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Estimating housing rent depreciation for inflation adjustments☆

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ABSTRACT

U.S. inflation measures, such as the Consumer Price Index, are adjusted for an aging-bias based on estimates of the average rent depreciation. This study analyzes the characteristics of rent depreciation using novel, market-based data on rental contracts in Las Vegas, NV. We find that the estimated annual depreciation rate for new properties is 0.9% for single-family residences and 1.5% for condominiums. The higher depreciation rate for condominiums is due to higher functional obsolescence instead of physical deterioration. Rent depreciation rates are lower for older and smaller structures and vary significantly across neighborhoods. Our results suggest that local inflation rates are biased downward where new and large units increased since the last update to the official rent depreciation estimates but upward where the housing stock became older. From an asset pricing perspective, failing to account for initially high depreciation results in an overvaluation of new properties and an undervaluation of old properties.

1. Introduction

Measuring inflation is essential to economic decision-making and public policy, including consumption choice, corporate investment, monetary policy, and social security. The mismeasurement of inflation distorts decision-making because real values are estimated by deflating observed nominal values. However, measuring inflation is not a straightforward task (e.g., Hausman, 2003; Lebow and Rudd, 2003; Reinsdorf and Triplett, 2009). In particular, "[t]he treatment of owner-occupied housing services costs in CPIs is arguably one of the most difficult issues" (International Monetary Fund et al., 2020) because owner-occupied housing services are not directly traded in the market. A bias in the measurement of housing rents will significantly impact inflation rates because shelter accounts for a large part of the consumption basket (33% for the U.S. Consumer Price Index (CPI) and 41% for the core CPI excluding food and energy). The recent turmoil from the coronavirus pandemic (COVID-19) brought concerns about inflation to the forefront of policy and academic debates. In particular, the relative importance of shelter may be even greater today following the sudden increase in demand for housing space during the COVID-19 pandemic (e.g., Armantier et al., 2020; Reinsdorf, 2020).

The U.S. Bureau of Labor Statistics (BLS, 2018) estimates inflation rates for both the rent of primary residence and owners' equivalent rent by conducting the CPI Housing Survey of renters. The BLS adjusts for the aging of the same housing unit by adding the average rent depreciation rate to the observed rent change for each unit in the Housing Survey.[1] Other inflation rates—such as the Personal Consumption Expenditure (PCE) Price Index—also depend on this BLS rent index. However, studies on rent depreciation are scarce despite its importance. The BLS uses depreciation rates estimated using a regression-based model from Lane et al. (1988); Randolph (1988); and Campbell (2006) that has several restrictions that could lead to inaccurate aging effects. Randolph (1988) estimates the average rent depreciation rate for the nation (0.36%) and major Metropolitan Statistical Areas (MSAs), ranging from 0.76% for Anchorage to −0.40% (appreciation) for Washington D.C. Similar rates are estimated by Lane et al. (1988) and Campbell (2006).

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[1] See https://www.bls.gov/cpi/factsheets/owners-equivalent-rent-and-rent.pdf.

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This study analyzes the characteristics of housing rent depreciation to improve the measurement of inflation rates and the valuation of residential real estate. The economic depreciation of rents includes the rate of functional obsolescence and physical deterioration such as the wear and tear of the residential structure. We estimate net depreciation based on the average level of maintenance in the market, which is the relevant depreciation concept for the aging adjustment of BLS's (2018) rent inflation measure that implicitly includes maintenance effects.[2] We use novel administrative data on residential rental contracts from the Las Vegas Realtors' multiple listing service (MLS) for single-family residences and condominiums, which contains rich information on contract terms, property characteristics, and location. These MLS data allow us to estimate depreciation rates for use in either the rent or rent equivalent indices because they mimic the local owner-occupied population of housing units. The Las Vegas MSA epitomizes growing cities in the West, which have become more significant for the U.S. economy but have received profoundly less attention than the much older Eastern and Midwestern metros. Over the past year alone, home prices in Las Vegas rose sharply to unprecedented levels as households from across the nation flee old cities such as San Francisco, New York, and Chicago, all known to be expensive and dense, in exchange for cities that foster larger living areas and newer homes.[3] From a methodological perspective, we provide an analysis that other researchers with access to MLSs in other cities can replicate.

We address four major challenges in estimating rent depreciation rates. First, we show that the annual depreciation rate is not a linear function of age after controlling for various property characteristics and time fixed effects following Lane et al. (1988). Annual depreciation rates based on a more flexible specification such as a non-linear age spline significantly differ from those based on a linear depreciation rate specification. We find that the estimated annual depreciation rate for new properties is 0.9% for single-family residences and 1.5% for condominiums. These estimates are significantly higher than the current age adjustment. However, annual depreciation rates are significantly lower for older properties. For example, the depreciation rate is 0.5% between 46 and 50 years for single-family residences. Diminishing depreciation rates are also commonly observed for price depreciation due to a diminishing proportion of structure values to non-depreciating land values (e.g., Bokhari and Geltner, 2018; Yoshida, 2020).

Second, the rent depreciation rate is high for a property with a larger living area. We find that the annual depreciation rate for single-family residences is 0.13 percentage points higher if the log living area is one-standard-deviation larger. For condominiums, the annual depreciation rate is higher by 0.43 percentage points for a one-standard-deviation larger log living area. The depreciation rate is higher if housing services are derived more from a depreciating structure rather than land, as in the case of condominiums where landownership is generally shared. Because the average structure size has changed significantly over time and varies by location, rent depreciation rates can significantly differ from the national average depreciation rate.

Third, the estimated depreciation rate changes significantly when controlling for location characteristics, especially census tract fixed effects. Because building ages are highly correlated with neighborhoods, the lack of fine location controls leads to a biased estimate of age coefficients. Furthermore, rent depreciation rates vary significantly across census tracts after controlling for a battery of neighborhood characteristics and census tract fixed effects. This neighborhood variation is likely caused by unobserved property characteristics that are prevalent in a neighborhood. Some of these characteristics, such as building functions and styles, are associated with depreciation. Thus, we find an advantage of allowing depreciation rates to vary by neighborhood even when observed neighborhood characteristics do not affect depreciation rates.

Fourth, when we decompose age, period, and cohort effects using the intrinsic estimator (IE) by Yang et al. (2004) and Yang et al. (2008), the cohort effects are significant even after controlling for a battery of property and neighborhood characteristics. Cohort effects refer to the vintage of architectural style or construction technology of a particular time that may affect the deterioration of rental structures. The age effects significantly decrease in magnitude, especially for condominiums when we remove cohort effects. Following Francke and van de Minne (2017), we interpret the attenuated age effects as representing physical deterioration because cohort effects capture both vintage effects and the obsolescence of housing functions. The estimated physical deterioration is comparable between single-family residences and condominiums. However, our estimate of functional obsolescence is much lower for single-family residences, possibly because single-family owners can upgrade housing more easily. The sum of physical deterioration and functional obsolescence suggests that the total economic depreciation rate for relatively new properties is 1.2% for single-family residences and 1.8% for condominiums.

From a policy perspective, our findings suggest that the depreciation rate heterogeneity and the estimation issues we demonstrate significantly affect rent-inflation measurements. Failing to account for these issues will result in biased inflation statistics and CPI computation. The official inflation statistics would underestimate the local inflation rate in a city where the composition of housing stock changed significantly over the past three decades, possibly by gentrification. In such cities, the housing stock is typically augmented by large condominiums at central locations and new structures in suburban locations. Because these properties have higher depreciation rates than the official depreciation adjustment, the estimated inflation rate would be biased downward in these cities.

Although the discrepancy in the inflation rate may be modest, it accumulates into a great error over time. For example, once correcting for the aging effect adjustment from 0.225% to 0.75% in the West Urban CPI with a back-of-the-envelope calculation, we find a significant divergence between the actual and official CPI that grows over time when the inflation rate is slightly underestimated each year. As of March 2020, the official CPI for cities in the West such as Las Vegas could be underreported by approximately 4.5%. By contrast, following a similar line of logic, we anticipate that inflation rates will be biased upward in cities where the housing stock has become older.

Moreover, depreciation heterogeneity can affect the aggregate CPI. As we show in Appendix A, the BLS first averages rents in a granular geographical unit, calculates a six-month average growth rate for the geographical unit, and adjusts the growth rate with a single depreciation rate for the entire city or region. Given the non-linearity of the aggregation process, heterogeneity will affect the aggregate index through Jensen's inequality. As Lane et al. (1988) suggest, it is better to adjust the rent growth rate for each survey unit with the unique depreciation rate that reflects the property's characteristics before aggregating rent growth rates.

Our findings on depreciation heterogeneity also have a significant implication for real estate investment analysis because an investor needs to adjust the expected growth in market rents for the aging of the same property. Using a constant average rent inflation rate will result in overestimated rents for new properties and underestimated rents for old properties. Long-term expected capital gains are determined by rental income growth because changes in interest rates cannot drive capital gains in the long run (Ambrose et al., 2013; Eichholtz et al., 2019). Rent depreciation directly decreases capital gains each year. In contrast, rent depreciation increases the equilibrium income return (i.e., cap rate). For example, our estimates imply that if a single-family residence is new (1–5 years), then the property would be overvalued

[2] For the distinction between net and gross depreciation, see Bokhari and Geltner (2019). Additional data on maintenance would allow one to disentangle the two forms of depreciation.

[3] See https://www.wsj.com/articles/these-home-buyers-are-taking-a-chance-on-las-vegas-11617899580.

by approximately $3,000 (or 1.5%) when using the average depreciation rate instead of the age-group-specific depreciation rate in a direct capitalization income valuation approach.[4] In contrast, if the single-family residence is older (51–55 years), then it would be undervalued by approximately $8,600 (or 4.3%).[5] Failing to account for large initial depreciation results in an overvaluation of new properties and an undervaluation of old properties. Similarly, valuation will be distorted for a different size, neighborhood, and property type. Thus, the rent depreciation estimate is a critical input in investment analysis.

The rest of the paper is organized as follows. Section 2 discusses the related literature. Section 3 provides an overview of the available data and sample. Section 4 presents the empirical model along with the corresponding results, including an analysis of heterogeneous effects. Section 5 examines cohort effects. Section 6 concludes.

2. Depreciation concepts and the related literature

2.1. Inflation measurement

Measuring the cost of owner-occupied housing has long been a challenge (e.g., Dougherty and Van Order, 1982; International Monetary Fund et al., 2020). Because of its difficulty, the European Union excludes owner-occupied housing from its Harmonized Index of Consumer Prices estimates (Hill et al., 2020). The numerous other countries that include owner-occupied housing in the consumption basket take several approaches to measuring housing inflation. The three major approaches are net acquisitions, user-cost, and rental equivalence. (Diewert, 2009; Diewert et al., 2009; Diewert et al., 2020; Hill et al., 2020).[6]

The acquisition approach attributes all of the expenditure to the period of purchase even though durable goods will provide services beyond the period of purchase. This approach is used for most durable goods in many countries and for housing in Australia and New Zealand. However, it does not measure the cost of living during each period. The user-cost approach measures the cost of housing services by adding the user-cost components such as interest, repairs, maintenance, property taxes, and the decline in asset value (Himmelberg et al., 2005). However, the user-cost approach is not widely used partly because interest as an input causes an endogeneity issue regarding monetary policy. The user-cost estimation also involves significant empirical challenges including the choice of the opportunity cost of capital and the expected capital gains (e.g., Blackley and Follain, 1996; Garner and Verbrugge, 2009; Verbrugge and Poole, 2010; Hill and Syed, 2016; Hill et al., 2020).

The rental equivalence approach, which we focus on in this study, has been used by many countries including the U.S., Mexico, Japan, Germany, Switzerland, and South Africa (Hill et al., 2020). It measures the cost of housing services based on owners' equivalent rent imputed from the rental price of equivalent houses. This approach is also recommended for national accounts (International Monetary Fund et al., 2020). A major challenge is how to measure rents that accurately represent the opportunity cost of home ownership. An obvious issue is that rental houses are often located in different neighborhoods from owner-occupied houses. The Bureau of Labor Statistics (2018) makes a careful reweighting of the rental housing sample to match the geographical distribution of owner-occupied housing. Another issue is that the marginal rent determined in the rental housing market can be different from rents observed in a survey because rents for sitting tenants can deviate from the marginal rent (Diewert, 2009; Johnson, 2015; Bentley, 2018). Crone, Nakamura and Voith (2010) point out that the U.S. CPI rent index omitted rent increases at the time of a tenant change until the end of 1977, thereby biasing inflation estimates downward. More recently, Ambrose et al. (2015) demonstrate that the CPI rent index still has the same issue in the 2000s by showing the divergence between the CPI rent index and their Repeat Rent Index constructed from newly contracted leases for housing units in apartment complexes. Ambrose, Coulson and Yoshida (2018) discuss the effect of inflation measurement on monetary policy. Our study also uses newly contracted leases because they reflect the marginal rent determined in the market as Ambrose et al. (2015) emphasize.

