models.

In contrast, the housing component of inflation displays strikingly different patterns. Despite stability in total leasing volume over the business cycle,¹⁸ the composition of rent changes is highly cyclical. Figure 3 depicts the evolution of the size and frequency of rent adjustments among units turning over within two years. Panel (A) reveals a strong correlation between the business cycle and the share of rent increases, decreases, and unchanged

¹⁶All AHS estimates restrict to units that experience household turnover between waves; zeros are thus not attributable to continuing tenants.

¹⁷See Figure 2, Panel (C).

¹⁸Appendix Figure A.3 shows that the number of new tenant leases in our sample is acyclical. Lease counts are flat from 2002 to 2013, decline modestly thereafter, and fall sharply during the COVID-19 pandemic before rebounding in 2021. This acyclicity implies that tenant mobility—and thus opportunities for rent resetting—is primarily governed by idiosyncratic household shocks rather than aggregate conditions.

rents. During periods of weak rental growth, rent decreases outnumber increases for units that turn over within two years, and over 20% of these contracts show unchanged rents.¹⁹ In contrast, in expansionary periods, more than 80% of new leases record rent increases, and rent cuts are virtually nonexistent, consistent with downward nominal rent rigidity.

Table 2, Panel (A) formalizes these patterns. Column (1) confirms that the aggregate number of new leases is uncorrelated with the rent index. Columns (2)–(4) document that the number of rent increases, decreases, and unchanged rents all exhibit strong systematic correlation with rent price inflation. All estimates are large, highly significant, and feature high R^2 values, implying that cyclical conditions explain a substantial share of variation in the composition of rent changes over time.

Figure 3, Panel (B) demonstrates that the intensive margin of rent adjustments—the size of price changes—also exhibits pronounced cyclical variation. As with the frequency of price changes, the size of both rent increases and decreases covaries closely with inflation. In the tightest markets, such as before the tech bust of 2001 and during the mid-2010s expansion, the median rent increase exceeds 10 log points. In contrast, in the weakest markets, the median rent increase falls to around 5 log points. The median rent decrease also varies over the business cycle, though its time-series variation is much less pronounced than that of rent increases.

Table 2, Panel (B) confirms these patterns using time-series regressions. Columns (1) and (2) report estimates of the effect of the rent index on the median size of rent increases and decreases for leases that turn over within two years. We find statistically significant correlations between the rent index and the size of both rent increases and decreases, with the effect being more than two times larger for rent increases. Columns (3) and (4) show nearly identical coefficients in a sample including all new leases. Overall, we find strong evidence that both the frequency and magnitude of rent increases and decreases covary with inflation, contrasting sharply with the findings of [Nakamura and Steinsson \(2008\)](#) for non-housing CPI components. However, rent decreases covary with inflation substantially less than rent increases.

Table 3, Panel (A) presents the results for the individual, lease-level data in the Berkeley sample, utilizing unit-level fixed effects.²⁰ Columns (1) – (3) examine the extensive margin. Consistent with the aggregate analysis, the likelihood of a rent increase rises with the rent

¹⁹Note that periods of weak rental growth are delayed relative to recession starts.

²⁰We use unit-level fixed effects to identify responses by comparing rent changes for the same unit when it turns over at different points in the cycle. This specification isolates variation arising from macroeconomic conditions rather than from differences in unit quality or composition. This addresses concerns related to changes in relative demand across market segments over the cycle.

index, while the likelihood of a rent decrease or an unchanged rent declines.²¹ Columns (4) and (5) show the effects on the magnitude of price changes (in log terms). Column (4) shows that, when including unit fixed effects, the elasticity of rent increases with respect to the rent index is 0.7, compared with 0.5-0.6 in the aggregate data. Column (5) shows a similar elasticity of -0.3 for rent decreases (versus -0.2 in the aggregate data). Overall, both the extensive and intensive margins of price changes respond strongly to the business cycle, even after controlling for time-invariant unit quality.

Table 3, Panel (B) replicates this analysis for the broader U.S. sample. Once again, we use detailed unit fixed effects to study how pricing behavior responds to the business cycle, while carefully controlling for compositional changes and the quality of transacted units. Overall, we estimate elasticities that are closely aligned with those from Berkeley. Columns (1) - (3) show the effects on the extensive margin, which are nearly identical in magnitude to those found in the Berkeley sample. The effects are highly statistically significant, though standard errors are roughly an order of magnitude larger—likely due to both higher sampling variance in survey data and heterogeneity in local markets not reflected in our national price index. Columns (4) and (5) show effects on the intensive margin: the elasticity of rent increases is about 1.1, compared to 0.7 in the Berkeley sample, while the elasticity for rent decreases is -0.3 , identical to the Berkeley estimate but statistically insignificant given the larger standard errors. Taken together, the unit-level results confirm that rental inflation is driven by adjustments on both the extensive and intensive margins in both samples, even after carefully controlling for unit quality.

3.3 Discussion of Facts 1 and 2

A natural question is what types of models of price-setting are consistent with our first two empirical facts. Our setting closely matches a traditional Calvo environment: turnover generates exogenous, acyclical opportunities to change prices that are not driven by the business cycle. We also find a strong positive relationship between the size of rent changes and the time between new leases, which is consistent with time-dependent pricing. In addition, the size and frequency of both price increases and decreases covary with inflation. This contrasts with the findings from [Nakamura and Steinsson \(2008\)](#), who find that for the non-housing CPI, inflation mainly covaries with the frequency of price adjustments rather than

²¹Because the dependent variables are binary indicators for specific types of price changes, coefficient magnitudes are not directly comparable to those in Table 2. Instead, these estimates are semi-elasticities of indicators for different extensive-margin rent adjustments to the business cycle.

their size, in line with menu-cost models. Taken together, these facts are consistent with time-dependent pricing playing an important role in rent setting.

At the same time, several features of our data are hard to reconcile with a pure Calvo model. First, we observe a pronounced spike at exactly zero in the rent-change distribution at turnover, whereas standard time-dependent models with full reoptimization imply essentially no mass at zero when a reset opportunity arrives. Second, the probability of leaving rents unchanged at turnover is state-dependent: zeros rise in weak rent markets, shrink in strong rent markets, and fall sharply with the time between leases (i.e., with the size of the price gap), pointing to a cost of reoptimizing that landlords pay when the benefit is large. Thus, our first two facts are naturally consistent with hybrid models, which combine an exogenous reset opportunity with a fixed cost to reoptimize in that period.²² Importantly, this cost is distinct from traditional menu/vacancy costs: a vacancy must be posted either way, so the residual margin more likely reflects information or managerial (cognitive) costs. Given that the median lease duration is about two years, failure to reoptimize can be costly, and is consistent with sizable information or cognitive costs.

A final question is whether these time-dependent features are generalizable beyond the Berkeley context, where rent control for continuing tenants is crucial for matching the Calvo institutional setting. However, the fact that we replicate key empirical patterns—the strong correlation of both the frequency and size of rent increases with inflation, the pronounced rent-change spike at zero, and the state-dependence of the spike at zero—in a nationally representative survey suggests that our findings provide useful guidance for models of the broader U.S. housing market. In addition, the fact that rents for continuing tenants have been found to be sticky even outside of strict rent control implies that, more generally, landlords rarely reoptimize prices without a new lease, reinforcing the importance of time-dependent mechanisms in rental price setting (Adams et al., 2024; Ball and Koh, 2025).

3.4 Fact 3: How Rents Respond to the Seasonal Cycle

For our third fact, we document how seasonality shapes housing demand, pricing, and rent changes. Appendix Figure A.5 displays the number of lease starts by month over the sample period in both Berkeley and the broader U.S. Two patterns emerge. First, in Berkeley, most leases are signed during the summer months between June and August. Second, lease activity

²²This contrasts with canonical “Calvo-Plus” models which combine exogenous reset timing with a menu cost that firms can pay at any time to reoptimize prices (Nakamura and Steinsson, 2010; Alvarez, Lippi and Oskolkov, 2021).

drops sharply between October and April. While Berkeley’s status as a university town likely contributes to the summer spike in demand, this pattern is not unique: nationally, 32% of leases begin between June and August.²³

The timing of lease start dates also affects rent prices. Figure 4 plots monthly rental premia on the average number of leases in each month in both Berkeley and the U.S. sample. The monthly premia are calculated using both neighborhood-by-year (or for the U.S. sample, city-by-year) and unit fixed effects, and thus strip out local trends and time-invariant differences across individual units. We estimate positive and significant slopes in both samples. Thus, months where the market is ‘hotter’ (i.e., months where there are many new leases, such as the summer months) command higher initial rents than cooler months. Quantitatively, the hottest months in the U.S. are associated with rents about 3% higher than the coolest months, while in Berkeley the difference between the coolest and hottest months is around 7%.

We next study how landlords adjust prices in response to seasonal variation. Table 4 decomposes adjustment at turnover into extensive and intensive margins.²⁴ In contrast to the dynamics over the business cycle, most seasonal adjustment in both Berkeley and the U.S. occurs through changes on the extensive margin (i.e., increase versus decrease), rather than on the intensive margin (i.e., the size of the rent change). Table 4 Panel (A) shows that, in peak months, landlords are more likely to raise rents and less likely to decrease rents or leave rents unchanged. Panel (B) shows similar patterns in the broader U.S. sample: in peak months, the share of rent increases rises, while the shares of decreases and unchanged rents falls. The estimated elasticities are somewhat smaller in Berkeley than in the national data.

Columns (4) – (5) in both panels of Table 4 report intensive-margin responses. In both samples we estimate null effects of the seasonal cycle on the size of rent increases, conditional on increasing. In Berkeley, we find larger rent cuts in weaker months, conditional on decreasing; in the U.S. sample, the corresponding estimates are imprecise and not statistically different from zero. Aggregating, we estimate elasticities of new-tenant rents with respect to market tightness (proxied by the number of lease starts) of about 0.02 in Berkeley and 0.04 in the U.S.

²³Appendix Figure A.5, Panel (B) compares level of seasonality in the rental purchase market to the degree of seasonality in the U.S. home purchase market documented by [Ngai and Tenreiro \(2014\)](#). We find comparable seasonality in both markets.

²⁴These regressions employ the same fixed effects as those shown in Table 3.

3.5 Discussion of Pricing Seasonality

Overall, we find substantial effects of the seasonal cycle on rental prices. Our seasonality estimates mirror [Ngai and Tenreyro \(2014\)](#) for home purchases. [Ngai and Tenreyro \(2014\)](#) argue that the large predictable variability in home prices is inconsistent with standard models and requires idiosyncratic preferences and thick-market effects. Because rental contracts are far less durable and confer modest match-specific surplus, the pronounced seasonal rent premia are unlikely to arise from match effects alone. Our results suggest that additional mechanisms must operate alongside any match effects to generate the observed patterns in both rental and home-purchase markets.

We also find differences between seasonal and business-cycle responses. Over the business cycle, landlords respond on both the extensive and intensive margins. In contrast, most of the seasonal variation in rent prices is driven by the extensive margin (the likelihood of increases versus decreases), with limited movement in the size of increases. Thus, our results suggest heterogeneity in how landlords respond to demand shocks due to the business cycle versus other types of shocks. Finally, we estimate slightly smaller seasonal elasticities in Berkeley than in the broader U.S. rental market. Because seasonality is more prominent in Berkeley than in the aggregate economy, this suggests that responses may be nonlinear with respect to the size of the shock.

4 Landlord Heterogeneity Drives Inflation Dynamics

We next document substantial heterogeneity in landlords’ pricing behavior, both on average and over the business cycle. These patterns highlight the important role of firm heterogeneity in shaping inflation dynamics and show how secular shifts in firm composition can alter aggregate inflation.

4.1 Fact 4: Heterogeneous Landlord Price Setting

Our fourth fact is that landlord heterogeneity is an important predictor of rent setting. We focus on landlord heterogeneity by size, proxied by the number of units an individual landlord owns in Berkeley.²⁵ Figure 5, Panel (A) plots the distribution of rents by the distance of each rent from the nearest multiple of \$100. An observation at 0 is a multiple of 100; an

²⁵We also look at heterogeneity by corporate status, proxied by whether the owner’s recorded name contains terms such as “LLC” or “Corp.”, and find similar results.

observation at -50 is a multiple of 50 (but not 100); an observation at -25 is \$25 below the nearest multiple of 100 (e.g., \$1,175 or \$1,375). We plot this separately for large landlords (owning more than 75 units) and small landlords.