2.2. Rent depreciation

In the inflation measurement, the quality of goods must be held constant. However, for the same housing unit, the housing structure ages over repeat observations of rents. Thus, the rent inflation measure needs to be adjusted for the age bias by adding the estimated depreciation rate to the observed rent changes (see Appendix A). The Bureau of Labor Statistics (2018) uses the depreciation rates estimated using the models proposed by Lane et al. (1988), Randolph (1988), and Campbell (2006). Their studies are most directly related to ours. To measure the age bias, they estimate a hedonic model that includes the building age, age squared, and age interacted with the number of rooms, a rent control dummy, a detached housing dummy, and a dummy for units built before 1900. The hedonic control variables include structural characteristics (e.g., dishwasher, central air conditioning), services included in rent (e.g., gas, electric), and neighborhood characteristics (e.g., proportion of the white population, proportion with a college degree). They estimate depreciation rates for 27 metropolitan areas. Their studies have several restrictions that we address in this study.

First, the depreciation rate is assumed to be a linear function of age between 1900 and 1980 (i.e., log rents are assumed to be a quadratic function of age). However, we demonstrate that depreciation rates exhibit a more complex pattern. Second, they assume that the inclusion of measured structural and neighborhood characteristics eliminates cohort effects. They argue that assuming no cohort effect is better than assuming no aging effect, but both effects can be significant. Third, they control for the effect of detached housing only at the rent level and the average depreciation rate. Thus, they assume all other hedonic coefficients are common for detached and non-detached housing. They also assume that the age profile of rents is common to both detached and non-detached housing.

Lane et al. (1988) estimate depreciation rates for selected metropolitan areas, including New York (0.36%), Chicago (0.22%), Dallas (0.14%), San Francisco (0.23%), and Washington, D.C. (0.17%). These area-average depreciation rates are applied equally to all properties in the same area. Malpezzi, Ozanne and Thibodeau (1987) estimate the average rent depreciation for more locations using a log-linear rent model with a polynomial age function and data from the American Housing Survey. For the Las Vegas MSA, the rent depreciation estimates that commingle single-family residences and condominiums range from 2.1% for new properties to 1.5% for older properties. More recent studies mention a rent depreciation issue but do not provide new estimates (e.g., Gordon and van Goethem, 2007; Diewert et al., 2009; Verbrugge et al., 2017).

Depreciation rates are also heterogeneous. Hill and Syed (2016) discuss how depreciation rates may differ for different segments of the market in their effort to estimate the user-cost of housing. Verbrugge et al. (2017) stress the importance of heterogeneity in rents across locations and identify a persistent relation between the change in rent and

[4] Lopez (2021) reports that the average price in residential transactions in Las Vegas from 2008Q1 to 2018Q2 is approximately $201,000, implying a capitalization rate of 8.3% for a single-family residence that generates the average rental income of $1392 per month shown in our sample. Hence, $\$3,000 \approx \$201K - \$1,392 \times 12/(0.083 + .009 - 0.0076)$, where 0.9% is the average deprecation rate for the 1–5 age group and 0.76% is the overall average depreciate rate for single-family residences.

[5] $-\$8,600 \approx \$201\text{K} - 1,392 \times 12/(0.083 + 0.0043 - 0.0076)$.

[6] Other approaches include payment and opportunity cost (Diewert and Nakamura, 2009), though we do not review them in this paper.

the change in the desirability of locations. Public intervention such as rent controls and subsidies also affect depreciation (e.g., Walters, 2009).

Dixon et al. (1999) call for more elaborate studies on rental depreciation as the basis for price depreciation. Because a house price is the present discounted value of future rents (or the owner's equivalent rent for owned housing), rent depreciation and price depreciation are tightly linked.

2.3. Price depreciation

Property depreciation usually refers to economic depreciation defined as a decline in the asset price due to aging (Hulten and Wykoff, 1981). Asset price depreciation is closely related with rent depreciation. In Appendix B, we develop a property valuation model built on depreciating housing rents to demonstrate how rent depreciation rates are related to value depreciation rates. Following DiPasquale and Wheaton (1995), we decompose housing rents into land rents and structure rents. We assume that land rents are constant over time after fluctuations and trends in rents are removed, whereas structure rents depreciate due to physical deterioration and functional obsolescence. The property value—the present discounted value of future rents—depreciates due to both rent depreciation and a shorter structure life. In general, the property value depreciation rate is higher than the rent depreciation rate in an economy in which slowly depreciating structures account for a significant part of the property value, as in the U.S. The opposite relation can be observed when the rent depreciation rate is high and land value is significant (e.g., Xu et al., 2018).

Most studies estimate the depreciation of property values partly because property value data are more easily available than rental rate data. Furthermore, to model depreciation, a cross-sectional hedonic regression is commonly used because transaction data for different properties with various ages are more easily available than panel data for the same properties (e.g., Hulten and Wykoff, 1981; Goodman and Thibodeau, 1995; 1997; 1998; Clapp and Giaccotto, 1998; Coulson and McMillen, 2008; Yoshida and Sugiura, 2015; Bokhari and Geltner, 2018; Francke and van de Minne, 2017).

Other studies estimate value depreciation by combining the aggregate flow investment data and real estate stock data, typically in the National Accounts (e.g., Hulten and Wykoff, 1981; Hayashi, 1991; Davis and Heathcote, 2005; Economic and Social Research Institute, 2011). These studies estimate the implicit depreciation rate in a stock accumulation equation. The third method utilizes data on demolished buildings (e.g., Yoshida, 2020). The building age at the time of demolition allows one to estimate the annual depreciation rate of a structure.

The estimated depreciation rates for the structure component of residential property value fall within a relatively narrow range in the U.S.: 1.36% (Leigh, 1980), 1.89% (Knight and Sirmans, 1996), and 1.94% (Harding et al., 2007). Based on the National Accounts, the rate is 1.57% between 1948 and 2001 (Davis and Heathcote, 2005). The depreciation rate for the entire property is lower than these rates due to the non-depreciating land component.

2.4. Cohort effects and depreciation decomposition

Economic depreciation is caused by both physical deterioration—wear and tear of the structure—and functional obsolescence from technological progress and changes in consumer tastes. External obsolescence caused by a change in neighborhood characteristics can be combined with functional obsolesce and thus affect economic depreciation (Wilhelmsson, 2008). For the purpose of inflation measurement and national accounts, the relevant depreciation concept is the total economic depreciation from both deterioration and obsolescence.

Nonetheless, the decomposition of economic depreciation helps us better understand the characteristics of depreciation. For an investor or homeowner, for example, the distinction between physical deterioration and functional obsolescence would influence decisions about maintenance and capital improvement expenditures. However, it is not easy to disentangle physical deterioration and functional obsolescence. Many hedonic regression studies include period effects (i.e., time fixed effects) that control for changes in market conditions but omit cohort effects, which could result in a biased estimate of the depreciation rate (Browning et al., 2012). Francke and van de Minne (2017) argue that functional obsolescence is associated with the time of construction (i.e., cohort effects) because the functional characteristics of a house are determined largely by the taste and technology prevalent at the time of construction. At the same time, cohort effects include additional vintage premia or discounts associated with construction qualities (Coulson and McMillen, 2008).

A significant challenge to estimating the physical depreciation rate net of functional obsolescence is perfect collinearity among age, period, and cohort. A linear model cannot simultaneously account for these three variables. Consequently, cohort effects are often omitted in depreciation rate estimations (e.g., Randolph, 1988; Lane et al., 1988). However, it is not desirable to arbitrarily restrict cohort effects to zero. Alternatively, the econometricians can impose a specific functional form on one of the three effects. A standard practice is to assume that log rents are a quadratic function of age while keeping the other two effects flexible. However, there is evidence that a quadratic function cannot represent the age function (e.g., Coulson and McMillen, 2008; Francke and van de Minne, 2017).

Coulson and McMillen (2008) address this empirical challenge by using the method proposed by McKenzie (2006), which can be considered a variant of constrained generalized linear models. Specifically, they estimate the second differences of age, period, and cohort effects with no normalization restrictions. Then, they recover the function for each effect by integrating the second differences by setting an arbitrary slope for a base segment of each function. However, this method is sensitive to the arbitrary choice of the identifying constraint, which is a common issue for any constrained linear model (Browning et al., 2012).

Francke and van de Minne (2017) address the multicollinearity problem by imposing a constraint based on the economic decomposition of property value into structure and land. Their constraint is that the age coefficient represents the physical deterioration of structures, the cohort coefficient represents the sum of functional obsolescence and vintage effects, and the time coefficient represents the effect of land price and current construction costs. A key identifying assumption is that functional obsolescence depends only on the time of construction. Rolheiser, van Dijk and van de Minne (2020) compare house price returns across vintages in the Netherlands because vintage-associated supply constraints can affect house price returns in later years. They find that properties built before 1900 exhibit significantly higher price appreciation during 2000 and 2017 than those build just prior to the sample period after controlling for granular location fixed effects.

In our study, we use the IE method, which is widely used in demography and epidemiological research to address collinearity among age, period, and cohort (Yang et al., 2004; Yang et al., 2008). The IE addresses the age-period-cohort multicollinearity problem using a principal components regression method. The method essentially decomposes parameters and removes the component that causes the singularity of regressors (i.e., the component corresponding to the eigenvalue zero). The IE is consistent and unbiased and is more efficient than constrained linear estimators (Yang et al., 2004; Yang et al., 2008). Browning, Crawford and Knoef (2012) show that the IE and their maximum entropy estimator provide more reasonable estimates than linear estimators with arbitrary constraints.

Table 1
Summary statistics by property type.

Panel A: Single-Family Residences (N = 188,219)					
Variable	Mean	SD	Q25	Q50	Q75
Contract Rent ($)	1,392	507	1,100	1,292	1,500
Building Age	14.8	10.2	8.0	12.0	19.0
Living Area (Size) Square-Footage	1,908	645	1,478	1,754	2,168
Lot Area Square-Footage	5,344	2,982	3,920	4,792	6,510
Bedrooms	3.4	0.7	3.0	3.0	4.0
Bathrooms	2.7	0.6	2.0	3.0	3.0
Fireplaces	0.50	0.61	0.00	0.00	1.00
Private Pool^d	0.13	0.33	0.00	0.00	0.00
Private Spa^d	0.09	0.28	0.00	0.00	0.00
Garage Car Spaces	2.05	0.58	2.00	2.00	2.00
Panel B: Condominiums (N = 89,324)					
Variable	Mean	SD	Q25	Q50	Q75
Contract Rent ($)	1,024	545	750	895	1,100
Building Age	17.7	10.4	10.0	15.0	24.0
Living Area (Size) Square-Footage	1,200	514	937	1,108	1,308
Lot Area Square-Footage	846	1,977	0	0	871
Bedrooms	2.0	0.7	2.0	2.0	2.0
Bathrooms	2.0	0.6	2.0	2.0	2.0
Fireplaces	0.37	0.51	0.00	0.00	1.00
Private Pool^d	0.00	0.07	0.00	0.00	0.00
Private Spa^d	0.02	0.13	0.00	0.00	0.00
Garage Car Spaces	0.65	0.80	0.00	0.00	1.00
Townhouse (TH)^d	0.28	0.45	0.00	0.00	1.00

This table reports the mean, standard deviation (SD), 25th percentile (Q25), 50th percentile (Q50), and 75th percentile (Q75) of select characteristics by property type. The sample includes leased properties advertised for rent on the MLS in Clark County, NV between 2009Q1 and 2019Q1. *d* denotes a dummy variable. The mean of the dummy variables can be interpreted as the share of the sample for which the dummy variable is 1.

3. Data

3.1. Sources

Our principal data source is the Las Vegas Realtors' MLS, which is a database of real estate listings powered by CoreLogic and updated by real estate agents with membership to the Las Vegas Realtors.[7] Real estate agents commonly advertise property for sale or rent on behalf of a property owner on the MLS because other real estate agents use the same MLS to help buyers or tenants find property. Although the Las Vegas Realtors' MLS provides information on only local properties, it feeds data to major online websites with a national presence such as Zillow, Trullia, and Redfin. When real estate agents complete a transaction (e.g., arrange a lease contract between a landlord and tenant), they update the corresponding listing record in the MLS with details such as the agreed price (or rental rate). The raw MLS rental data contain more than 330,000 rental listings, of which approximately 288,000 resulted in newly contracted leases.

We focus on the records of new rental contracts for single-family and condominium properties in Clark County, NV, put on the market between 2009Q1 and 2019Q1.[8] New rental rates better reflect the marginal rent determinied in the rental market (Ambrose et al., 2015). For each new lease, we observe the initial contract rent amount, the utility costs the tenant must pay (i.e., whether a lease is net or gross), and whether a unit is equipped with appliances such as a washer and a dryer. Furthermore, we observe standard property characteristics such as the building's age, living area size in square-footage, lot area square-footage, bedrooms, and bathrooms. Neighborhood amenities (e.g., gated community, school zoning) are also observable. However, we enhance the MLS data by merging it with public assessor tax records from Clark County, NV. We subsequently observe (as of March 2019) the assessed property value (i.e., structure, land), assessed quality (low, fair, average, good, very good, or excellent), property type (i.e., single-family, condominium), and geographical location information (e.g., longitude and latitude, census tract, etc…). Lastly, we collect demographic characteristics at the census tract level from the 2014–2018 American Community Survey (5-year estimates).

3.2. Sample selection

We remove MLS observations that did not correctly report parcel numbers (approximately 0.5% of the sample) because we rely on parcel numbers to merge the MLS data with assessor records. To ensure that outliers do not influence our results, we also exclude records on lease contracts for residential properties with: 1) rents greater than $10,000 per month or less than $300 per month, 2) a living area larger than 6,000 square feet or smaller than 400 square feet, 3) a lot size larger than 50,000 square feet, 4) more than five bedrooms, 5) more than six bathrooms, 6) a garage that fits four or more cars, 7) more than four fireplaces, 8) an age of 60 years or more, 9) a referral commission amount greater than $2,400, and 10) missing pertinent variables for the study such as census tract. Our final sample comprises 188,219 new leases for single-family residences and 89,324 new leases for condominiums, representing approximately 96% of all the new leases registered in the MLS rental database.

Table 1 provides the mean, standard deviation, and percentiles (25th, 50th, and 75th) of the key characteristics by property type. A dictionary that describes each variable is available in Table D.1 in Appendix D, and the summary statistics for all variables in our sam-

[7] Las Vegas Realtors are formally known as the Greater Las Vegas Association of Realtors. For further details, see https://www.lasvegasrealtor.com/.

[8] We define a condominium as an individually owned unit within a multi-family complex. We include individually owned units in townhouses, duplex, triplex, and fourplex structures in the condominium sample because they are not detached and by definition share a common wall or floor/ceiling with a neighbor.

Table 2
Comparison of non-MLS and MLS Residences in Clark County, NV.

Variable	Non-MLS	MLS	Difference	t-stat	d-stat
Land Value	24,242	21,788	−2454	−42.03***	-0.13^{s}
Structure Value	59,026	52,068	−6959	−38.97***	-0.12^{s}
Size (Square-Footage)	1938	1713	−224	−90.35***	-0.28^{sm}
Lot Acreage	0.14	0.09	−0.05	−143.66***	-0.44^{m}
Year Built	1996	1998	2	44.74***	0.14^{s}
Bedrooms	3.18	3.09	−0.09	−31.53***	-0.10^{s}
Bathrooms	2.36	2.35	−0.01	−3.65***	-0.01^{s}
Fireplaces	0.49	0.38	−0.11	−57.26***	-0.18^{s}
Pool	0.19	0.09	−0.10	−85.40***	-0.26^{sm}
Quality: Low	0.19	0.15	−0.04	−30.93***	-0.10^{s}
Quality: Fair	0.39	0.48	0.09	60.70***	0.19^{s}
Quality: Average	0.39	0.33	−0.06	−38.61***	-0.12^{s}
Quality: Good	0.04	0.03	−0.01	−14.93***	-0.05^{s}
Quality: Very Good	0.01	0.02	0.01	39.68***	0.12^{s}
Quality: Excellent	0.00	0.00	0.00	−8.78***	-0.03^{s}
Property Type: Single Family	0.83	0.70	−0.13	−106.92***	-0.33^{sm}
Property Type: Condominium	0.10	0.21	0.12	114.93***	0.35^{sm}
Property Type: Other (e.g., townhouse)	0.07	0.09	0.02	18.50***	0.06^{s}
Unique Count of Properties:	494,493	130,967			

This table reports the mean value of assessor characteristics for unique properties in Clark County, NV. The Non-MLS sample consists of unique, non-commercial residences that were not listed for lease in the MLS from 2009Q1 to 2019Q1. The MLS sample consists of unique residences in Clark County, NV that were listed for lease in the MLS from 2009Q1 to 2019Q1. This table also reports the corresponding statistics from a two-tailed mean difference test and Cohen's d statistics. The quality and assessed values for land and structure are as of March 2019. *** represents statistical significance at the 1% level. *s*, *sm*, and *m* represent d-statistics that imply a small, small-to-medium, and medium-sized economic effect, respectively.

ple are available in Table E.1 in Appendix E. The typical leased single-family residence is 14.8 years old with a living area of 1908 square feet, which often includes about three bedrooms, two to three bathrooms, and a two-car garage. A fifth of the single-family residences are in a gated community, and more than 73% are located in a community with covenants, conditions, and restrictions (e.g., rules generally set by a homeowner's association). The typical leased-condominium is 17.7 years old with a living area of 1200 square feet. However, approximately 54% of the condominiums are located in a gated community and approximately 79% have community rules. Many of the condominium communities provide amenities such as a community pool (82%), spa (48%), clubhouse (35%), and gym (34%).

3.3. Representativeness

Since inflation measurements may rely on the principle that the owners' equivalent rent can be imputed from the rental price of equivalent properties, we check whether our sample is representative of the local housing stock by comparing unique properties in our sample (MLS) with other non-commercial, residential properties (non-MLS) in the Clark County tax assessor records that do not show up as leased in the MLS.[9] We focus on variables in the tax assessor records, including the property's assessed value and assessed quality as of March 2019. Table 2 reports the mean, mean difference, and corresponding t-statistics of a two-tailed mean difference test along with Cohen's d-statistic for each variable. While the t-statistic provides information on the statistical significance of a mean difference, Cohen's d-statistic provides a measure of the economic significance of the two-tailed *t*-test (see Cohen, 2013). Commensurate with the d-statistic's value, the economic significance of a mean difference may be small ($|d| = 0.2$), medium ($|d| = 0.4$), or large ($|d| = 0.8$) depending on the ratio of the mean difference to pooled standard deviation.

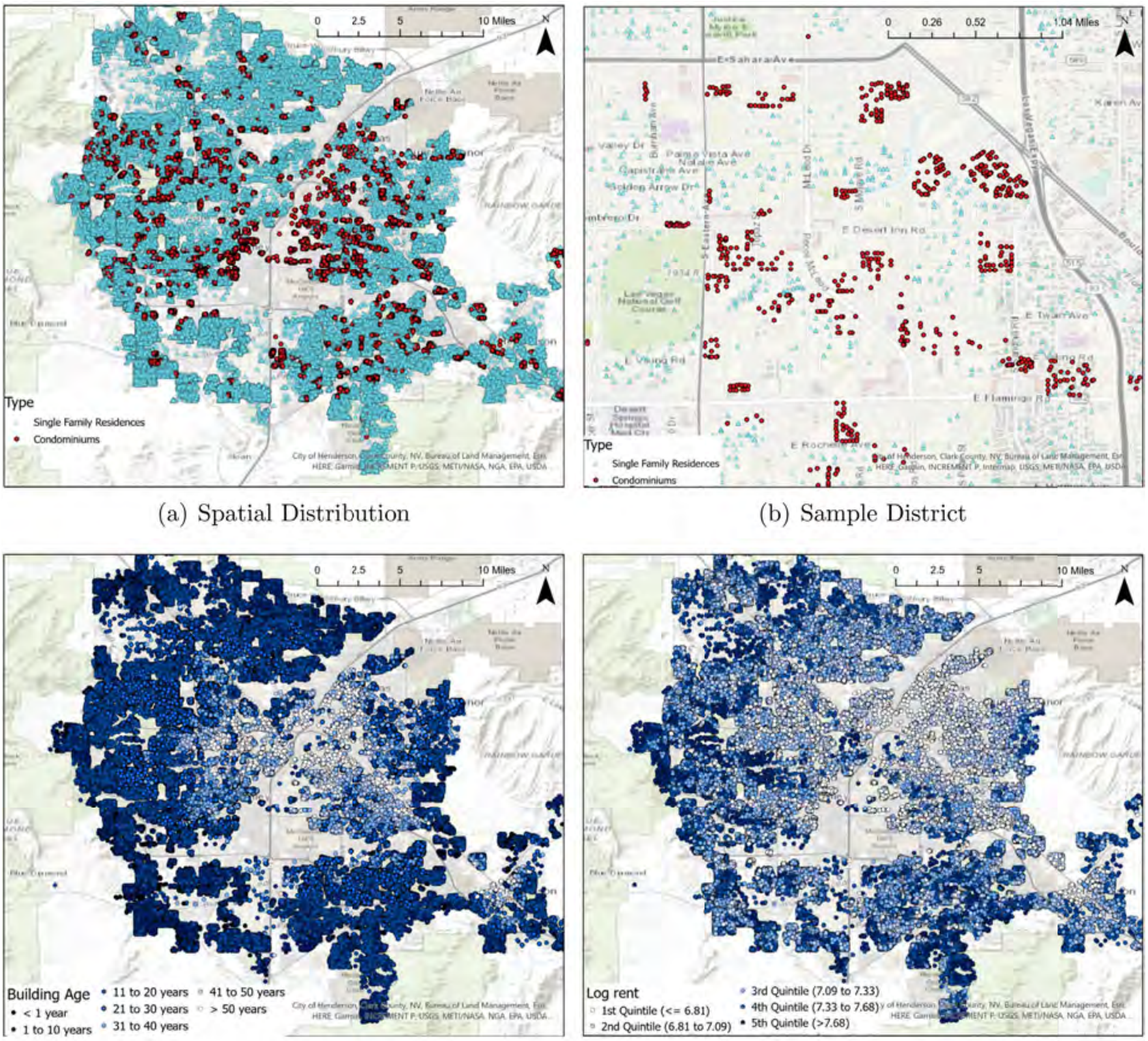
Approximately 131,000 unique residential properties are in our MLS sample and 494,493 are not in our MLS sample, implying that our sample accounts for approximately 21% of the single-family and condominium stock in Clark County, NV. The assessed value for non-MLS properties is approximately 12.7% higher than that of MLS properties. Moreover, MLS properties appear to be of lower quality than non-MLS properties, suggesting that real estate structures depreciate at a greater rate when used as an investment vehicle. However, these differences are inconsequential. Although the t-statistic from a mean difference test is statistically significant for each variable in Table 2, the Cohen's d-statistics indicate that the mean difference for the assessed value, assessed quality, and several other variables is small and not economically meaningful.

Figure F.1 in Appendix F plots the kernel density of the effective year built for the entire population of single-family/condominium properties in Clark County and the population of MLS rental properties. As Figure F.1 shows, the distributions of year-built are similar across the two samples, which further mitigates concerns about whether the sample of MLS properties is representative of the local housing stock. Therefore, using the MLS sample to determine the depreciation expenses that make up part of the opportunity cost of home-ownership would be reasonable for local inflation measurement purposes.

3.4. Location, rent, and age profile

We examine the location of rentals along with age and rent patterns across the county. Fig. 1(a) plots the locations of single-family and condominium rentals. Both types of housing are widely distributed throughout the county, which encloses the Las Vegas MSA. Condominium blocks and single-family blocks are located next to each other, as shown in Fig. 1(b). Fig. 1(c) maps the distribution of rentals by structure age. The oldest buildings tend to be in the downtown Las Vegas area, whereas newer structures are in the peripheries. Fig. 1(d) provides a heat map of the log contract rents, which inversely mirror the

[9] For a parallel comparison, we limit the non-MLS properties to single-family residences, condominiums, and other attached residences such as townhouses, duplexes, or triplexes that have a living area size between 400 and 6,000 square-feet, lot size less than 50,000 square-feet, fewer than six bedrooms, fewer than seven bathrooms, less than five fireplaces, and are less than 60 years old.