Panel (A) documents substantial bunching in the Berkeley rent distribution. Three patterns stand out. First, a large share of rents bunch exactly at multiples of 100. In our main sample, around 35% of observations fall at these round numbers, which is similar to the share of wages ending in round numbers reported in the CPS (Dube, Manning and Naidu, 2025). Second, there is a smaller but still significant spike at rents that are multiples of 50 but not 100; in our baseline sample, about 24% of observations fall into this category. We also find smaller bunching at finer increments (multiples of 25, 10, and 5). In the full sample, 97% of initial rents are at multiples of 5, and 99% are whole dollars. These bunching rates are substantially higher than those documented in earlier survey data. Genesove (2003) finds that 7–11% of rents were set at multiples of 100, and 8–12% at multiples of 50 (but not 100) in the 1970s and early 1980s. In contrast, our estimates are more than three times higher for multiples of 100 and about twice as high for multiples of 50. Both Genesove (2003) and Aysoy, Aysoy and Tumen (2014) argue that a substantial portion of nominal rent rigidity can be explained by landlords using coarse pricing patterns, where landlords set rents at multiples of round numbers. However, since we observe the same level of rigidity despite finding a much larger degree of price clustering, our results suggest that coarse pricing alone is not sufficient to explain nominal rent stickiness.

Third, the rent distribution shows clear evidence of left-digit pricing (Anderson and Simester, 2003; Lacetera, Pope and Sydnor, 2012; Strulov-Shlain, 2022, 2024). There is a notable spike exactly \$5 below the multiple of \$100, with the mass at this point equal to roughly 42 percent of the spike at the corresponding round number. More broadly, we observe excess mass just below round numbers and missing mass just above. There are roughly 39.5 times as many observations in the interval $x \in [-9, 0)$ as in $x \in (0, 9]$, where x is the distance from the nearest multiple of \$100. This suggests that landlords believe left-digit bias significantly influences tenant behavior. To our knowledge, this is the first paper to document left-digit pricing in the rental housing market.

Figure 5, Panel (B) shows that this bunching varies substantially by landlord characteristics. Panel (B) shows that large landlords are much less likely to set rents at multiples of \$100 and are much more likely to set rents just below multiples of \$100. Only about 25% of rents set by large landlords are multiples of \$100, compared to more than 40% of rents set by small landlords. In contrast, almost 30% of rents set by large landlords are set at amounts

that are \$5 less than multiples of \$100, compared with only 10% for small landlords.²⁶

Figure 5 Panels (C) and (D), show that the propensity to bunch varies smoothly with landlord size. Panel (C) plots a binscatter of the share of rents set exactly at multiples of \$100 against log landlord size, residualized on neighborhood-by-year fixed effects.²⁷ The relationship is tightly estimated and negative. We estimate a semi-elasticity of bunching of -0.05 , implying that for the smallest landlords, nearly 50% of rents are set at \$100 multiples, while for the largest landlords the degree of bunching is roughly half as large.

Panel (D) reports the mirror pattern for left-digit pricing. The semi-elasticity with respect to size is 0.06 , implying that the smallest landlords engage in essentially no left-digit pricing, whereas for the largest landlords nearly 35% of rents are set just below \$100 thresholds.

A natural interpretation of these results is that large and corporate landlords employ more systematic pricing systems, whereas small individual landlords rely on coarser heuristics. The coexistence of extensive bunching among small landlords and pervasive left-digit pricing among large and corporate landlords therefore points to heterogeneity in pricing sophistication and optimization behavior—not demand-side preferences—as the primary driver of rent-setting patterns. Our results thus suggest that landlord heterogeneity is an important determinant of rent-setting behavior. An implication of this result is that landlords have significant market power: Landlords are able to set systematically different rents and still successfully fill units. Our results thus provide new evidence on the extent of market power in the rental housing market (Watson and Ziv, 2024; Baker, 2024).

While the AHS does not include information on landlords that would allow us to directly compare our Berkeley estimates to the broader U.S. population of owners, we find similar evidence of coarse pricing in the national AHS sample of renter households. Appendix Figure C.2, Panel (A) reveals substantial bunching in the nominal rent distribution, though somewhat less pronounced than in Berkeley. In the AHS, approximately 23% of rents are set at multiples of \$100 and 18% at multiples of \$50, but not \$100. These shares exceed those reported by Genesove (2003) using the same dataset for an earlier period, suggesting that round-number bunching has become a pervasive feature of modern rental markets, not one confined to Berkeley.

The differences likely reflect that bunching at round multiples becomes more attractive as nominal rent levels rise. Appendix Figure C.2 Panel (B), which is restricted to 1999-2013,

²⁶Appendix Figure A.4 shows similar patterns when we split the sample into corporate and individual landlords. Corporate landlords are about 10 p.p. less likely to bunch at multiples of \$100, and about 10 p.p. more likely to set rents exactly \$5 below a multiple of \$100.

²⁷The inclusion of these fixed effects ensures that the pattern is not driven by cross-market composition or business-cycle heterogeneity.

and thus more closely aligned with our Berkeley sample, shows higher rates of bunching: 29% of rents at \$100 multiples and 19% at \$50 multiples. Overall, we find strong evidence of round-number pricing comparable to our results for Berkeley alone, with differences plausibly explained by Berkeley’s higher rent levels and the later sample period. Our results suggest that coarse pricing has increased substantially over time and that rising nominal rents may further amplify the prevalence of round-number pricing.

In contrast, we observe substantially less left-digit pricing in the broader AHS sample compared to the Berkeley administrative data. The AHS still exhibits a clear spike at prices exactly \$5 below each \$100 threshold, but that spike is only 17% as large as the spike at the round \$100 itself, versus 42% in Berkeley. These differences may stem from the superior precision of our administrative data, particularly if respondents themselves round to multiples when responding to the survey.

This disparity is unlikely to stem from Berkeley-specific features such as its large student population. Appendix Figure A.6 maps left-digit pricing across neighborhoods. Although we detect considerable bunching in student-dominated areas near downtown and U.C. Berkeley’s campus, we also find substantial bunching in neighborhoods with minimal student presence, including southern areas bordering Oakland, West Berkeley, and the affluent Berkeley hills. By design, our dataset excludes much of the housing for undergraduate students: campus dormitories, large shared houses, student co-ops, and Greek residences. Notably, all but one Berkeley census tracts contain more bunching than is observed in the AHS. Our analysis underscores the value of contract-level administrative datasets and illuminates the need for additional research utilizing similar rent registries to assess left-digit bunching patterns in the broader rental market.

Table 5 Panel (A) shows that landlord heterogeneity is also an important determinant of how rents change at tenant turnover. Columns (1) through (3) indicate that, on average, large landlords are less likely to leave rents unchanged, but are more likely to reduce rents when a new tenant moves in. Column (4) shows that large landlords are also more likely to implement large rent increases of more than 20% at turnover. As a result, the average rent change at turnover is larger for large landlords (Column (5)). These regressions include detailed controls for the time between leases and neighborhood-by-year fixed effects, ensuring that the results are not driven by market-level differences or variation in the optimal reset price. Because larger landlords are more likely to decrease rents, and less likely to leave rents unchanged, our results suggest that large landlords are less bound by the nominal rigidities documented in Section 3.1. However, because rents set by larger landlords increase more on

average, our results suggest that increased ownership of rental housing by large landlords could lead to non-trivial price increases.

These findings provide further evidence that cross-landlord heterogeneity reflects differences in sophistication and optimization behavior rather than tenant demand. While tenants may prefer salient or round-number rents, it is implausible that they hold systematic preferences over the change in rent between leases, especially since a new tenant occupies the unit after turnover. The fact that large and small landlords respond so differently to identical opportunities to reset rents therefore suggests that the observed heterogeneity in rent-setting behavior primarily reflects variation in pricing sophistication and optimization, not differences in tenant composition or demand.

4.2 Fact 5: Heterogeneous Adjustment Over the Business Cycle

Our final fact is that landlord identity is a strong predictor of how rents respond to the business cycle. Table 5 Panel (B) shows that heterogeneity in rent changes at tenant turnover is largely driven by differential cyclical responses. The table reports regressions of rent-change indicators on landlord size interacted with terciles of average rent growth in Berkeley.

Column (1) shows that while, on average, large landlords increase rents at the same rate as small landlords, there is significant heterogeneity over the business cycle. The negative coefficient in the first row indicates that during the weakest phases of the rental cycle, large landlords are significantly less likely to increase rents. In contrast, during high-growth periods, large landlords are more likely than small landlords to increase rents.

Column (2) shows an analogous pattern for rent decreases: large landlords are much more likely to cut rents during downturns, and are slightly less likely to lower rents during booms. Finally, Column (3) indicates that larger landlords are less likely to leave rents unchanged during downturns, suggesting that they adjust prices more actively when market conditions deteriorate. These results also suggest that the absence of binding downward nominal rent rigidity in downturns is largely driven by the behavior of large landlords, who are more willing to cut rents. Overall, our results indicate that larger landlords adjust more strongly on the extensive margin in response to the business cycle, whereas the extensive-margin rent-setting decisions of small landlords are much less responsive to market conditions.

Column (4) shows that this same pattern exists for the intensive margin, or the size of rent changes. Column (4) shows that large landlords are no more likely than small landlords to make large rent increases (exceeding 20 percent) during busts, but are more likely to do so during periods of moderate and especially strong rent growth. Column (6) summarizes

the aggregate effect: large landlords increase rents by smaller amounts during downturns, slightly more during normal times, and substantially more during booms. Taken together, these findings indicate that large landlords are substantially more responsive to the business cycle than smaller landlords, both in the likelihood of adjusting rents and in the magnitude of their adjustments.

These cyclical patterns reinforce our interpretation that cross-landlord differences in pricing reflect variation in sophistication and optimization behavior, and they highlight the broader role of firm heterogeneity in shaping inflation dynamics. Larger landlords appear more attentive to the business cycle: in downturns, they reoptimize by cutting or adjusting rents rather than leaving prices unchanged, while in expansions they implement larger rent increases. These results also imply that a shift in market composition toward larger, more professional landlords would increase the volatility of rental prices over the cycle. By amplifying the sensitivity of rents to aggregate conditions, such compositional shifts may in turn influence the persistence and volatility of shelter inflation.

Additionally, we find that the propensity to use coarse or left-digit rent pricing is itself a function of the business cycle. Figure 6 Panel (A) plots the propensity to set rents at multiples of \$100 as a function of the change in the rental price index. There is a strong, non-monotonic relationship between the prevalence of heuristic pricing and changes in the rent price index. The propensity to use coarse pricing practices is at its lowest when rent growth is near its median value (approximately 4% over the sample period, denoted by the dashed vertical line), and significantly higher when rents are either falling or rising sharply. In contrast, Panel (B) shows the opposite pattern for left-digit pricing: it is most prevalent during periods of moderate rent growth and declines during unusually large increases or decreases in rents. For both outcomes, we estimate precisely measured, statistically significant differences in the slope on either side of the median rent growth rate.

This non-monotonic pattern indicates that the precision of rent setting varies with the complexity of the pricing environment. When rent growth is moderate, landlords appear to optimize more precisely by avoiding coarse pricing and strategically employing left-digit pricing. In contrast, when rents are falling or rising rapidly, the deviation from typical nominal adjustment may reduce landlords' capacity or willingness to fine-tune prices, leading to greater reliance on round-number rules. These results suggest that pricing sophistication is itself cyclical: landlords price most precisely when market conditions are stable and revert to coarser, less optimized strategies during periods of sharp market change. More broadly, the findings point to a potential cost of inflation volatility: periods of rapid or falling prices

may erode pricing precision across the rental market.

Table 6 provides a formal test for this in both Berkeley and the broader U.S. sample. We regress three different measures of pricing precision on the absolute value of the deviation of rental price inflation from its median rate of increase.²⁸ Panel (A) shows the results for Berkeley. Across all three measures of pricing imprecision, we find that periods of unusual price changes lead to more bunching at round numbers and less left-digit pricing, suggesting that inflation volatility reduces the precision of rental pricing. Panel (B) shows that these patterns are found in the broader U.S. sample as well. We find that bunching at multiples of \$50 and \$100 are much more likely in times of abnormal inflation. In the broader U.S. sample, the coefficients are actually 3-4 times larger than in the Berkeley sample, despite the fact that coarse pricing overall is less common in the national sample. In contrast, we do not estimate a significant effect of inflation volatility on left-digit pricing in the U.S. sample, although this may reflect the much lower average incidence of left-digit pricing found in the AHS. Overall, however, we find substantial evidence that inflation volatility reduces pricing precision, as proxied by an increase in the share of prices at round numbers and a reduction in left-digit pricing.