(a) Spatial Distribution (b) Sample District

(c) Age Distribution (d) Contract Rent Distribution

Fig. 1. Maps of Rental Lease Contracts in Clark County, NV. Panel (a) maps single-family residences and condominium leases in Clark County, NV from 2009Q1 to 2019Q1. The blue and red dots represent single-family and condominium leases, respectively. Panel (b) zooms in to a sample district. Panel (c) plots the age distribution of single-family and condominiums, where darker colors indicate newer properties. Panel (d) plots the log rent distribution, where darker colors indicate higher rents. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

building age heat map. The maps suggest a strong correlation between price and age.

To take a first look at rent depreciation, we identify new properties and partition those at least one year or older into ten-year age groups, that is, 1–10 years, 11–20 years, and so on. Fig. 2 is a bar graph of contract rents in hundreds by age group for single-family residences and condominiums. The median contract rent generally decreases with building age for both property types. For example, a new single-family residence that is less than one year of age is leased for $1500 per month, whereas a 60-year-old single-family residence is leased for $950 per month, representing a 37% discount or an annual depreciation rate of 0.61% (or an approximately 0.76% depreciation rate if measured geometrically). The variation in contract rents is much more substantial for condominiums. New condominiums have a lease rate of $1400 per month, whereas 60-year-old condominiums have a lease rate of $560 per month, implying a rental depreciation rate of approximately 1% per year (or 1.5% geometrically).

4. Empirical analysis

4.1. Baseline model

Median age discounts are not accurate estimates of depreciation rates because they do not account for housing and location characteristics. For instance, rents are generally lower around the peripheries where newer properties tend to be built. Moreover, other attributes could also play a role in rents and affect depreciation estimates. To account for variation in the observable characteristics and examine heterogeneity in rent depreciation across several dimensions, we estimate a hedonic model:

$$\ln Y_{it} = f(A_i, C_i) + X_i\beta + \alpha_j + \tau_t + \epsilon_{it}, \tag{1}$$

where $\ln Y_{it}$ denotes the natural log of the contract rent of property i at time t, $f(A_i, C_i)$ is a function of building age A_i and a vector of property and neighborhood characteristics C_i, and X_i denotes the vector

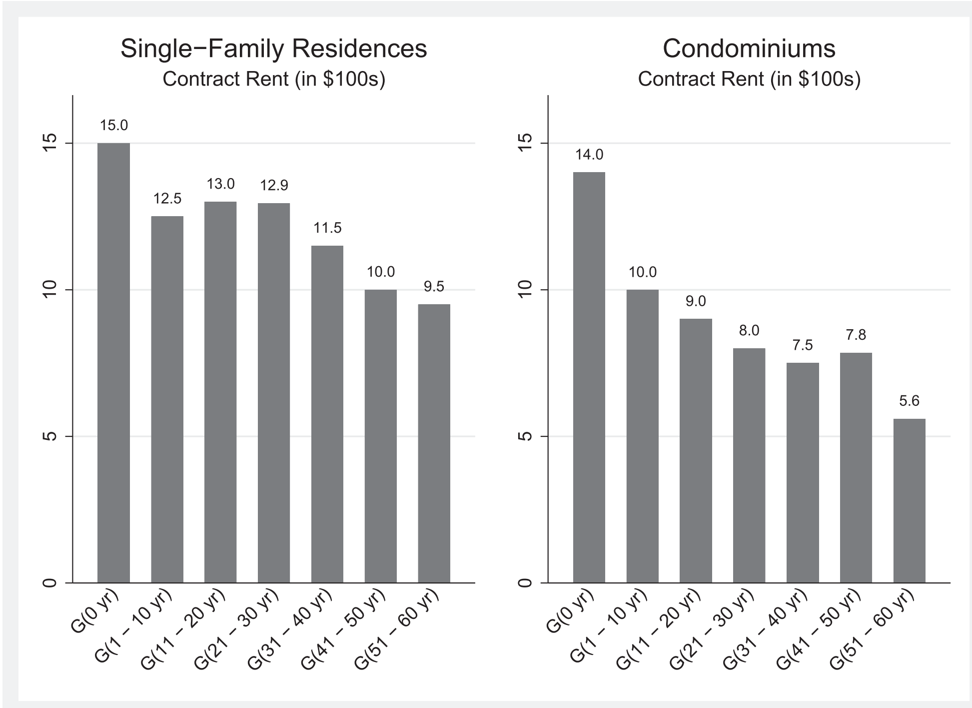


Fig. 2. Median Contract Rent by Building Age and Property Type. This figure reports median contract rent by the building age group for single-family and condominium leases in Clark County, NV from 2009Q1 to 2019Q1. Median rents are reported in hundreds.

of controls that include several observable characteristics. α_j denotes location (census tract) fixed effects and τ_t denotes time (listing year-quarter) fixed effects. Finally, ϵ_{it} denotes the error term.

Our objective is to estimate the rent depreciation rate, which is the marginal effect of age on log rent: $\partial f(A_i, C_i)/\partial A_i$. To allow depreciation to vary by characteristic, we interact building age with the characteristic variables:

$$f(A_i, C_i) = A_i C_i \delta, \tag{2}$$

where A_i is a scalar, C_i is a vector of characteristics, and δ is a parameter vector. In our main estimation, we use two specifications of C_i:

$$C_i^1 = \left[1\ A_i\ Size_i\right], \tag{3}$$

$$C_i^2 = \left[G_g\ Size_i\right], \tag{4}$$

where $Size_i$ denotes the demeaned log square-footage of the property's living area.[10]

Both specifications allow the depreciation rate to vary by age. In the first specification, log rents are a quadratic function of age, as in Lane et al. (1988) and Randolph (1988). In the second specification, G_g denotes a set of indicator variables for 5-year age groups. That is, G_g takes a value of one if a building's age is in age group g, where $g = \{0\text{years}, 1\text{–}5\text{years}, 6\text{–}10\text{years}, 11\text{–}15\text{years}, \cdots\}$; it is zero otherwise. Thus, the parameter vector δ for C_i^2 gives the age-group-specific depreciation rates.

We also analyze whether depreciation rates vary significantly by neighborhood characteristics by adding neighborhood variables to C_i^k where $k \in \{1, 2\}$:

$$C_i^{3,k} = (C_i^k\ Neighborhood_j), \tag{5}$$

$$C_i^{4,k} = (C_i^k\ Tract_j). \tag{6}$$

In the third specification (equation (5)), $Neighborhood_j$ denotes a vector of neighborhood characteristics for census tract j, including the homeownership rate, share of population 65 years or older, Hispanic population share, non-Hispanic Black population share, Asian population share, log population density per square-mile, and log median household income. We demean each variable in $Neighborhood_j$ by the appropriate single-family or condominium subsample average value to ensure that the level effect of age (which is embedded in δ) represents that of the average property or census tract in the sample.

In the fourth specification (equation (6)), $Tract_j$ denotes a set of census tract indicator variables. Thus, both observed and unobserved neighborhood characteristics can affect depreciation rates in equation (1) through the interaction of $Tract_j$ with Age. We set the reference census tract to the tract with the mean depreciation rate among all census tracts for each property type subsample to ensure that estimates with the other specifications are comparable.[11]

Put differently, we allow for non-constant depreciation rates by the term A_i^2 for equations (3), (5) and (6) and $A_i G_g$ for equations (4)–(6). We also introduce level shifts by size ($A_i Size_i$), observable neighborhood characteristics ($A_i Neighborhood_j$), and unobservable neighborhood characteristics ($A_i Tract_j$).

To ensure that the age coefficients (δ) capture economic depreciation and not other factors that may correlate with both age and rent, X_i includes a rich set of service, structure, and neighborhood characteristics, which we list in Table D.1 in Appendix D. Many of these variables

[10] For the condominium sample, we also use an indicator to control for townhouse, duplex, or triplex (*TH*) by including *TH* in equation (4). For every regression, we demean the living area square-footage using the appropriate sample to ensure that δ in equation (2) describes the rental depreciation rate for the averaged sized property in the sample.

[11] We find the means census tract in a two step procedure. First, we run the regression with the $Tract_j \times Age$ interaction, allowing Stata to choose the reference group. Second, we manually find the census tract where the absolute difference between the coefficient on the $Tract_j \times Age$ interaction and the same coefficient (but weighted by the share of rentals in the respective census tract) from the first step is minimized. This mean census tract reference number is 4912 for single family residences and 2501 for condominiums.

overlap with those in the existing depreciation models (e.g., Lane et al., 1988; Randolph, 1988; Coulson and McMillen, 2008).

The service characteristics control for whether the tenant pays for cable, gas, power, sewer, water, garbage disposal, or other services. Among these services, Lane et al. (1988) account only for gas and power. Since utilities makeup the operating expenses of rental property that could be directly or indirectly shifted to tenants, by including indicators for the expenses tenants must pay, we tease out the implicit effect of triple net leases, modified gross leases, and full-service gross leases on rents. Generally, the tenant pays for all the operating expenses in a triple net lease, while the landlord pays for all the operating expenses in a full-service gross lease. The modified gross lease is a mixture of the other two lease types. Thus, the rental rate of a property in a triple net lease may appear to be lower than in a full-service lease or modified gross lease if we do not account for the differences in the services included in the rent (e.g., Wiley, 2014). Differences in rent across property type could occur because rental contracts tend to be more net for single-family residences. Table E.1 in Appendix E reports that tenants pay for power (99%), gas (97%), water (95%), cable (81%), garbage pickup (78%), and sewer (68%). In contrast, tenants in condominiums are less likely to pay for water (38%), sewer (26%), and garbage pickup (27%).[12]

The structure characteristics account for the natural log of the living area square-footage, natural log of the lot square-footage, number of bedrooms, number of bathrooms, number of fireplaces, number of car spaces in the garage, and indicators of a private pool and/or spa. They also account for categorical variables for the heating fuel type, cooling fuel type, and installed appliances (i.e., dishwasher, washer, dryer). For categorical variables, the most prevalent class is set as the base.

Lastly, the neighborhood characteristics flag whether a property is located in an age-restricted community or gated community. They also flag several community features (pool, spa, park, golf, basketball, gym, rules) and the corresponding high school and junior high school districts. According to Randolph (1988), neighborhood characteristics mitigate concerns that depreciation estimates could capture cohort effects.

4.2. Baseline results

Table 3 reports the results of separate ordinary least squares (OLS) estimations of equation (1) for each property type (single-family residence or condominium). The odd columns show the coefficients of the age function based on equation (3), whereas the even columns show the age-group-specific coefficients based on equation (4). The dependent variable is the log contract rent for leased properties and the standard errors reported in parentheses are clustered by census tract location. Building age is divided by 100 (and building age squared by 1000) to observe the coefficients in percentage form, as in Coulson and McMillen (2008). The coefficients for the suppressed variables are reported in Appendix E, Table E.3.[13]

We see in column (1) of Table 3 that the coefficients on Building Age/100 and Building Age^2/1000 are −0.78 and 0.07, respectively. Both coefficients are statistically significant at the 1% level. We evaluate the marginal effect of age on rent at age 15 (i.e., $\delta_1 + 0.2\delta_2 15$), which is close to the average age of a property in the sample. The annual depreciation rate for the average single-family residence is approximately 0.57% and decreases in magnitude by approximately 0.07% points for every additional five years of age. In contrast, column (2) suggests that the depreciation rate of a single-family residence in the 11–15 years age group is higher, at a rate of 0.75%, which is statistically significant at the 1% level. Furthermore, the annual depreciation rate varies non-linearly by age group. The annual depreciation rate is 0.9% between 1 and 5 years, but 0.38% between 56 and 60 years of age. The two point estimates are statistically different from each other at the 1% level. To formally test if depreciation is heterogeneous, in Section E of the Appendix (column (1) of Table E.8), we include the level effect of Age and omit the 1–5 years age group in the non-parametric model. A Wald test of joint significance across the 11 remaining age group interactions with age produces an F-statistic of 14.7 (and p-value of 0.000), rejecting the null hypothesis that the rent depreciation rate is constant across all ages.

Fig. 3(a) plots the coefficients corresponding to columns (1) and (2) along with 95% confidence intervals. The annual depreciation rate monotonically decreases in magnitude as a property ages with both specifications. Put differently, newer properties depreciate at a much faster rate than older properties. The age-group-specific model shows that the depreciation rate of a 1–5 years old property is 1.5 times higher than that of a 21–25 years old property and 2.25 times higher than that of a 56–60 years old property. Similarly, the depreciation rate plot from the quadratic age model shows that a 5-year-old property depreciates at a much faster rate than a 60-year-old property. This high initial depreciation shown by both age functions is consistent with the findings by Coulson et al. (2019) that the first year of use can have a rather dramatic effect on price in Las Vegas.

However, we observe a significant difference in the estimated depreciation rates between the two age function specifications. In particular, the difference between the linear and non-linear depreciation estimates increases with age. Whereas the quadratic age function implies that rent depreciation reverses and becomes positive for a 60-year-old property, the age-group-specific model indicates that the annual depreciation rate is approximately 0.38% for a property that is 60-years. At the bottom of Table 3, we report the Akaike information criterion (AIC) and Bayesian information criterion (BIC) in each column to test the fit of each rent model. The AIC and BIC measures are lower when using equation (4) as the age function in column (2) than when using equation (3) as the age function in column (1), rejecting the quadratic log model of rent depreciation in favor of an age-group-specific model.

Condominiums depreciate at a significantly higher rate than single-family residences, across all age profiles. Column (3) implies that the average annual depreciation rate is 1.72% at age 15, or three times the depreciation rate of single-family residences. The average age-group-specific depreciation rate for condominiums in the 11-15-year-old group is 1.91% and statistically significant at the 1% level. However, unlike for single-family residences, annual depreciation rates do not seem to significantly vary by age group for condominiums. For example, the depreciate rate estimate for condominiums 1–5 years of age is not statistically different from that of condominiums 56–60 years of age or other age groups. These results suggest that there are differences in the depreciation rate across property types.

We formally test whether the coefficients in the rent model are different across single-family and condominium rents in a two step procedure. First, we estimate equation (1) without the age function and retrieve the residuals, separately for each property type. Second, we regress each set of residuals on the age function being tested (i.e., equation (3) or (4)). A Chow test of equality on the coefficients of equation (3) across single-family residences and condominiums yields an F-statistic of 4,810.55 (with a p-value of 0.000). Likewise, a Chow test on equation (4) by property type yields an F-statistic of 5,597.57 (with a p-value of 0.000). These two tests indicate that rent depreciation estimates (whether linear or non-linear) differ by property type at the 1% significance level.

Fig. 3(c) illustrates the coefficients across the age profiles for condominiums by model, showing that the depreciation estimates for the age-group-specific plot for the other age groups generally fall within

[12] Table E.2 in the Appendix shows further variation across age groups in who is responsible for paying various operating expenses or services, which could affect observable differences in rent.

[13] For all analyses, we use the "reghdfe" Stata package by Correia (2014, 2016), which iteratively removes "singleton" observations depending on the categorical variables and fixed effects in the regression model. Removing the singleton observations improves the precision of standard errors.

Table 3
Annual rent depreciation rates.

Dep. var. ln(Rent) Sample:	(1) SFR	(2) SFR	(3) COND	(4) COND
Age/100	−0.78***		−2.14***	
	(0.04)		(0.44)	
$Age^2/1000$	0.07***		0.14**	
	(0.01)		(0.06)	
G(1–5 yrs) × (Age/100)		−0.90***		−1.50***
		(0.07)		(0.31)
G(6–10 yrs) × (Age/100)		−0.86***		−1.75***
		(0.04)		(0.24)
G(11–15 yrs) × (Age/100)		−0.75***		−1.91***
		(0.04)		(0.28)
G(16–20 yrs) × (Age/100)		−0.67***		−1.84***
		(0.03)		(0.29)
G(21–25 yrs) × (Age/100)		−0.60***		−1.75***
		(0.03)		(0.30)
G(26–30 yrs) × (Age/100)		−0.57***		−1.64***
		(0.03)		(0.25)
G(27–35 yrs) × (Age/100)		−0.54***		−1.56***
		(0.03)		(0.22)
G(36–40 yrs) × (Age/100)		−0.49***		−1.51***
		(0.02)		(0.20)
G(41–45 yrs) × (Age/100)		−0.47***		−1.52***
		(0.03)		(0.18)
G(46–50 yrs) × (Age/100)		−0.46***		−1.49***
		(0.02)		(0.19)
G(51–55 yrs) × (Age/100)		−0.43***		−1.49***
		(0.03)		(0.19)
G(56–60 yrs) × (Age/100)		−0.38***		−1.35***
		(0.03)		(0.17)
$(Age/100) \times \ln(Size)^{dm}$	−0.41***	−0.42***	−1.32***	−1.30***
	(0.04)	(0.04)	(0.21)	(0.21)
(Age/100) × TH			0.81***	0.81***
			(0.16)	(0.15)
Observations	188,216	188,216	89,318	89,318
Adjusted R^2	0.88	0.89	0.86	0.86
AIC	−342,009.09	−342,154.73	−101,151.37	−101,424.57
BIC	−341,613.43	−341,657.61	−100,765.97	−100,945.17
Structure controls	✓	✓	✓	✓
Neighborhood controls	✓	✓	✓	✓
Service controls	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Census Tract FE	✓	✓	✓	✓

This table reports the OLS estimates of the hedonic model specified by equation (1) for single-family residences (columns 1 and 2) and condominiums (columns 3 and 4). The age function is specified by equation (3) for columns (1) and (3), and equation (4) for columns (2) and (4). The dependent variable is log contract rents. $G(\cdot)$ denotes an indicator function for each age group. Variables with the *dm* superscript are demeaned. Structure controls include log unit size, log lot area, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel, cooling fuel, dishwasher, and washer/dryer. Service controls include indicators of tenant payments for cable, gas, power, sewer, water, garbage pickup, and other services. Neighborhood controls include age restriction, gated community, community amenities such as pool, clubhouse, schools, and a townhouse/duplex/triplex flag (TH). All regressions have a constant. Table D.1 in the appendix provides definitions for each variable, and Table E.3 in the appendix reports the suppressed coefficients of several characteristics. The properties were advertised for rent on the MLS in Clark County, NV between 2009Q1 and 2019Q1. AIC stands for Akaike information criterion, and BIC stands for Bayesian information criterion. Robust standard errors are in parentheses and clustered by census tract. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

the 95% confidence interval of the depreciation rate of approximately 1.5% for age group 1–5 years. This lack of significance is partly due to less precise estimates, possibly due to the smaller sample size of condominiums than single-family residences or different cohort effects, as we discuss later. However, a Wald test indicates that the age-group-specific coefficients are critical at the 1% statistical significance level for condominium rents (see Table E.9). Moreover, the AIC and BIC measures (in columns (3) and (4) of Table 3) indicate that the age-group-specific model produces a better fit than the linear depreciation model. Thus, the depreciation rate profile from the age-group-specific model suggests that a non-linear log depreciation model is a good approximation for condominiums.

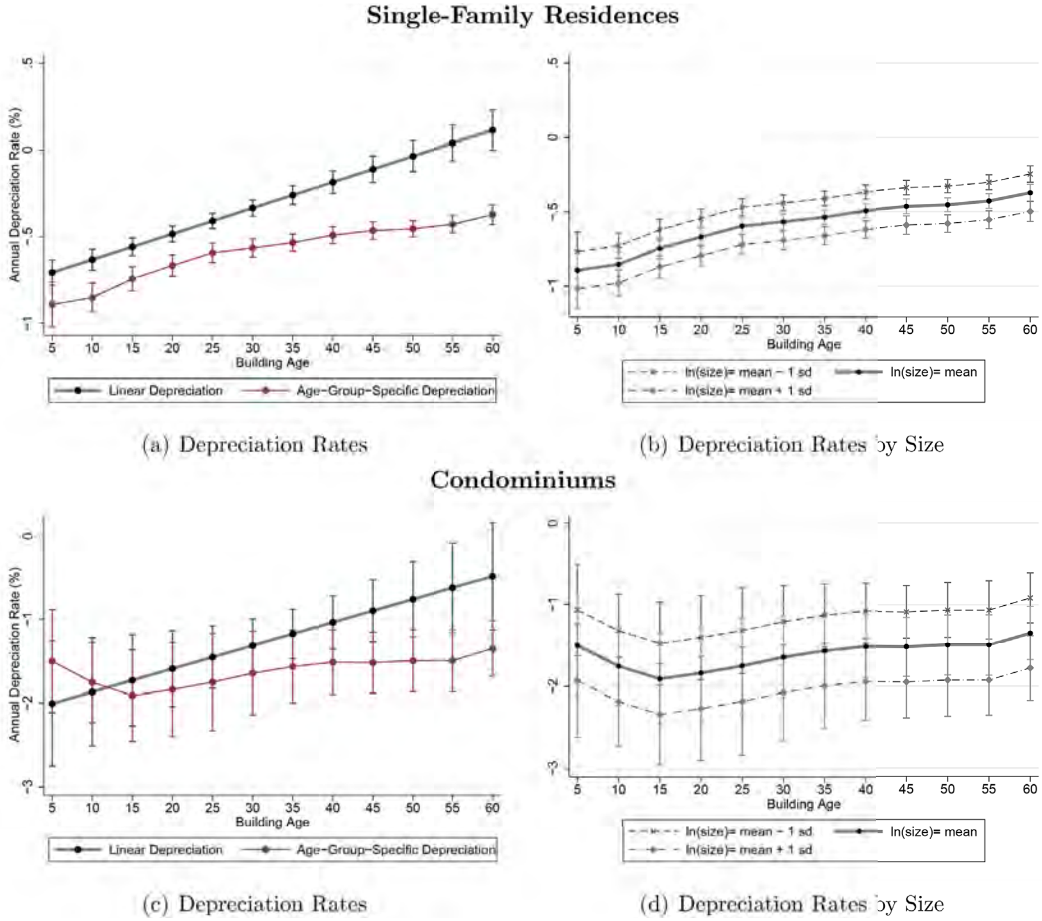


Fig. 3. Rent Depreciation by Property Type, Age, and Size. This figure depicts the economic rent depreciation for single-family residences (panel a) and condominiums (panel c) according to the model results in Table 3. Panels (b) and (d) report the age-group-specific depreciation rate at the mean log size, one-standard-deviation above the mean log size, and one-standard-deviation below the mean log size for single-family residences and condominiums, respectively. On the horizontal axis, building age corresponds to the end year of the age groups from 1 to 5 years, 6–10 years, and so on.

In addition to variations in depreciation across age groups and property types, we observe a correlation between depreciation and property size. The coefficients on the interactions between building age and size (demeaned) in columns (1)–(4) in Table 3 are negative and statistically significant at the 1% level, providing evidence of cross-sectional variation in the age profile. These findings imply that properties with a larger structure depreciate faster than properties with a smaller structure because of a larger proportion of structure rent (see Appendix B). This type of size variation is also observed in price depreciation (Himmelberg et al., 2005). The coefficients on $(Age/100) \times ln(Size)^{dm}$ suggest that for every one-standard-deviation increase in the living area the depreciation rate increases by approximately 0.13 percentage points for a single-family residence and by 0.43 percentage points for condominiums.

Fig. 3(b) and (d) depict the variation in depreciation rates by a one-standard-deviation change in unit size from the mean log value based on the age-group-specific depreciation estimates from columns (2) and (4). Between ages 11 and 15 years, contract rents depreciate by approximately 0.62% each year for a small 1,350 square-foot single-family residence but by 0.87% for a large 2,500 square-foot residence. The depreciation rate is 40% higher for large residences (Panel (b)). We observe even greater variation with condominium leases (Panel (d)). For the 11–15 years age group, the rent depreciation rate is 1.48% for a small 800 square-foot condominium but 2.34% for a large 1,600 square-foot condominium.[14]

In sum, we observe variation in depreciation estimates along the dimensions of age group, property type, and living area size (square-footage).[15] Therefore, using the same depreciation rate to model rental cash flows across various residential properties of different types or ages or both could result in biased estimates of the local inflation rate, home-ownership costs, and property values.