We further validate our interpretation that volatile inflation reduces pricing precision using an alternative source of variation in the magnitude of optimal rent adjustment—the time elapsed between leases—and find similar results. Appendix Figure A.7 shows that larger price changes associated with longer gaps between contracts are linked to coarser pricing patterns. Panel (A) shows that when the interval between leases is longer, landlords are substantially more likely to set rents at round numbers. Panel (B) shows the mirror pattern for left-digit pricing. These results provide direct evidence for our proposed mechanism: larger nominal price changes reduce the precision of rent setting, as reflected in the shift from fine-tuned to coarser pricing practices.

Consistent with our results on heterogeneous landlord sophistication, we find that this fall in pricing sophistication is driven by the smallest landlords. Figure 6, Panels (C) and (D) show how coarse pricing patterns respond to business cycle variation separately for large and small landlords. Overall, the patterns are strongest for smaller landlords. The coefficients for small landlords are similar to the coefficients for the full sample and statistically significant. However, we also find similar qualitative patterns for larger landlords, though they are smaller in magnitude. We also see an interesting asymmetry for larger landlords, where less precise pricing becomes more and more common as inflation becomes more and more

²⁸We again utilize unit fixed effects, thus estimating whether pricing precision falls within the exact same unit when it is transacted in more vs. less normal times for rent price growth.

negative. This suggests that while cognitive constraints triggered by volatile inflation are larger for small, less sophisticated firms, they also affect larger firms, especially when inflation is negative. We find similar results for large versus small landlords when using lease contract gaps as a source of variation in the magnitude of ideal price adjustments.²⁹

Overall, our heterogeneity results are consistent with our interpretation that cognitive costs drive the response of pricing precision to volatile inflation and large nominal adjustments. We find the results are primarily driven by smaller, less sophisticated landlords, though we do still find significant effects for larger landlords, especially when inflation is negative.

4.3 Discussion

Our final two facts highlight the role of landlord heterogeneity in price setting, both on average and in response to shocks. The facts presented in Section 3 suggested that housing markets were best modeled by a Calvo, time-dependent pricing friction combined with a fixed cost that landlords had to pay to actively reoptimize. The facts presented in this section suggest that this second cost comes from managerial or cognitive costs and varies across different landlords.

In particular, our results suggest that large landlords either face lower costs or have stronger incentives to set prices optimally. We show that larger landlords are more responsive to changing business cycle conditions, and are less bound by nominal rent rigidities. Larger landlords also engage in more sophisticated pricing strategies, especially during times of predictable inflation. In contrast, small landlords are less responsive to the business cycle, often utilize coarse pricing, and are particularly reliant on coarse pricing during times of high or low inflation.

These results imply that larger landlords amplify the response of shelter prices to shocks, and that the increasing share of large landlords increased the volatility of shelter prices over the business cycle. Our results thus complement recent work by [Calder-Wang and Kim \(2024\)](#) who find algorithmic pricing makes rents more responsive to economic shocks.

Interestingly, these patterns are inconsistent with a traditional model where the cognitive or managerial costs are modeled as a pure fixed cost. In a traditional cognitive fixed cost model, paying the cost of gathering information allows the firm to set prices optimally. Our results suggest that even when firms pay the cost to reoptimize, unusually large nominal

²⁹Panels (C) and (D) of Appendix Figure A.7 shows the heterogeneous effects of lease contract gaps on pricing precision. As with the response to the business cycle, we find the largest effects for smaller landlords.

adjustments or unusual volatility cause increases in pricing errors. Thus, our results suggest a trade-off where paying the optimization cost results in more responsive prices, but these larger adjustments also result in less precise pricing strategies. Thus, we document a novel cost of inflation, where volatility in inflation causes a reduction in pricing precision.

5 Conclusion

In this paper, we use detailed administrative data from a single city and nationally representative survey data to document new facts about rental price setting in the United States. Our results provide new information on how shelter prices adjust over time, which is crucial for understanding both aggregate inflation and the cost of living. Our work also provides new empirical moments that can be used more broadly for calibrating models with time-dependent pricing frictions.

We highlight two novel implications of our results. First, we provide new evidence that firm heterogeneity is an important determinant of pricing decisions and inflation dynamics. We find evidence that more sophisticated landlords are more responsive to the business cycle and less bound by nominal rent rigidities. This suggests that firm heterogeneity and structural transformation, including the rise of large, superstar firms, are an important determinant of inflation dynamics. Second, we document that unusually volatile inflation and large nominal price adjustments cause firms to use coarser pricing strategies. This suggests a novel cost of inflation, whereby unusually volatile inflation reduces pricing precision. Future work could study the extent to which these trends are common more broadly outside of the housing sector.

Finally, our work provides guidance for modeling price-setting in macroeconomic models with housing. We find that rental pricing exhibits distinct dynamics from other sectors of the economy. Our results suggest that pricing frictions in the housing market are most consistent with time-dependent Calvo models. Interestingly, this finding holds even in the broader U.S. market, which suggests that a combination of long-term rental contracts and rent rigidity among lease renewals makes new tenant pricing more akin to Calvo than menu-cost models (Adams et al., 2024; Ball and Koh, 2025). However, we also find that Calvo frictions alone cannot explain pricing patterns in the shelter sector. Instead, a combination of time-dependent frictions and a cost of reoptimizing is necessary to fit the empirical patterns in the data, including the large degree of rigidity in the rental housing market. Our findings suggest that these reoptimization costs stem from cognitive or managerial frictions in price

adjustment, and that larger, more sophisticated landlords either face lower costs or have stronger incentives to set prices optimally.

Our results have important implications for public policy. We contribute to a large debate about the welfare implications of large landlords. More responsive price setting might allow for a more efficient allocation of housing and, if it increases profits, more rental housing supply. However, differences in pricing strategies across landlords might also cause a reallocation between consumer and producer surplus, especially as our results show that landlords have substantial pricing power in the rental housing market. Future work could disentangle the overall welfare impacts of our findings for consumers and producers.

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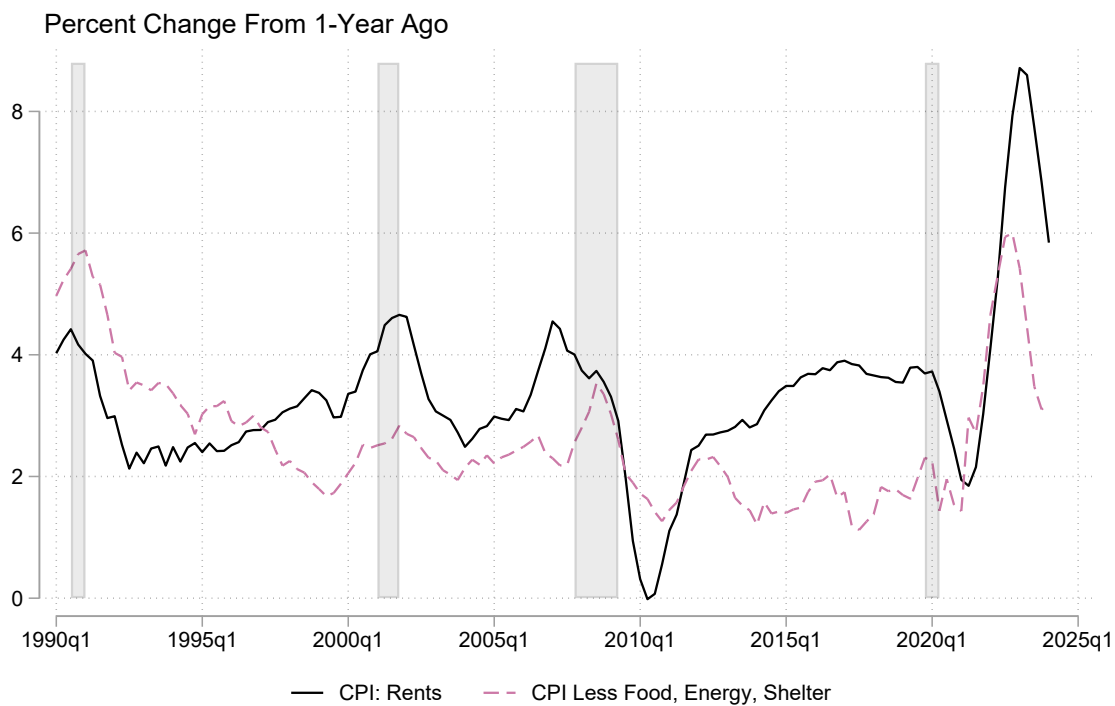
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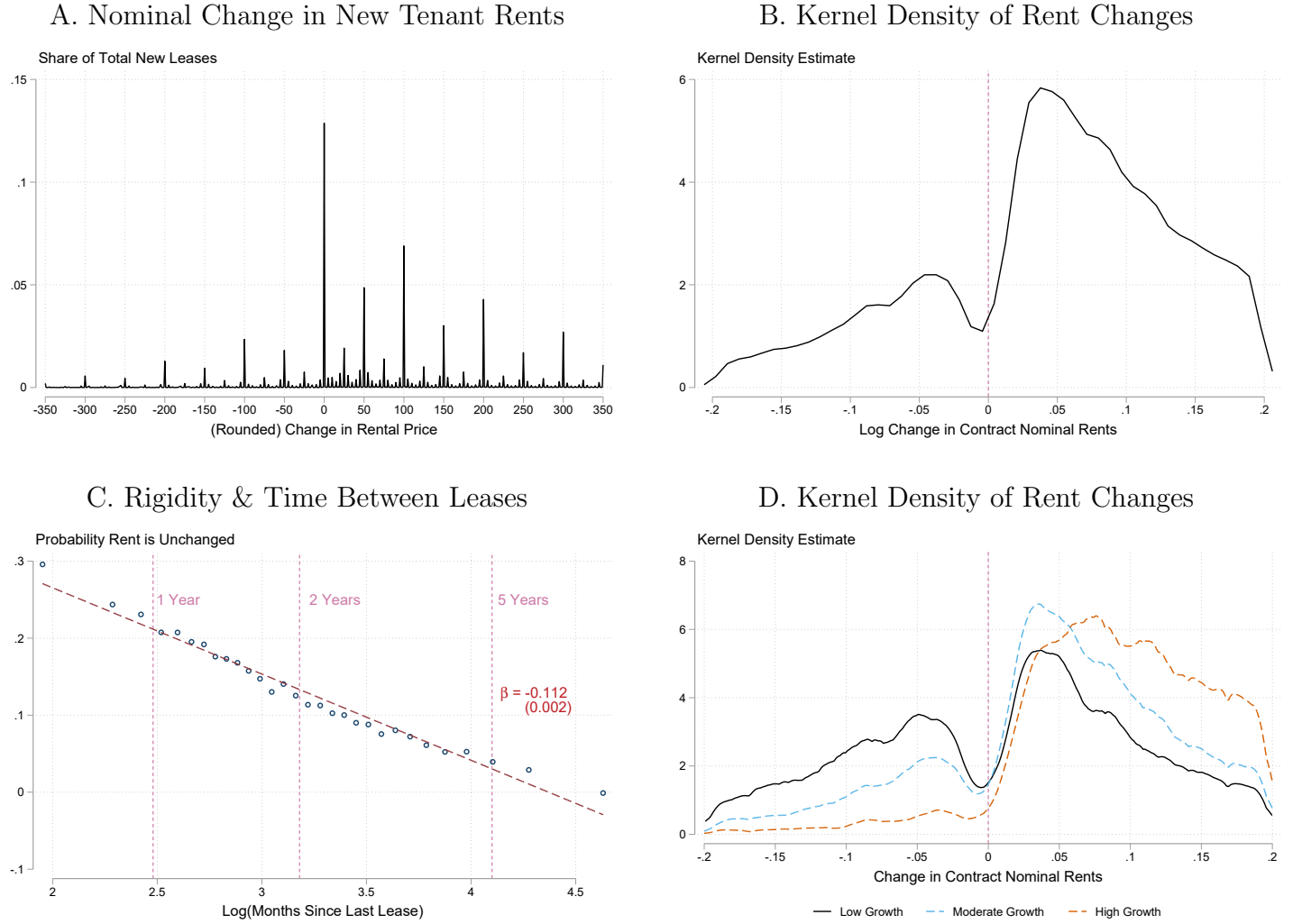
6 Figures

Figure 1: Time Series of Rent and Non-Housing Components of CPI



Notes: This figure plots the Consumer Price Index, excluding shelter, energy, and food in pink. The line in black shows the rental price component of the CPI.