[14] In the Appendix, we examine whether the floor-to-area ratio affects the rents of single-family residences. The floor-to-area ratio (FAR) is a measure of physical density and calculated as the living area square-footage divided by the lot area square-footage (winsorized at the 1% tails). We find that FAR does not impact the depreciation rate (see Table E.4). Thus, variation is not driven by the physical density of a single-family property but is associated with the structure size. This result can be because a high physical density is associated with high land prices, which will decrease the proportion of structure rents to housing rents. We cannot conduct this analysis for condominiums. The lot area is zero for most condominiums because they often have only air-rights, causing FAR to be undefined for 70% of the sample of condominium rentals.

[15] In Appendix E, we replicate our baseline analysis using asking rents and a sample that includes unsuccessful listings. The depreciation profile varies similarly with asking rents for all properties (see Table E.5). We also re-estimate our results using census-tract-time fixed effects and street name fixed effects as in Rolheiser, van Dijk and van de Minne (2020). Although the census tract fixed effects in equation (1) calibrate the model for time-in-variant attributes that could affect rent, neighborhood characteristics may change over time. We find slightly lower depreciation estimates, but the variation in the estimates are qualitatively similar (see Table E.6).

4.3. Depreciation heterogeneity by location

We probe the role of location in rent depreciation by estimating a set of rent models that allow age effects to vary by location. Since rent depreciation is proportional to the fraction of the structure rent relative to the total rent (see Appendix B), rent depreciation may vary with the underlying land rent. For example, in high land value locations, rent depreciation could be low because the total rent paid is mostly for the non-depreciating land. The opposite may occur in low land value locations as the structure rent becomes a larger component of the total rent.

We consider three alternative specifications for the parametric and non-parametric depreciation functions, and estimate the rent deprecation models by property type. For the first specification, we remove the neighborhood characteristics and census tract fixed effects from our baseline model (equation (1)) to better understand the importance of location controls. The second specification (equations (1) and (5)) retains neighborhood characteristics and census tract fixed effects and further adds interactions of building age with de-meaned demographic variables at the census tract level to examine how depreciation rates vary systematically across neighborhood profiles. The census tract demographic variables are based on the 5-year estimates from the 2014–2018 American Community Survey (home-ownership rate, share of population 65 years or older, Hispanic population share, non-Hispanic Black population share, Asian population share, log population density per square-mile, and log median household income). The third specification (equations (1) and (6)) allows depreciation rates to vary by census tract using interaction terms between building age and census tract indicators. For each property type subsample, the reference census tract is the tract with the mean depreciation rate among all census tracts.

Table 4 reports the results for the first specification without neighborhood controls. Column (1) shows that the average depreciation rate reduces in magnitude to 0.52% and the age-squared term becomes statistically insignificant. In contrast, column (2) shows that the depreciation rate for new single-family residences (1–5 years) increases to 1.16%, which is approximately 29% larger than the main result (column (2), Table 3). Single-family residences between 11 and 30 years old appear to depreciate at slightly lower rates than previously estimated, whereas older properties depreciate at similar rates. Columns (3) and (4) provide the same analyses for condominiums. The average condominium depreciation rate for each age profile slightly increases in magnitude compared to the baseline estimates (columns (3) and (4), Table 3) except for a few cases. These results suggest that the omission of location and neighborhood characteristics may result in mismeasurement of the depreciation rate because the age coefficients include locational variation in rents, which is correlated with building age, as evident in Fig. 1.

More formally, we test for differences in the age function coefficients between each column in Table 3 and the corresponding column in Table 4 using a Hausman test. To do so, we first condition out the variables in equation (1) except for those that make up the age function and neighborhood controls (including the census tract fixed effects). We then estimate fixed and random effects models using the residuals as the dependent variable and the remaining controls as regressors. The random effects model that excludes the neighborhood controls is efficient under the null hypothesis, whereas the fixed effects model that includes the neighborhood controls is consistent. We carry out the Hausman test on the common variables (i.e., age function) separately by property type and age function. Table E.7 in Appendix E reports the Chi-squared statistics and corresponding p-values from a set of Hausman tests. Each test rejects the null hypothesis that there are no systematic differences in the age function coefficients with the inclusion of neighborhood controls. Therefore, the inclusion of neighborhood controls (and census tract fixed effects) are critical for both single-family residences and condominiums irrespective of whether the rent depreciation model is quadratic or age-group-specific. We obtain similar results using a generalized Hausman test.

Table 5 reports the results for the second specification, in which depreciation estimates vary by *Census Variables*. Columns (1) and (2) show that for single-family residences, the average depreciation rate for each age profile does not significantly change from the baseline estimates (columns (1) and (2), Table 3) when we allow depreciation rates to vary by observable neighborhood characteristics. This is by design as the census variables are demeaned to preserve the age effects of the average location and ensure consistency with the baseline estimates. Rent depreciation seems to vary with deviations from the average 65+ population share and Hispanic share at a statistically significant level, but not with the other census variables (i.e., home-ownership, Black share, Asian share, population density, median household income). However, the variation in depreciation rates with the two neighborhood characteristics is not economically meaningful. A one-standard-deviation increase in the share of either the 65+ year population or Hispanic population is associated with only a 0.06 ($=0.56\times0.1$) or 0.05 ($=0.35\times0.155$) percentage points lower depreciation rate, respectively. Moreover, a Wald test across all the interactions of census variables with age (once factoring out the linear age trend) indicates that their effects are not statistically significant at a conventional level (see column (3) of Table E.8).

In contrast, we observe statistically and economically significant variations for condominiums. In Table 5, columns (3) and (4) indicate that condominium rent depreciation is lower in locations with a high home-ownership rate or population density but higher in locations with a high Asian population share. Column (3) of Table E.9 reports a Wald test across all the interactions of census variables with age that indicates that their effects on rent depreciation are jointly significant at the 1% level. A one-standard-deviation increase in the Asian population share or a home-ownership rate is associated with a 0.25 ($= -4.02 \times 0.0642$) percentage points higher or 0.56 ($= 2.86 \times 0.197$) percentage points lower depreciation rate, respectively. Home-ownership rates are generally low in the central area and high in the surrounding areas. The Asian share is also high in the southwest section of the metro. Thus, these variables may capture variations in depreciation rates between central and suburban locations. Therefore, we do not find any meaningfully systematic regional variation based on observable demographic information. The importance of census tract fixed effects and other neighborhood controls is not due to demographic characteristics but likely due more to unobserved characteristics such as building functions and styles of an entire condominium complex.

Table 6 reports the results for the third specification that allows depreciation rates to vary by location through *Census Tract* × *Age* interactions. A joint significance test across all the *Census Tract* × *Age* interactions for each regression indicates that they are statistically different from zero at the 1% level when using either the single-family or condominium samples, suggesting that they improve the fit of the rent model. The joint significance tests hold even after removing the linear age effect in the age-group-specific models (see Tables E.8 and E.9 in Appendix E).

Fig. 4 summarizes the results by depicting the implied location specific depreciation rates for 11–15 years old properties using the coefficients on the age interactions with census tract. Lighter colors represent the areas with higher depreciation rates, whereas darker colors represent lower depreciation rates. With a benchmark (median) depreciation rate for the Las Vegas MSA of 0.76% per year for single-family residences and 1.5% per year for condominiums (see Section 3.D), the regions with the lightest (darkest) colors represent areas where depreciation would be underestimated (overestimated). Overall, the results show that depreciation rates vary significantly within a city. In Appendix E, we present the result of joint significance tests of homogeneity in the average rent depreciation rate of single-family residences (Column (4) of Table E.8) and condominiums (Column (4) of Table E.9). For each property type, we find that the variation in rent depreciation

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Table 4
Annual rent depreciation rates without neighborhood controls.

Dep. var.: ln(Rent)	(1)	(2)	(3)	(4)
Sample	SFR	SFR	COND	COND
Age/100	−0.52***		−2.22***	
	(0.09)		(0.36)	
Age^2/1000	0.02		0.16**	
	(0.01)		(0.07)	
G(1–5 yrs) × (Age/100)		−1.16***		−1.52***
		(0.10)		(0.46)
G(6–10 yrs) × (Age/100)		−0.86***		−2.00***
		(0.08)		(0.31)
G(11–15 yrs) × (Age/100)		−0.61***		−2.33***
		(0.07)		(0.41)
G(16–20 yrs) × (Age/100)		−0.56***		−1.92***
		(0.07)		(0.28)
G(21–25 yrs) × (Age/100)		−0.54***		−1.69***
		(0.06)		(0.22)
G(26–30 yrs) × (Age/100)		−0.54***		−1.86***
		(0.05)		(0.22)
G(31–35 yrs) × (Age/100)		−0.56***		−1.85***
		(0.05)		(0.23)
G(36–40 yrs) × (Age/100)		−0.52***		−1.57***
		(0.04)		(0.24)
G(41–45 yrs) × (Age/100)		−0.50***		−1.46***
		(0.04)		(0.25)
G(46–50 yrs) × (Age/100)		−0.50***		−1.57***
		(0.03)		(0.23)
G(51–55 yrs) × (Age/100)		−0.47***		−1.64***
		(0.03)		(0.24)
G(56–60 yrs) × (Age/100)		−0.40***		−1.40***
		(0.04)		(0.22)
(Age/100) × $\ln(\text{Size})^{dm}$	−0.37***	−0.37***	−2.03***	−2.01***
	(0.07)	(0.07)	(0.28)	(0.28)
(Age/100) × TH			1.04***	1.06***
			(0.19)	(0.19)
Observations	188,219	188,219	89,323	89,323
Adjusted R^2	0.80	0.80	0.56	0.56
Structure controls	✓	✓	✓	✓
Neighborhood controls				
Service controls	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Census Tract FE				

This table reports the OLS estimates of the hedonic model specified by equation (1) for single-family residences (columns 1–2) and condominiums (columns 3–4). The dependent variable is log contract rents. $G(\cdot)$ denotes an indicator function for each age group. Variables with the *dm* superscript are demeaned. Structure controls include log unit size, log lot area, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel, cooling fuel, dishwasher, and washer/dryer. Service controls include indicators of tenant payments for cable, gas, power, sewer, water, garbage pickup, and other services. Neighborhood controls include age restriction, gated community, community amenities such as pool, clubhouse, schools, and a townhouse/duplex/triplex flag (TH). All regressions have a constant. Table D.1 in the appendix provides definitions for each variable. The properties were advertised for rent on the MLS in Clark County, NV between 2009Q1 and 2019Q1. Robust standard errors are in parentheses and clustered by census tract. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

by *Census Tract* is statistically significant at a conventional level.

5. Age, period, and cohort effects

In our preceding analysis of the age function, we followed Randolph (1988) and Lane et al. (1988) and did not account for cohort effects while controlling for year-quarter period effects and neighborhood fixed effects. Thus, the estimated economic depreciation rate is comparable to the current age-bias adjustment in inflation. They argue that cohort effects are likely negligible once controlling for service, property, and neighborhood characteristics in rent depreciation models. Indeed, these variables in our baseline specification are significant.

Although neighborhood characteristics are likely to capture significant cohort effects, whether additional cohort effects are large is an empirical question. Cohort effects may not be large relative to old European cities (Rolheiser, van Dijk and van de Minne, 2020), but there are significant cohort effects for Chicago (see Coulson and McMillen, 2008), which developed much more recently than European cities. One reason is that construction technology and the material used for residential development changes from one period to the next. Moreover, rents may reflect preferences for certain architectural styles or vintage that likely change over time. Las Vegas is a newer city than Chicago and European cities. Still, significant vintage effects can exist because of the past changes in the construction market conditions. For example, units built

Table 5
Annual rent depreciation rates with census variables.