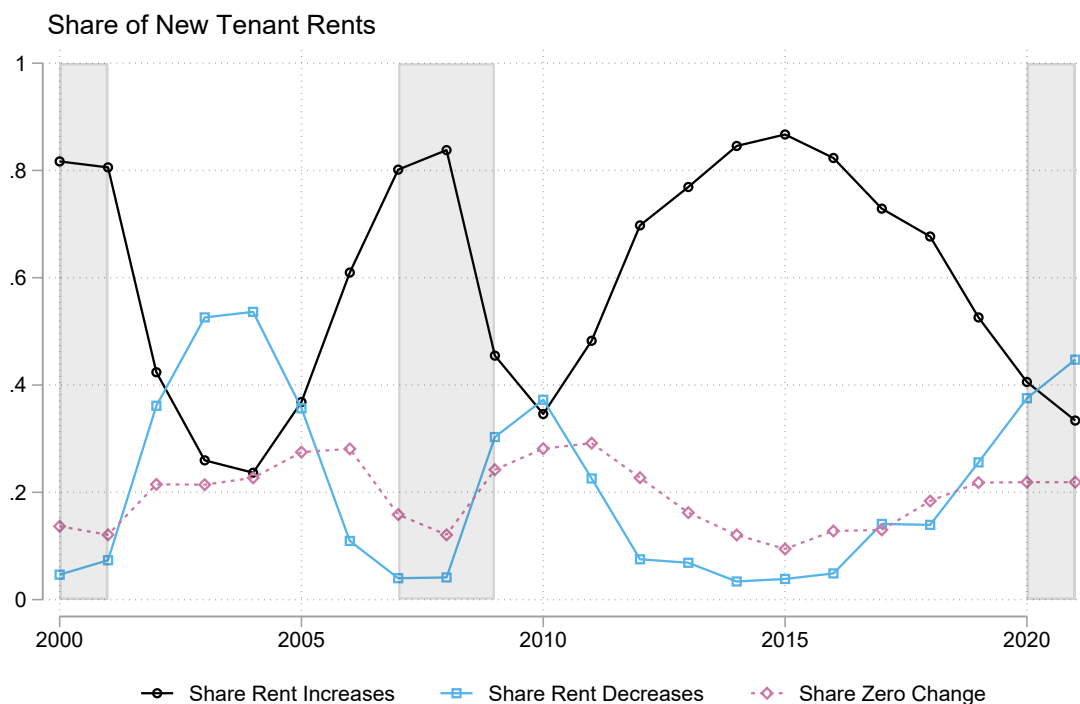
Figure 2: Evidence for State-Dependent Downward Nominal Rent Rigidity



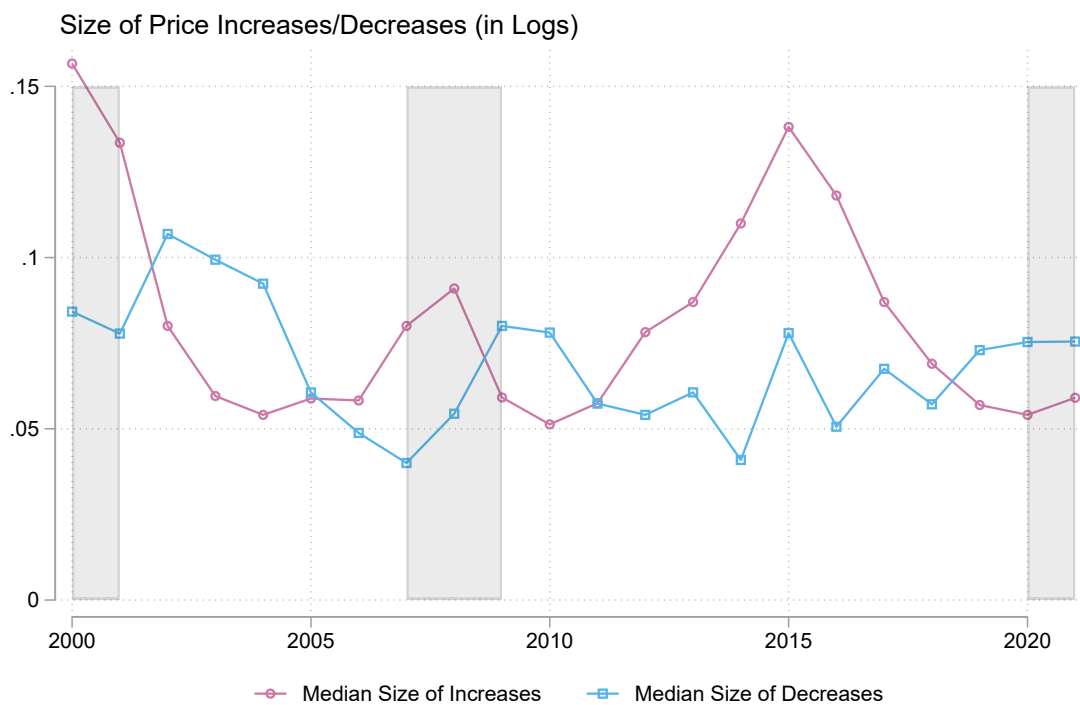
Notes: Panel (A) shows a histogram of the share of new leases with each nominal rent change, rounded to the nearest dollar. Panel (B) shows the kernel density estimate of log rent changes after excluding observations with zero rent change. For readability, we only include rent changes that are less than 20 log points. Panel (C) shows a binned scatter plots of a regression of the number of months since the previous lease on the probability the new lease comes with a zero rent change. The regression includes neighborhood-year and unit fixed effects. Point estimates and standard errors clustered at the unit level are shown in parentheses. Panel (D) shows the kernel density estimate of log rent changes after excluding observations with zero rent change. For readability, we only include rent changes that are less than 20 log points. We split the sample into terciles of annual rent growth, based on an estimated repeat-rent index, and show the estimates separately by tercile of annual rent growth.

Figure 3: Frequency and Magnitude of Price Adjustments and the Business Cycle

A. Share of Rent Adjustments



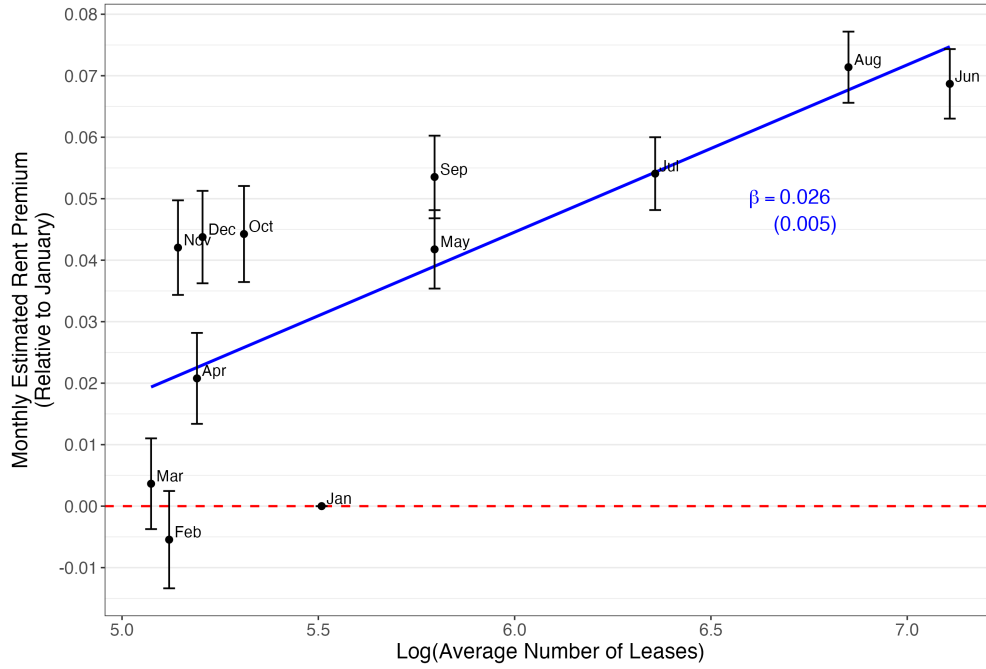
B. Size of Rent Adjustments



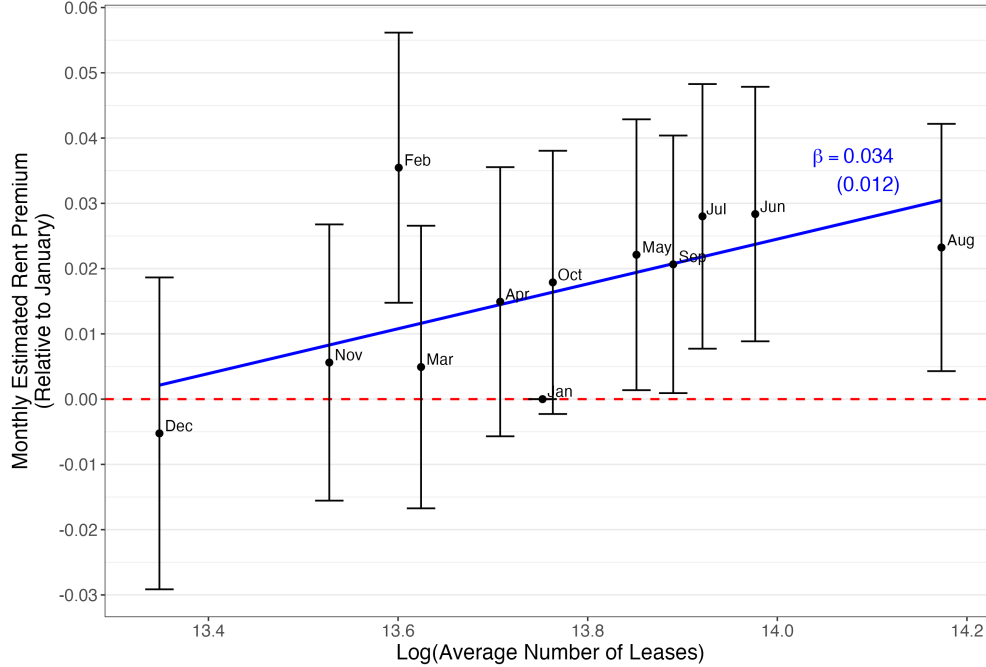
Notes: Panel (A) shows the share of new rental contracts that represent rent increases, rent decreases, or are unchanged in each year. Panel (B) shows the median size of rent increases and decreases separately. For both figures, we subset to units that turn over within two years.

Figure 4: Rental Price Premia and the Seasonal Cycle

A. Seasonal Price Premia in Berkeley Rental Market



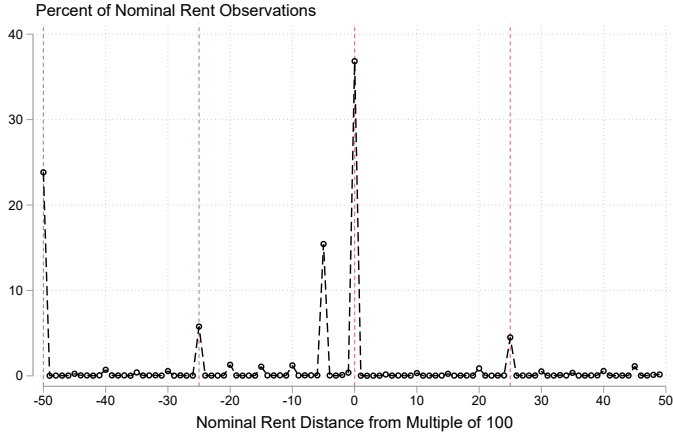
B. Seasonal Price Premia in American Rental Market



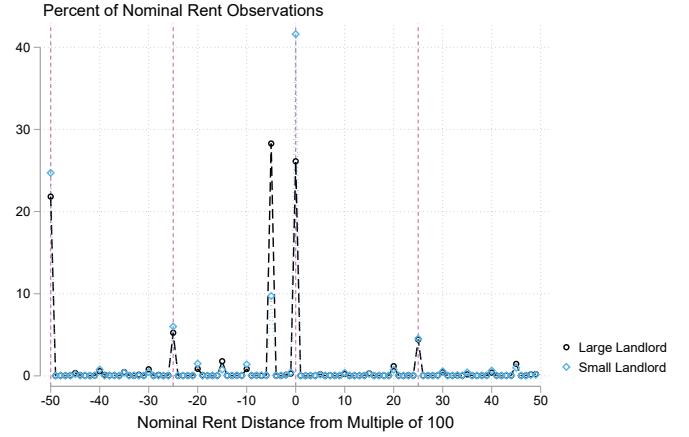
Notes: This figure shows estimated rental premia in both Berkeley and the broader American rental market. Panel (A) shows scatter plot of the estimated rent premia on the average number of leases per month (in logs) in Berkeley. Monthly rent premia are estimated from a regression of log rents on month fixed effects, controlling for neighborhood-year, month of last lease, number of months since last lease, and unit fixed effects. We only include pre-Covid years in these estimates, to avoid changes in the seasonal cycle caused by the pandemic. Estimated rent premia and standard errors are shown, as is the regression coefficient from a regression of the rent premia on the log(average number of leases). Point estimates and robust standard errors for that regression are shown. Panel (B) shows scatter plot of the estimated rent premia on the average number of leases per month (in logs) in the broader American market. Monthly rent premia are estimated from a regression of log rents on month fixed effects, controlling for city-by-year and unit fixed effects. Estimated rent premia and standard errors are shown, as is the regression coefficient from a regression of the log(average number of leases) on the rent premia. Point estimates and robust standard errors for that regression are shown.

Figure 5: Evidence for Heterogeneity in Landlord Sophistication

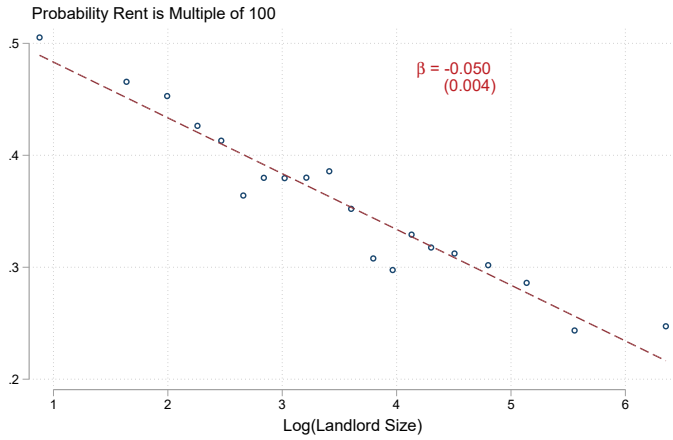
A. Bunching at Round Number Prices



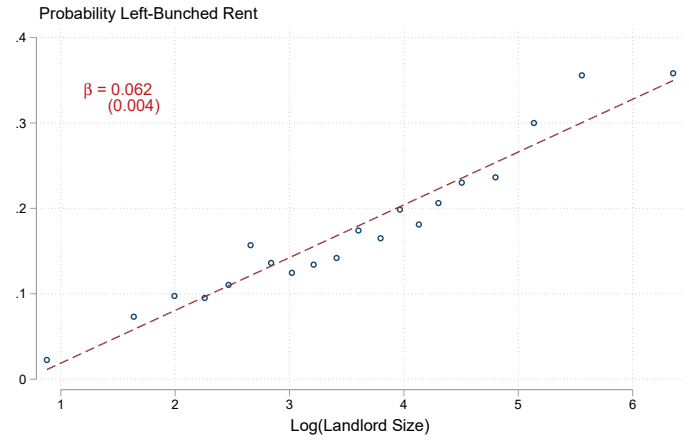
B. Heterogeneity by Landlord Size



C. Bunching at Multiples of 100



D. Left-Digit Pricing



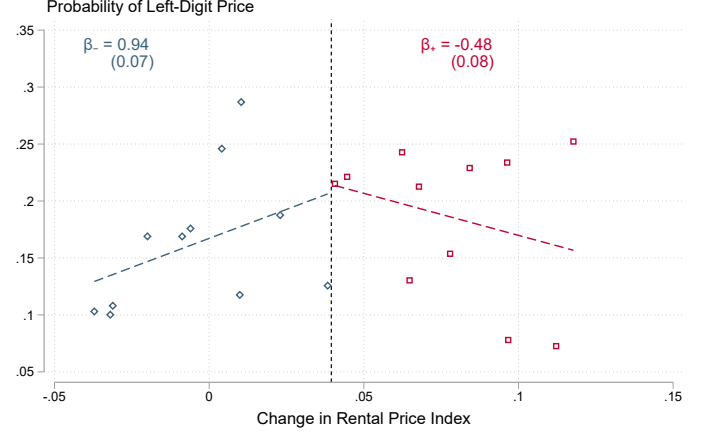
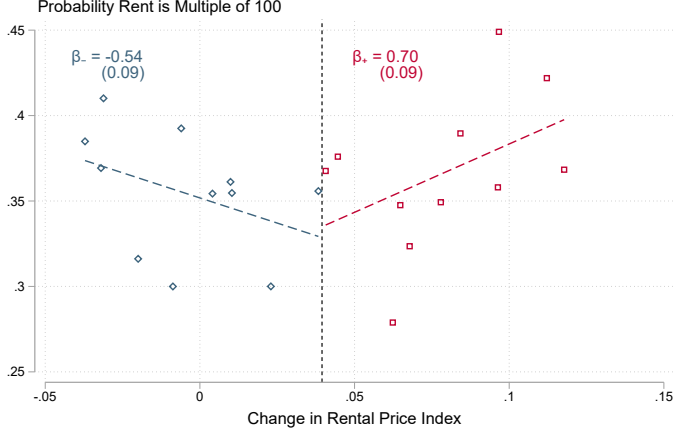
Notes: Panel (A) shows the percent of all observations in the dataset with numbers based on their distance from the nearest multiple of \$100. Panel (B) shows the same figures separately for large landlords (defined as landlords with more than 75 units in Berkeley) and small landlords (all other observations). Panels (C) and (D) show binned scatter plots of different rent characteristics on Log(Landlord Size). All regressions include month-of-lease-start by month-of-last-lease-start and census-tract-by-year fixed effects. In Panel (C), the outcome variable is the probability that the rent is an exact multiple of \$100. In Panel (D), the outcome variable is the probability of a left-bunched rent, defined as the probability that a rent observation is \$1 to \$9 less than a multiple of \$100.

Figure 6: Coarse Pricing Patterns Across The Business Cycle

Aggregate Effects

A. Bunching at Multiples of 100

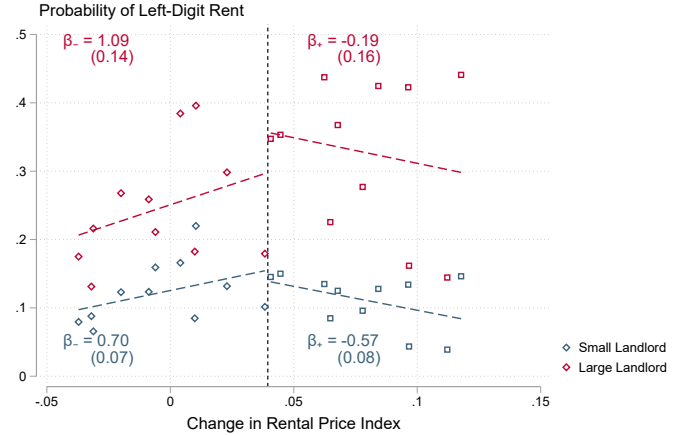
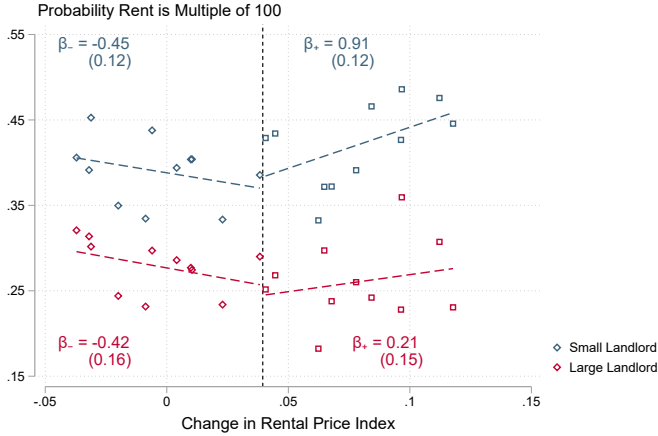
B. Left-Digit Pricing



Heterogeneity by Landlord Size

C. Bunching at Multiples of 100

D. Left-Digit Pricing



Notes: Panels (A) and (B) show binned scatter plots of the probability that a rent matches a particular characteristic on the annual change in the rental price index. We fit separate lines on either side of median price growth in our sample. In Panel (A), the outcome variable is the probability the rent is a multiple of \$100. In Panel (B), the outcome variable is the probability of a left-digit price, defined as any price where the rent is \$1 to \$9 below a multiple of \$100. Outcome variables are residualized on time-since-last-lease fixed effects. Panels (C) and (D) show the same figures, but separately for large and small landlords, defined based on whether a landlord owns more than 75 units in Berkeley. Outcome variables are residualized on census-tract-by-year fixed effects. Point estimates and standard errors clustered by unit are shown.

7 Tables

Table 1: Summary Statistics

Panel A: Berkeley Sample

	N	Mean	Median	SD	P10	P90
Nominal Rent	92,370	1,692	1,495	1,142	850	2,800
Change in Rents	92,370	199	100	982	-100	605
Months Between Leases	92,370	34	24	31	11	70
Units at Address	92,370	19	12	23	2	44
Units per Landlord	92,370	88	28	140	4	287
Number of Bedrooms	92,370	1	1	1	0	2

Panel B: U.S. Sample

	N	Mean	Median	SD	P10	P90
Nominal Rent	55,451	617	550	336	280	1,000
Change in Rents	55,451	73	45	224	-75	280
Units in Building	55,451	17	6	41	1	40
Number of Bedrooms	55,451	2	2	1	1	3

Notes: This table shows summary statistics for both our main samples. Panel (A) shows summary statistics for the Berkeley sample, while Panel (B) shows summary statistics for the broader U.S. sample.

Table 2: Aggregate Dynamics of Price Adjustment

Panel A: Frequency of Price Adjustment				
	Tot. Leases	Increases	Decreases	Unchanged
D. Rents	-0.22 (0.47)	3.44*** (0.68)	-18.5*** (1.62)	-5.46*** (1.39)
N	22	22	22	22
R^2	0.0090	0.58	0.84	0.33

Panel B: Median Size of Price Adjustments				
	≤ 2 Yrs. Since Last Lease		All Leases	
	Increase	Decrease	Increase	Decrease
D. Rents	0.53*** (0.090)	-0.20** (0.087)	0.55** (0.20)	-0.16** (0.067)
N	22	22	22	22
R^2	0.71	0.29	0.27	0.30

Notes: This table shows the relationship between changes in rental prices and various measures of price adjustment. In all regressions, the independent variable is the change in the rental price index (in logs). Panel A reports correlations with the frequency of price adjustments across different categories. All frequency variables are in logs. Panel B shows the relationship with the median size of price increases and decreases. All size variables are in log changes. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Dynamics of Rent Adjustment, Controlling for Unit Fixed Effects

Panel A: Berkeley Sample

	Share of Rent Changes			Size of Rent Changes		
	Increases	Decreases	Unchanged	Increases	Decreases	Combined
D. Rent Index	3.390*** (0.034)	-2.697*** (0.029)	-0.693*** (0.025)	0.743*** (0.018)	-0.346*** (0.052)	1.344*** (0.016)
N	87452	87452	87452	59208	10343	87452
R^2	0.304	0.263	0.258	0.487	0.429	0.406
Unit FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Mean	0.69	0.18	0.13	0.20	0.11	0.12

Panel B: U.S. Sample

	Share of Rent Changes			Size of Rent Changes		
	Increases	Decreases	Unchanged	Increases	Decreases	Combined
D. Rent Index	3.861*** (0.309)	-3.162*** (0.280)	-0.699*** (0.175)	1.137*** (0.335)	-0.338 (1.494)	2.106*** (0.422)
N	50356	50356	50356	33587	6265	50356
R^2	0.208	0.218	0.274	0.431	0.522	0.146
Unit FE	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Mean	0.70	0.21	0.08	0.27	0.37	0.12