Dep. var.: ln(Rent) Sample	(1) SFR	(2) SFR	(3) COND	(4) COND
Age/100	−0.76***		−1.85***	
	(0.04)		(0.28)	
$Age^2/1000$	0.07***		0.12***	
	(0.01)		(0.04)	
G(1–5 yrs) × (Age/100)		−0.87***		−1.23***
		(0.07)		(0.25)
G(6–10 yrs) × (Age/100)		−0.83***		−1.35***
		(0.04)		(0.19)
G(11–15 yrs) × (Age/100)		−0.73***		−1.53***
		(0.04)		(0.20)
G(16–20 yrs) × (Age/100)		−0.66***		−1.50***
		(0.03)		(0.19)
G(21–25 yrs) × (Age/100)		−0.59***		−1.46***
		(0.03)		(0.19)
G(26–30 yrs) × (Age/100)		−0.57***		−1.40***
		(0.03)		(0.16)
G(31–35 yrs) × (Age/100)		−0.54***		−1.34***
		(0.03)		(0.15)
G(36–40 yrs) × (Age/100)		−0.51***		−1.27***
		(0.03)		(0.14)
G(41–45 yrs) × (Age/100)		−0.48***		−1.28***
		(0.03)		(0.14)
G(46–50 yrs) × (Age/100)		−0.48***		−1.28***
		(0.03)		(0.14)
G(51–55 yrs) × (Age/100)		−0.45***		−1.22***
		(0.04)		(0.14)
G(56–60 yrs) × (Age/100)		−0.40***		−1.03***
		(0.04)		(0.15)
(Age/100) × $\ln(\text{Size})^{dm}$	−0.41***	−0.41***	−1.36***	−1.35***
	(0.04)	(0.04)	(0.21)	(0.21)
(Age/100) × TH			0.59***	0.58***
			(0.14)	(0.14)
(Age/100) × $\text{Home-ownership}^{dm}$	0.02	0.01	2.83***	2.86***
	(0.14)	(0.13)	(0.64)	(0.64)
(Age/100) × Population 65+ share^{dm}	0.64**	0.56*	−0.46	−0.61
	(0.29)	(0.30)	(1.09)	(1.18)
(Age/100) × Hispanic share^{dm}	0.30**	0.34**	0.30	0.27
	(0.13)	(0.14)	(0.70)	(0.71)
(Age/100) × Black share^{dm}	0.26	0.19	−0.76	−0.96
	(0.18)	(0.17)	(1.06)	(1.04)
(Age/100) × Asian share^{dm}	−0.28	−0.20	−4.03***	−4.02***
	(0.18)	(0.18)	(1.50)	(1.50)
(Age/100) × $\ln(\text{Population density})^{dm}$	0.03	0.01	0.35***	0.35***
	(0.02)	(0.02)	(0.12)	(0.13)
(Age/100) × $\ln(\text{Median household income})^{dm}$	0.12	0.08	−0.34	−0.38
	(0.12)	(0.11)	(0.45)	(0.45)
Observations	188,216	188,216	89,318	89,318
Adjusted R^2	0.89	0.89	0.87	0.87
Structure controls	✓	✓	✓	✓
Neighborhood controls	✓	✓	✓	✓
Service controls	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Census tract FE	✓	✓	✓	✓

This table reports the OLS estimates of the hedonic model specified by equation (1) for single-family residences (columns 1–2) and condominiums (columns 3–4). The dependent variable is log contract rents. $G(\cdot)$ denotes an indicator function for each age group. Variables with the *dm* superscript are demeaned. Structure controls include log unit size, log lot area, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel, cooling fuel, dishwasher, and washer/dryer. Service controls include indicators of tenant payments for cable, gas, power, sewer, water, garbage pickup, and other services. Neighborhood controls include age restriction, gated community, community amenities such as pool, clubhouse, schools, and a townhouse/duplex/triplex flag (TH). All regressions have a constant. Table D.1 in the appendix provides definitions for each variable. The properties were advertised for rent on the MLS in Clark County, NV between 2009Q1 and 2019Q1. Robust standard errors are in parentheses and clustered by census tract. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 6
Census tract specific annual rent depreciation rates.

Dep. var.: ln(Rent) Sample:	(1) SFR	(2) SFR	(3) COND	(4) COND
Age/100	-0.79^{***}		-1.59^{***}	
	(0.07)		(0.33)	
$\text{Age}^2/1000$	0.08^{***}		0.11^{***}	
	(0.01)		(0.04)	
G(1–5 yrs) × (Age/100)		-0.82^{***}		-1.42^{***}
		(0.08)		(0.36)
G(6–10 yrs) × (Age/100)		-0.81^{***}		-1.20^{***}
		(0.06)		(0.29)
G(11–15 yrs) × (Age/100)		-0.71^{***}		-1.40^{***}
		(0.05)		(0.32)
G(16–20 yrs) × (Age/100)		-0.66^{***}		-1.40^{***}
		(0.05)		(0.35)
G(21–25 yrs) × (Age/100)		-0.59^{***}		-1.33^{***}
		(0.04)		(0.36)
G(26–30 yrs) × (Age/100)		-0.56^{***}		-1.28^{***}
		(0.04)		(0.34)
G(31–35 yrs) × (Age/100)		-0.52^{***}		-1.22^{***}
		(0.03)		(0.32)
G(36–40 yrs) × (Age/100)		-0.48^{***}		-1.17^{***}
		(0.03)		(0.30)
G(41–45 yrs) × (Age/100)		-0.47^{***}		-1.18^{***}
		(0.04)		(0.31)
G(46–50 yrs) × (Age/100)		-0.48^{***}		-1.16^{***}
		(0.04)		(0.31)
G(51–55 yrs) × (Age/100)		-0.47^{***}		-1.08^{***}
		(0.04)		(0.31)
G(56–60 yrs) × (Age/100)		-0.42^{***}		-0.97^{***}
		(0.05)		(0.32)
(Age/100) × $\ln(\text{Size})^{dm}$	-0.40^{***}	-0.40^{***}	-1.36^{***}	-1.36^{***}
	(0.04)	(0.04)	(0.21)	(0.21)
(Age/100) × TH			0.50^{***}	0.50^{***}
			(0.15)	(0.15)
Observations	188,216	188,216	89,318	89,318
Adjusted R^2	0.89	0.89	0.88	0.88
Structure controls	✓	✓	✓	✓
Neighborhood controls	✓	✓	✓	✓
Service controls	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Census Tract FE	✓	✓	✓	✓
Census Tract FE x Age	✓	✓	✓	✓

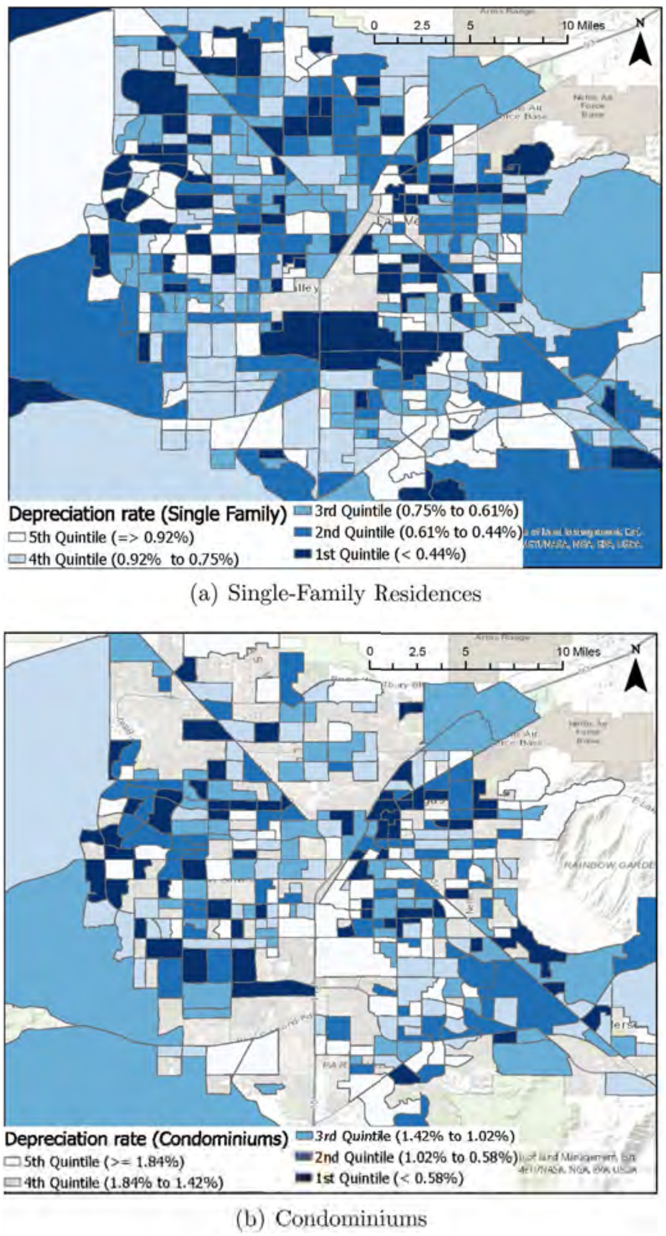
This table reports the OLS estimates of the hedonic model specified by equation (1) for single-family residences (columns 1–2) and condominiums (columns 3–4). The dependent variable is log contract rents. $G(\cdot)$ denotes an indicator function for each age group. Variables with the *dm* superscript are demeaned. Structure controls include log unit size, log lot area, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel, cooling fuel, dishwasher, and washer/dryer. Service controls include indicators of tenant payments for cable, gas, power, sewer, water, garbage pickup, and other services. Neighborhood controls include age restriction, gated community, community amenities such as pool, clubhouse, schools, and a townhouse/duplex/triplex flag (TH). All regressions have a constant. Table D.1 in the appendix provides definitions for each variable. The properties were advertised for rent on the MLS in Clark County, NV between 2009Q1 and 2019Q1. Robust standard errors are in parentheses and clustered by census tract. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

during the headiest days of the housing boom (from 2003 to 2006) in Las Vegas could be of lower quality, and if true, these properties could be associated with a rent discount. Functional obsolescence can also be significant in U.S. cities.

In this section, we provide additional insights into the source of economic depreciation by separating physical deterioration from functional obsolescence and vintage. We follow Francke and van de Minne (2017) and estimate physical deterioration after removing cohort effects from depreciation. They argue that once separating cohort and period effects, age effects are a measure of the physical deterioration of the structure, whereas cohort effects measure the impact of both functional obsolescence and vintage effects. Furthermore, we take an additional step to decompose cohort effects into functional obsolescence and vintage effects, although our data do not allow us to separate maintenance from physical deterioration, as Francke and van de Minne (2017) and Bokhari and Geltner (2019) do. Appendix C illustrates how we estimate a constant average rate of functional obsolescence from cohort effects. Negative cohort effects for earlier construction years are likely to be caused by functional obsolescence, whereas random fluctuations around the linear trend is likely to be vintage effects specific to particular construction years. We decompose cohort effects on log rents into a linear trend and a mean-zero error term. Our assumption is that a linear trend in cohort effects represents the average rate of functional obsolescence over time.

We modify equation (1) as follows to include cohort effects:

$$\ln Y_{it} = Neighborhood_j\alpha + X_i\beta + \gamma_a + \tau_p + \kappa_c + \epsilon_{it}, \tag{7}$$



(a) Single-Family Residences

(b) Condominiums

Fig. 4. Rent Depreciation by Census Tract. This figure depicts location (census tract) heterogeneity in the economic rent depreciation rate of 11–15-year-old single-family residences in panel (a) and condominiums in panel (b) using the estimated results in columns (2) and (4) in Table VI. The lightest shade represents the steepest depreciation rate, whereas the darkest shade represents the lowest depreciation rate. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

where $Neighborhood_j$ denotes the neighborhood characteristics specified in equation (5), and X is the same set of controls as in equation (1). We do not estimate census tract fixed effects because some census tracts do not have a sufficient number of observations for all age-cohort combinations. An age effect γ_a denotes the coefficient for the 5-year age group between a and $a+4$ years old for $a = \{0, 5, \ldots, 60\}$, a period effect τ_p denotes the coefficient for the 5-year period group between list years p and $p+4$ for $p = \{2005, 2010, 2015\}$, and a cohort effect κ_c denotes the coefficient for the 5-year cohort group between c and $c+4$ for $c = \{1945, 1950, \ldots, 2015\}$. The five-year grouping scheme is standard practice and allows us avoid an under-identification problem arising from too few observations in any age-period-cohort intersection (see Yang et al., 2008).

However, it is an empirical challenge to estimate cohort effects with period and age effects. We cannot simply add indicators for years built to a linear model that already includes age and period because age is a linear combination of the year built and the year leased, which creates an identification problem (i.e., $p - c = a$).[16] To address the perfect collinearity issue we discussed in Section 2, we use the age-period-cohort (APC) model based on the IE method (Yang et al., 2004; Yang et al., 2008). The IE is a generic method of decomposing age, period, and cohort effects based on a principal component analysis.