Notes: This table shows the relationship between changes in rental price indexes and the size and frequency of price adjustment at the unit level. In the first three columns, the dependent variables are indicators for whether rents increased, decreased, or were unchanged respectively. In the next three columns, the dependent variables are the size of price increases, price decreases, and all price changes, in logs. All regressions include individual unit fixed effects. Panel (A) shows results for the Berkeley sample, while Panel (B) shows results for the U.S. sample. The regressions in Panel (A) also include controls for the month in which the previous lease started. Standard errors clustered at the unit level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Pricing Response to the Seasonal Cycle, Controlling for Unit Fixed Effects

Panel A: Berkeley Sample

	Share of Rent Changes			Size of Rent Changes		Total
	Increases	Decreases	Unchanged	Increases	Decreases	Log(Rent)
Avg. Num. Leases	0.028*** (0.002)	-0.025*** (0.002)	-0.004** (0.002)	-0.001 (0.001)	-0.010*** (0.002)	0.024*** (0.001)
N	82828	82828	82828	57831	8021	82828
R^2	0.374	0.325	0.289	0.554	0.589	0.938
Unit FE	Yes	Yes	Yes	Yes	Yes	Yes
Nbhood-Yr	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Mean	0.71	0.16	0.13	0.20	0.11	7.28

Panel B: U.S. Sample

	Share of Rent Changes			Size of Rent Changes		Total
	Increases	Decreases	Unchanged	Increases	Decreases	Log(Rent)
Avg. Num. Leases	0.057*** (0.013)	-0.034*** (0.012)	-0.024*** (0.007)	0.004 (0.013)	0.015 (0.075)	0.039*** (0.012)
N	45068	45068	45068	29603	4743	45068
R^2	0.307	0.308	0.335	0.495	0.678	0.703
Unit FE	Yes	Yes	Yes	Yes	Yes	Yes
SMSA-Yr	Yes	Yes	Yes	Yes	Yes	Yes
Dep. Mean	0.70	0.22	0.08	0.26	0.36	6.30

Notes: This table shows how rental pricing varies across the seasonal cycle. The independent variable is the average number of leases in each month across the sample periods. Columns (1) - (6) show the effect of the seasonal cycle on rental prices. Panel (A) shows the effect in the Berkeley sample. Regressions represented by Columns (1) - (6) in the Berkeley sample include fixed effects for the neighborhood-by-year, the number of months between leases, the month the previous lease started, and the individual unit. Panel (B) shows the effects in the broader U.S. sample. Regressions represented by Columns (1) - (6) in the U.S. sample include city-year and unit fixed effects, including a residual category for units that are not identified with a particular city for disclosure reasons. Standard errors clustered at the unit level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Heterogeneity in Pricing Behavior Over the Business Cycle

Panel A: Pooled Effects					
	Rent Change is...				
	Increase	Decrease	Unchanged	Big Increase	Log Change
Landlord Size	-0.001 (0.001)	0.006*** (0.001)	-0.005*** (0.001)	0.008*** (0.001)	0.002*** (0.000)
N	89946	89946	89946	89946	89946
R^2	0.239	0.183	0.104	0.359	0.407
Nbhood-YR FE	Yes	Yes	Yes	Yes	Yes
Dep. Mean	0.69	0.18	0.13	0.25	0.12

Panel B: Business Cycle Effects					
	Rent Change is...				
	Increase	Decrease	Unchanged	Big Increase	Log Change
Landlord Size	-0.013*** (0.002)	0.019*** (0.002)	-0.006*** (0.002)	0.000 (0.001)	-0.002** (0.001)
x Mod. Growth	0.014*** (0.003)	-0.014*** (0.002)	0.001 (0.002)	0.007*** (0.002)	0.005*** (0.001)
x High Growth	0.021*** (0.002)	-0.024*** (0.002)	0.003 (0.002)	0.016*** (0.002)	0.008*** (0.001)
N	89946	89946	89946	89946	89946
R^2	0.239	0.184	0.104	0.359	0.407
Nbhood-YR FE	Yes	Yes	Yes	Yes	Yes
Dep. Mean	0.69	0.18	0.13	0.25	0.12

Notes: This table shows how landlords of different sizes adjust prices over the business cycle. Panel (A) shows the pooled (or average) effect of large landlords over the entire sample period. Panel (B) shows the effect over the business cycle. The coefficients of interest in Panel (B) are interaction terms between landlord size (in logs) and terciles of rent price growth in Berkeley, California. The omitted category is the lowest tercile of the rent growth distribution. Both sets of estimates include neighborhood-by-year fixed effects, as well as fixed effects for the month the previous lease started by month the current lease started (to account for seasonal effects), as well as the number of years between leases. Standard errors clustered at the unit level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Inflation Volatility and Heuristic Pricing, Controlling for Unit Fixed Effects

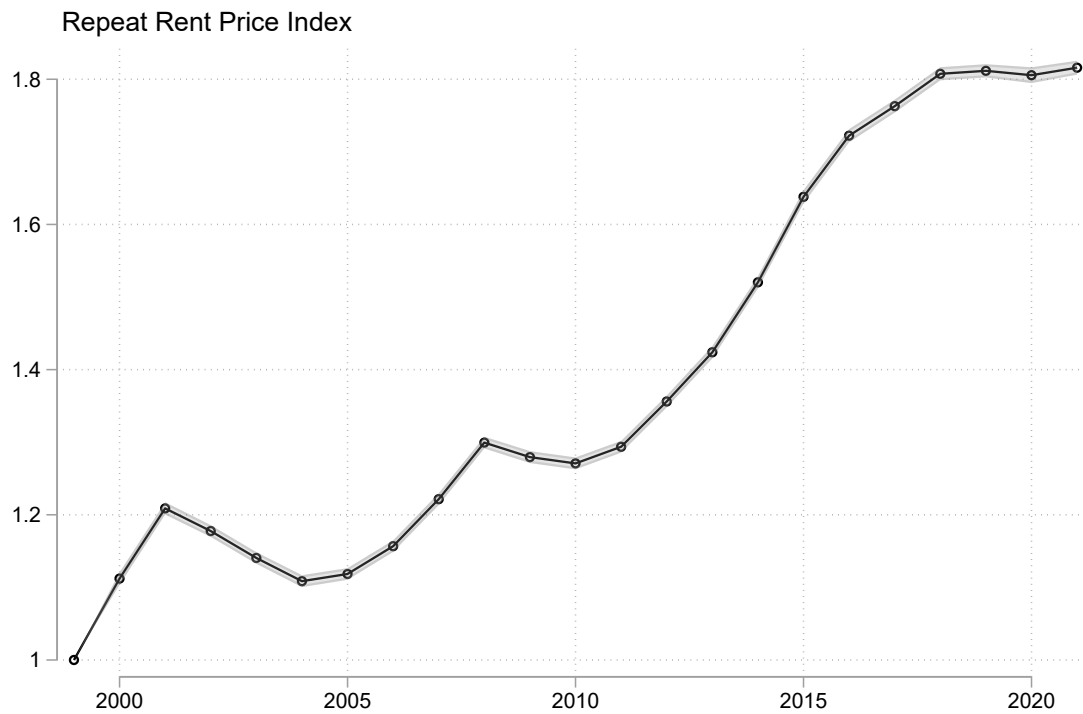
Panel A: Berkeley Sample			
	Bunch at 50	Bunch at 100	Left-Digit Price
Dist. to Median Price	0.665*** (0.067)	0.490*** (0.067)	-0.486*** (0.051)
N	87452	87452	87452
R^2	0.385	0.354	0.396
Unit FE	Yes	Yes	Yes
Dep. Mean	0.69	0.35	0.18

Panel B: U.S. Sample			
	Bunch at 50	Bunch at 100	Left-Digit Price
Dist. to Median Price	1.840*** (0.516)	1.936*** (0.457)	0.014 (0.271)
N	50356	50356	50356
R^2	0.394	0.343	0.254
Unit FE	Yes	Yes	Yes
Dep. Mean	0.39	0.21	0.06

Notes: This table shows the relationship between deviations of rental price inflation from its usual trend and measures of heuristic pricing. The independent variable is the distance between annual rent inflation and its median value during the sample period. In Column (1), the dependent variable is whether a rent is a multiple of 50. In Column (2), the dependent variable is whether a rent is a multiple of 100. In Column (3), the dependent variable is whether or not a rent shows evidence of “left-digit pricing”, defined as being between \$1 and \$9 less than a multiple of 100. Panel (A) shows the Berkeley sample, while Panel (B) shows the U.S. sample. All estimates include unit fixed effects, and the Berkeley sample includes controls for the number of months between lease dates. Standard errors clustered at the unit level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

A Appendix Figures

Figure A.1: Prices in the Berkeley Rental Market



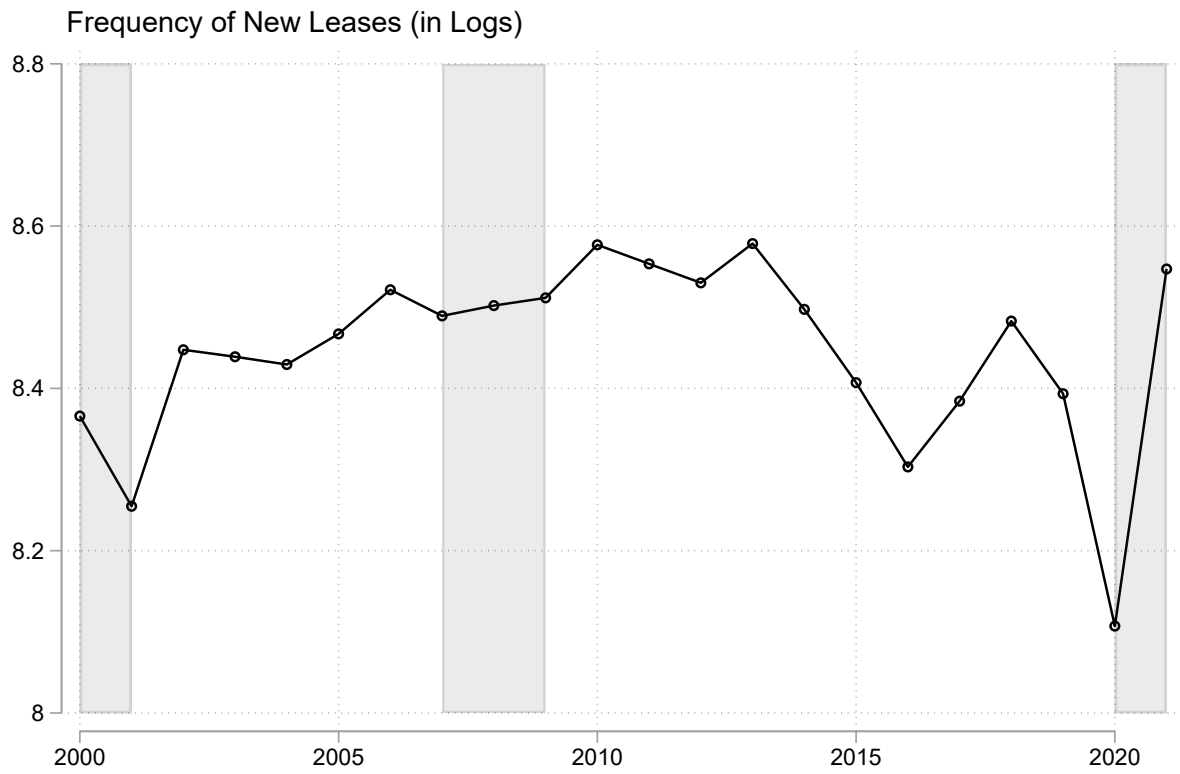
Notes: This figure plots the new-tenant rent price index in Berkeley, CA, extracted from a regression of new tenant rents on year and unit fixed effects.

Figure A.2: Reset Prices Increase with the Time Between Leases



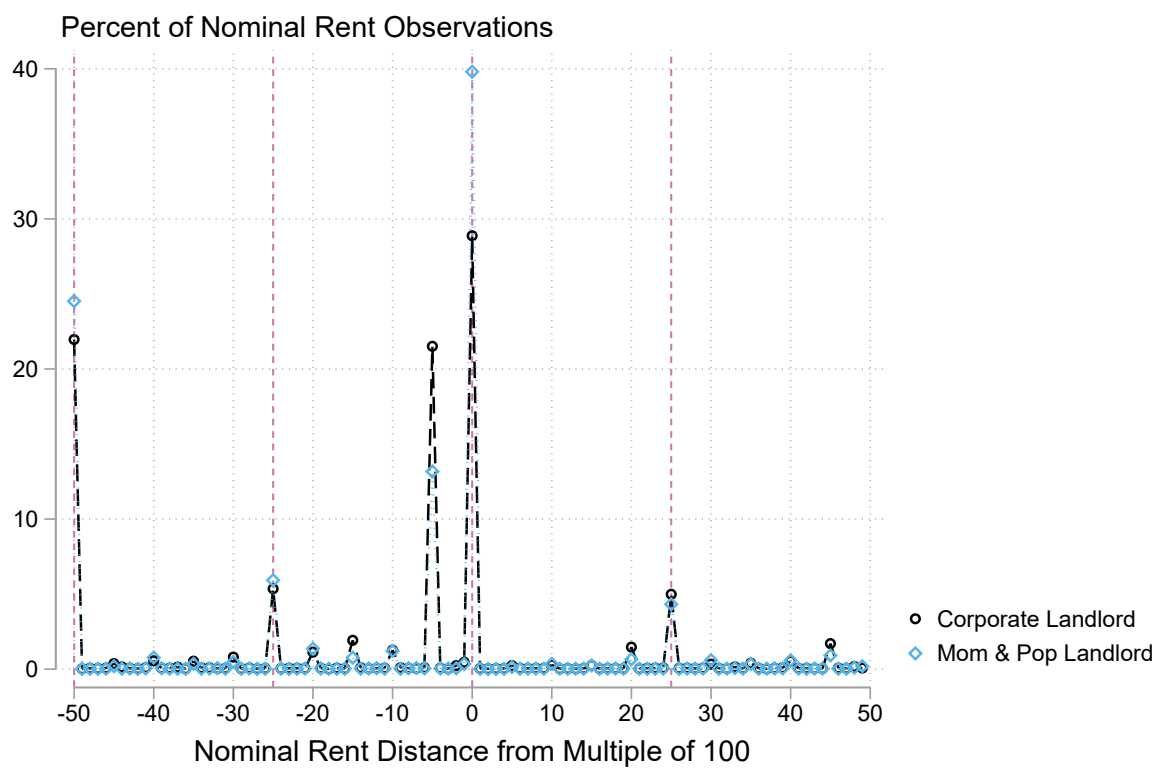
Notes: This figure shows binned scatter plots of the change in log rental prices on the number of months since the last lease (in logs). The regression includes census-tract-by-year and unit fixed effects. Point estimates and standard errors clustered at the unit level are shown.

Figure A.3: Aggregate Mobility Does Not Vary Over Time



Notes: This figure shows the time series of annual new leases in Berkeley, CA.

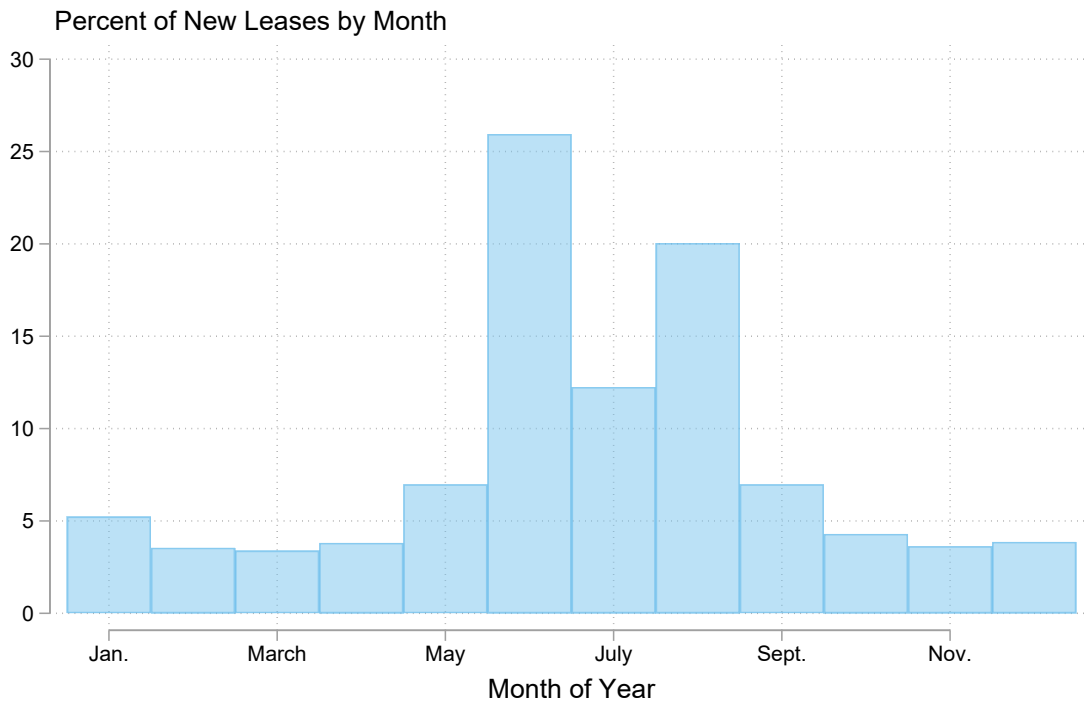
Figure A.4: Bunching for Corporate and Individual Landlords



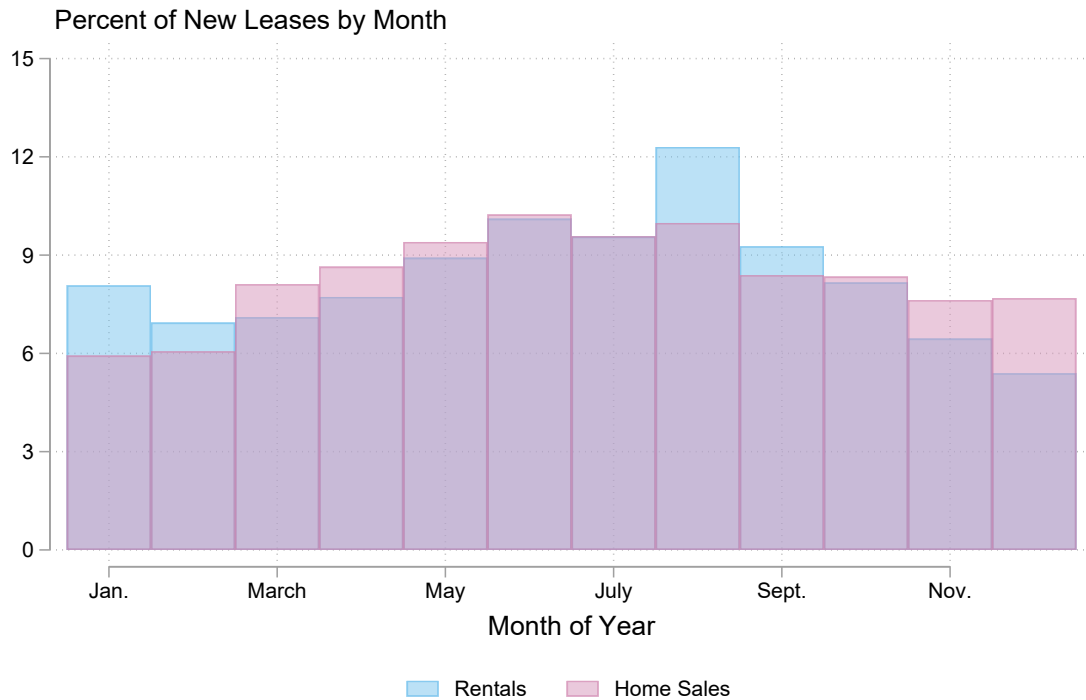
Notes: This figure shows bunching in the rent distribution separately for corporate and mom & pop landlords.

Figure A.5: Number of New Leases by Month

A. Berkeley Sample

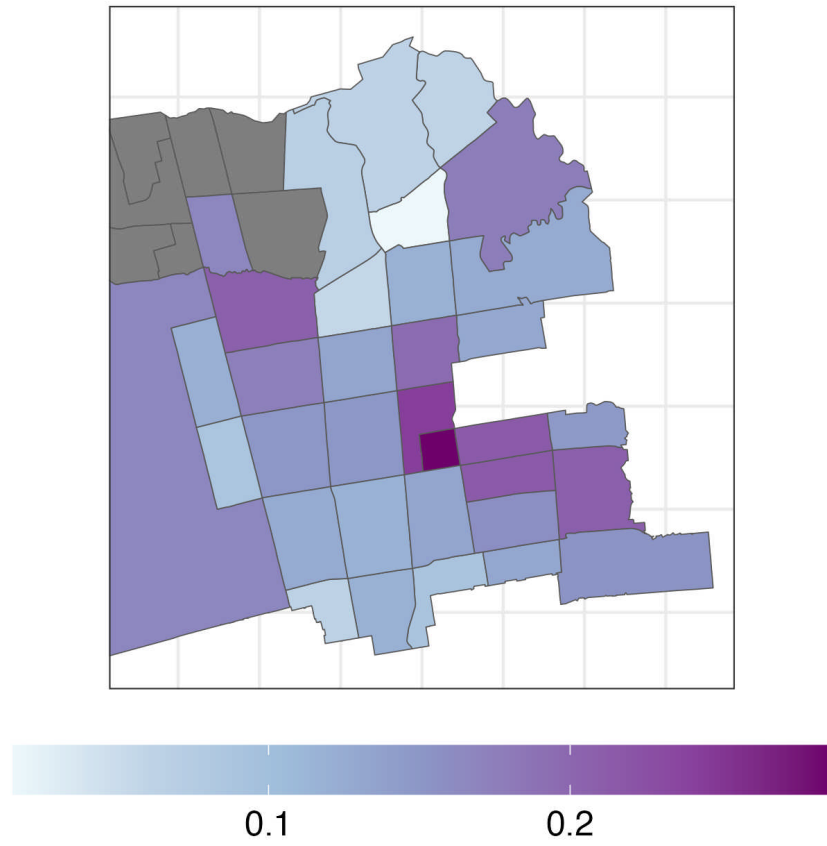


B. U.S. Sample



Notes: Panel (A) shows the percent of new leases by month in the Berkeley sample. Panel (B) shows the same thing but for the broader U.S. sample. Panel (B) also shows seasonality in the home purchase market for the entire U.S., taken from sales data from the National Association of Realtors in [Ngai and Tenreiro \(2014\)](#). For the Berkeley sample, we end the sample in 2020 to avoid any unusual changes due to the pandemic.

Figure A.6: Map of Left-Digit Pricing in Berkeley, California



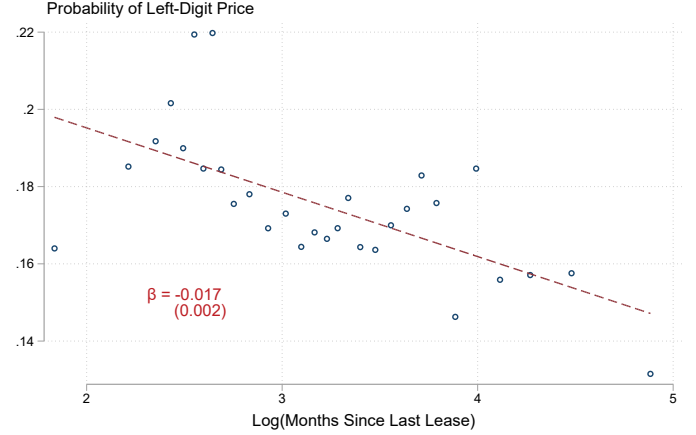
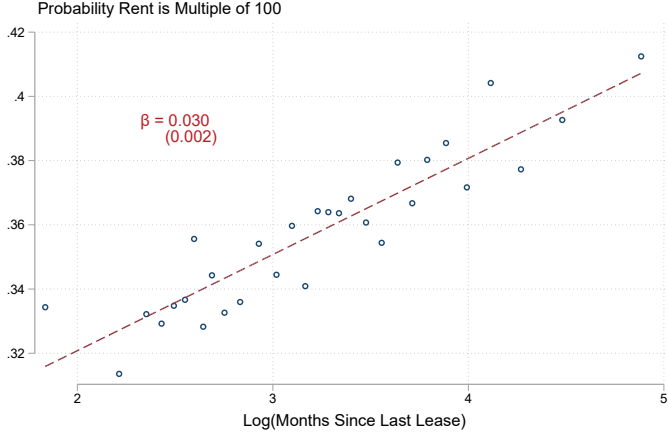
Notes: This figure shows a census tract level map with the average level of left-digit pricing in each census tract in Berkeley.

Figure A.7: Coarse Pricing Patterns Across Lease Contract Gaps

Aggregate Effects

A. Bunching at Multiples of 100

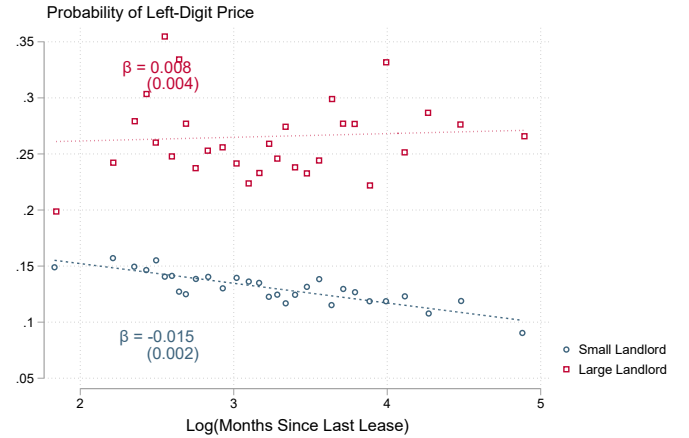
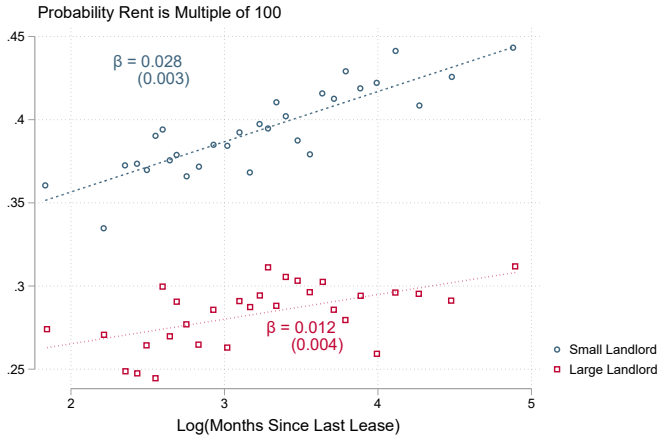
B. Left-Digit Pricing



Heterogeneity by Landlord Size

C. Bunching at Multiples of 100

D. Left-Digit Pricing



Notes: Panels (A) and (B) show binned scatter plots of the probability that a rent matches a particular characteristic on the time since the previous lease. In Panel (A), the outcome variable is the probability the rent is a multiple of \$100. In Panel (B), the outcome variable is the probability of a left-digit price, defined as any price where the rent is \$1 to \$9 below a multiple of \$100. Panels (C) and (D) show the same graphs, but separately for large (≥ 75 units in Berkeley) and small landlords. Outcome variables are residualized on census-tract-by-year fixed effects. Point estimates and standard errors clustered by unit are shown.

B Appendix Tables

Table B.1: Heterogeneity in Pricing Behavior Over the Business Cycle

Panel A: Pooled Effects					
	Rent Change is...				
	Increase	Decrease	Unchanged	Big Increase	Log Change
Corp. Landlord	0.002 (0.003)	0.002 (0.003)	-0.004 (0.003)	0.016*** (0.003)	0.011*** (0.001)
N	89946	89946	89946	89946	89946
R^2	0.239	0.182	0.104	0.358	0.407
Nbhood-YR FE	Yes	Yes	Yes	Yes	Yes
Dep. Mean	0.69	0.18	0.13	0.25	0.12

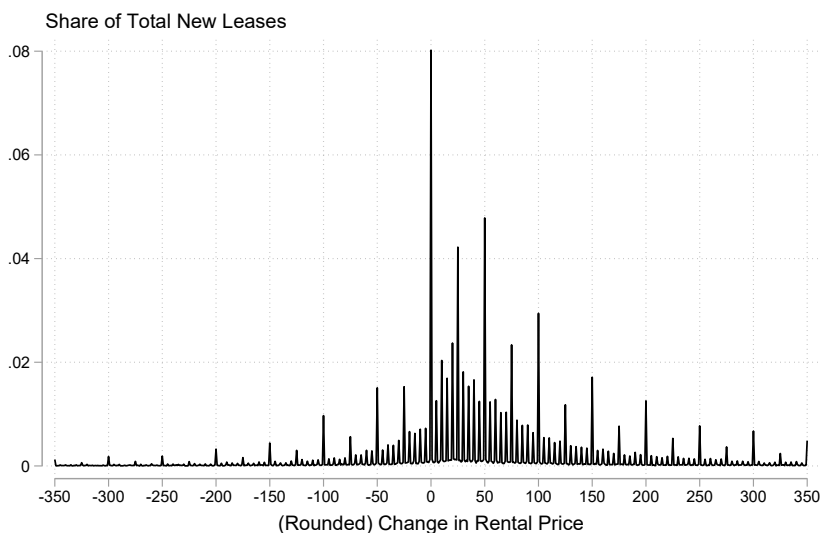
Panel B: Business Cycle Effects					
	Rent Change is...				
	Increase	Decrease	Unchanged	Big Increase	Log Change
Corp. Landlord	0.001 (0.006)	0.017*** (0.006)	-0.018*** (0.005)	0.004 (0.004)	0.002 (0.002)
x Mod. Growth	0.001 (0.009)	-0.019** (0.008)	0.018*** (0.007)	0.020*** (0.006)	0.013*** (0.003)
x High Growth	0.002 (0.008)	-0.026*** (0.007)	0.025*** (0.006)	0.014* (0.007)	0.014*** (0.004)
N	89946	89946	89946	89946	89946
R^2	0.239	0.182	0.104	0.358	0.407
Nbhood-YR FE	Yes	Yes	Yes	Yes	Yes
Dep. Mean	0.69	0.18	0.13	0.25	0.12

Notes: This table shows how corporate vs. non-corporate landlords adjust prices over the business cycle. The coefficients of interest are interaction terms between an indicator for corporate landlords and terciles of rent price growth in Berkeley, California. The omitted category is the lowest tercile of the rent growth distribution. The regressions include neighborhood-by-year fixed effects, as well as fixed effects for the month the previous lease started by month the current lease started (to account for seasonal effects), as well as the number of years between leases. Standard errors clustered at the unit level in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

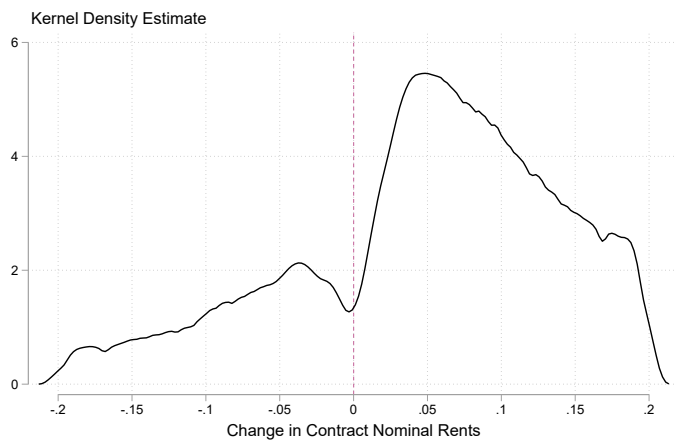
C More Evidence from the American Housing Survey

Figure C.1: Downward Nominal Rent Rigidity in the AHS

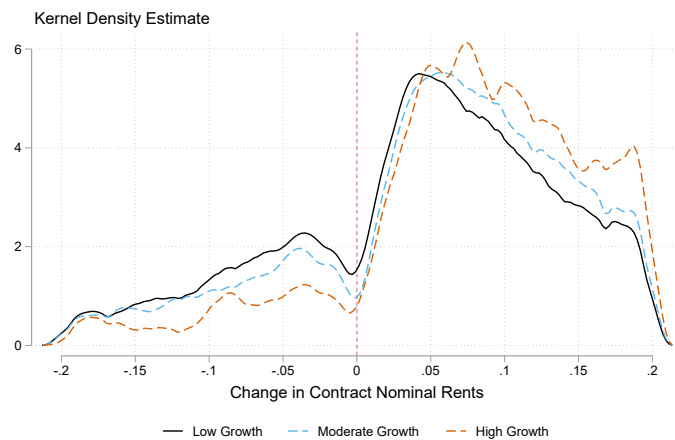
A. Overall Bunching at Zero Rent Changes



B. Kernel Density (excl. Zeros)



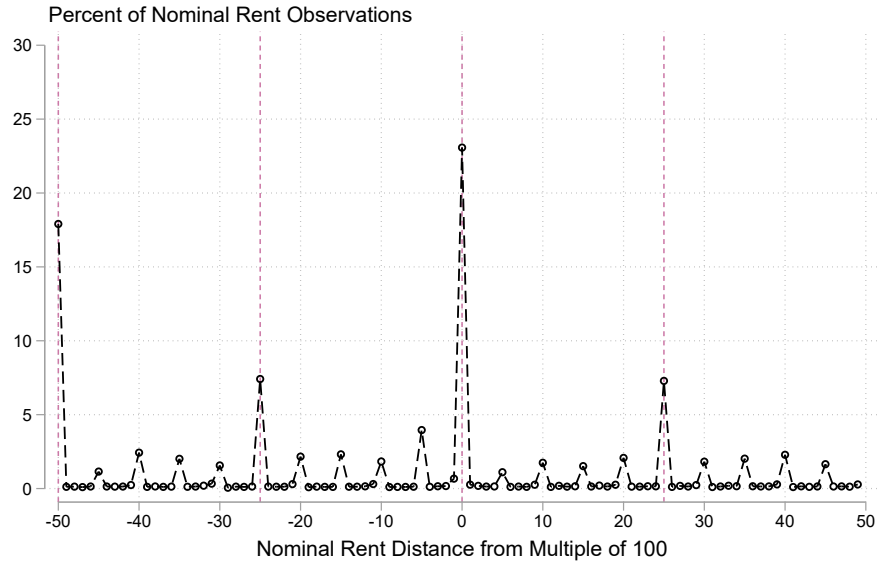
C. Kernel Densities by Rent Growth (excl. Zeros)



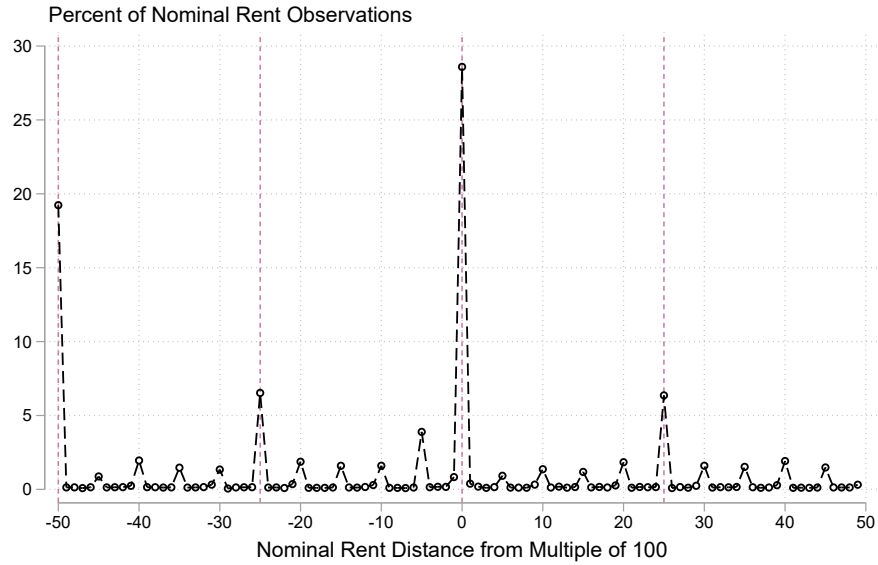
Notes: Panel (A) shows the histogram of the nominal dollar change in rents, rounded to the nearest dollar, in the AHS. We only include observations where the household differs from the household interviewed in the previous survey wave. Panel (B) shows the kernel density plots of the log change in contract rents, excluding zeros and dropping observations where the rent change is large at 20 log points. Panel (C) shows the same kernel density plots, but separately for low, moderate, and high rent growth periods.

Figure C.2: Heuristic Pricing in the Broader American Rental Market

A. 1985 - 2013 Sample



B. 1999 - 2013 Sample



Notes: This figure shows the percent of all observations in the AHS dataset with numbers based on their distance from the nearest multiple of \$100. Panel (A) shows the results for the period between 1985 and 2013, while Panel (B) shows the results for the period between 1999 and 2013. All counts are weighted using their sampling weights.