To illustrate the IE method, let us define $\mathcal{Y} \equiv \ln Y - Neighborhood_j \alpha - X\beta$ and rewrite equation (7) as:

$$\mathcal{Y} = Z\theta + \epsilon, \tag{8}$$

where $\theta = (\gamma_0, \gamma_5, \ldots, \gamma_{55}, \tau_{2005}, \tau_{2010}, \kappa_{1945}, \kappa_{1950}, \ldots, \kappa_{2010})'$ by omitting γ_{60}, τ_{2015}, and κ_{2015}. Matrix Z consists of a set of dummy variables for age, period, and cohort groups. The ordinary least squares estimator $\hat{\theta} = (Z'Z)^{-1}Z'\mathcal{Y}$ is not defined well because of singularity of Z. However, because Z is one less than full column rank, the parameter space of the regression model (8) can be decomposed into the direct sum of

[16] We first define the age and cohort groups and derive period groups by adding cohort and age ($p = c + a$). Thus, we allow some noise in period groups because our primary focus is on age and cohort effects.

Table 7
Intrinsic estimators.

Dep. var.: ln(Rent) Sample:	(1) SFR	(2) COND	(Continued)	(1) SFR	(2) COND
Age: 0–4 yrs	0.06***	0.14***	Cohort: 1945–1949	0.18***	0.09
	(0.01)	(0.02)		(0.05)	(0.15)
Age: 5–9 yrs	0.01*	0.09***	Cohort: 1950–1954	−0.06***	−0.09*
	(0.01)	(0.02)		(0.01)	(0.05)
Age: 10–14 yrs	−0.01**	0.04***	Cohort: 1955–1959	−0.08***	−0.10***
	(0.00)	(0.01)		(0.01)	(0.04)
Age: 15–19 yrs	−0.02***	0.02*	Cohort: 1960–1964	−0.03***	−0.14***
	(0.00)	(0.01)		(0.01)	(0.03)
Age: 20–24 yrs	−0.02***	0.02***	Cohort: 1965–1969	−0.06***	−0.14***
	(0.00)	(0.01)		(0.01)	(0.03)
Age: 25–29 yrs	−0.02***	0.02***	Cohort: 1970–1974	−0.02***	0.04
	(0.00)	(0.01)		(0.01)	(0.02)
Age: 30–34 yrs	−0.01***	−0.00	Cohort: 1975–1979	−0.02***	0.00
	(0.00)	(0.01)		(0.01)	(0.02)
Age: 35–39 yrs	−0.02***	−0.02	Cohort: 1980–1984	−0.02***	−0.02
	(0.00)	(0.01)		(0.01)	(0.02)
Age: 40–44 yrs	−0.01***	−0.05***	Cohort: 1985–1989	0.01	−0.03**
	(0.00)	(0.01)		(0.00)	(0.01)
Age: 45–49 yrs	0.00	−0.05***	Cohort: 1990–1994	0.01**	−0.00
	(0.01)	(0.02)		(0.00)	(0.01)
Age: 50–54 yrs	−0.01**	−0.18***	Cohort: 1995–1999	0.03***	0.04***
	(0.01)	(0.02)		(0.00)	(0.00)
Age: 55–59 yrs	0.04***	−0.07***	Cohort: 2000–2004	0.02***	0.05***
	(0.01)	(0.02)		(0.00)	(0.00)
Age: 60–64 yrs	0.02	0.04	Cohort: 2005–2009	0.02***	0.12***
	(0.01)	(0.05)		(0.00)	(0.01)
Period: 2005–2009	−0.04***	−0.05***	Cohort: 2010–2014	0.00	0.12***
	(0.00)	(0.00)		(0.00)	(0.01)
Period: 2010–2014	−0.05***	−0.07***	Cohort: 2015–2019	0.04***	0.06***
	(0.00)	(0.00)		(0.01)	(0.02)
Period: 2015–2019	0.08***	0.11***			
	(0.00)	(0.00)			
Observations	188,166	89,194			
Property controls	✓	✓			
Census Variables	✓	✓			

This table reports the age, period, and cohort effects on the natural log of the contract rate based on the IE method. The sample in column 1 (2) consists of leases for single-family residences (condominiums). The properties were advertised for rent on the MLS in Clark County, NV between 2009Q1 and 2019Q1. Age, period, and cohort flag the structure age group, rent lease listing date, and the structure year-built group, respectively. Property controls include log size square footage demeaned, log lot area square footage, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel, cooling fuel, dishwasher, washer/dryer, cable availability, tenant pay indicators (i.e., cable, gas, power, sewer, water, garbage pickup, other services), age restriction, gated community, community amenities (pool, spa, park, golf, basketball, clubhouse, gym, rules), high school, middle school, a townhouse/duplex/triplex flag (TH, for the condominium sample), and a constant. Census variables include the home-ownership rate, log median household income, log population density per square-mile, Hispanic population share, Non-Hispanic Black population share, Asian population share, and Population 65+ share at the census-tract level. Table D.1 in the appendix provides definitions for each variable. Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

two linear subspaces that are perpendicular to each other. One subspace corresponds to the unique zero eigenvalue of $Z'Z$, which is termed the null subspace of Z. Because of orthogonality, the non-unique parameter vector θ can be written as:

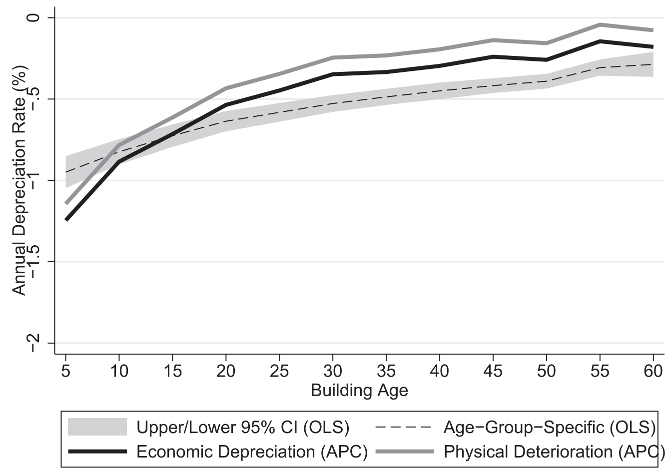
$$\theta = T + sT_0, \tag{9}$$

where T_0 is a unique eigenvector of unit length in the null subspace of Z, and s is a scalar corresponding to a specific set of parameter values. Vector T_0 is independent of $\mathcal{Y}$ and satisfies $ZT_0 = 0$ because of the singularity of Z. Parameter vector T is the intrinsic estimator (IE) corresponding to the projection of the parameter vector θ onto the non-null space of Z: $T = (I - T_0T_0')\theta$.

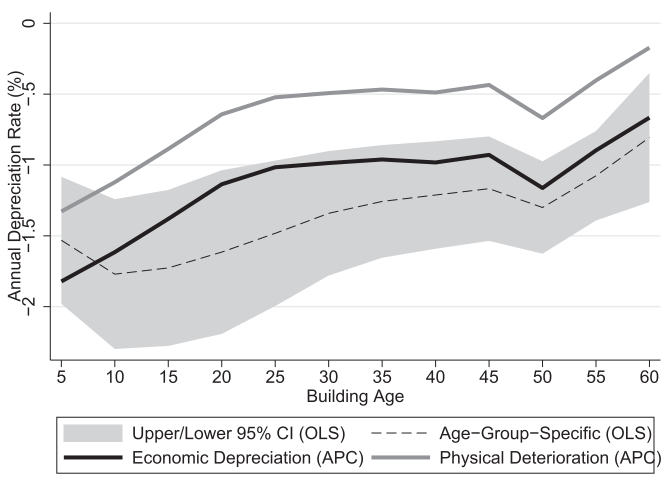
We estimate IE parameters by applying a principal components regression. We first apply an orthonormal matrix transformation to $Z'Z$ to produce the nonzero eigenvalues and corresponding eigenvectors of the matrix. We use these eigenvectors to estimate the principal components regression model. Then, we transform the estimated coefficients and the variance-covariance matrix of the principal components regression model back to the space of age, period, and cohort coordinates to make the coefficients interpretable. In the last step, we impose the constraint that the sum of coefficients in each set is zero ($\Sigma_a\gamma_a = \Sigma_p\tau_p = \Sigma_c\kappa_c = 0$) instead of omitting one reference category from each set of indicator variables.[17]

Table 7 reports the estimated age, cohort, and period (list year) effects in decimal form on log rents for single-family residences in column (1) and condominiums in column (2). The age coefficient represents relative log rents associated with the subject age group compared with other groups. The age profile suggests that log rents generally decrease with age. For single-family residences and condominiums, respectively, the relative log rents are 0.06 and 0.14 for the youngest age group (0–4 years) but quickly decrease for older age groups. Thus, the APC model confirms the existence of physical deterioration. The

[17] We use the statistical software package for Stata by Schulhofer-Wohl and Yang (2006). See Rutherford et al. (2010) for details on the procedure.



(a) Single-Family Residences



(b) Condominiums

Fig. 5. Decomposition of Economic Depreciation. This figure depicts the economic depreciation of rents for single-family residences (panel (a)) and condominiums (panel (b)) based on Table 7. The economic depreciation is the sum of the physical deterioration and the functional obsolesce rates, where the physical deterioration rate is calculated based on age effects and the functional obsolesce rate is the slope of the linear trend in cohort effects. The age-group-specific estimates (OLS) with a 95% confidence interval are based on Table E.11. On the horizontal axis, building age corresponds to the beginning year for each age group (5 for 5–9 years, 10 for 10–14 years, and so on).

table also shows that the variations in cohort effects are statistically significant. Importantly, cohort effects tend to increase with cohort year for both single-family residences and condominiums. Except for the 1945–1949 cohort, which has only a few observations, relative log rents are negative for earlier cohorts and positive for more recent cohorts. Cohort effects are robust to the inclusion of interactions between building age and census tract variables (see Table E.10 in the Appendix).

We use the estimated age and cohort effects in Table 7 to infer the average annual rate of physical deterioration and functional obsolescence. We calculate the annual rate of physical deterioration by dividing the difference in age effects between the subject and first age group by the mean age difference. For the rate of functional obsolescence, we estimate the slope β of the following equation using a weighted least squares estimation with cohort frequency weights:

$$Cohort\ Effect_k = \alpha - \beta Year_k + \varepsilon,$$

where $Year_k$ denotes the mean year built for cohort k, and ε represents the mean-zero vintage effects. Using the single-family cohort effects from column (1), we estimate a β of 0.001 that is statistically significant at the 1% level. For condominiums, β equals 0.0049 and is also statistically significant at the 1% level. Thus, we find significantly greater obsolescence for condominiums: 0.1% per year for single-family residences and 0.5% for condominiums. The sum of the functional obsolescence and physical deterioration yields an estimate of the total economic depreciation, excluding vintage effects.

Fig. 5 depicts the implied economic depreciation rates for properties from 5 to 64 years old based on the IEs for single-family residences (panel a) and condominiums (panel b). We use the initial age group (0–4 years of age) as a reference group. As a benchmark, we superimpose the corresponding age-group-specific depreciation estimates (with 95% confidence bounds) without cohort controls based on an OLS model with census tract fixed effects.[18] In panel (a) for single-family residences, the physical deterioration rate from the APC model begins at 1.14% per year for the 5–9 years age group and approaches a value close to zero for older age groups (0.08% for the 60–64 years age group). Adding the average functional obsolescence rate of 0.1% per year, the total economic depreciation rates range from 1.24% to 0.18%. Economic depreciation rates vary more significantly by age group with the APC model. The APC-based economic depreciation tends to fall outside the 95% confidence interval of the OLS estimates. Thus, when we do not separate cohort effects (labeled OLS in the figure), we tend to

[18] We use the same building age groups as for the APC model. To increase comparability between the OLS and APC estimates, we remove the non-age-group-specific interaction terms from the OLS models. Table E.11 in Appendix E reports the OLS regression results.

overestimate the economic depreciation rate, except for the newest age group.

In panel (b) for condominiums, the physical deterioration rates from the APC model are consistent with those for single-family residences, ranging from 1.3% for the 5–9 years age group to 0.17% for the 60–64 years age group. Thus, the variation in depreciation rates by property type is not caused by physical deterioration. However, because the rate of functional obsolescence of 0.5% per year is much higher for condominiums, the total economic depreciation rate ranges from 1.8% to 0.67%. Similar to the single-family case, economic depreciation rates vary more significantly by age group with the APC model. Although the APC-based economic depreciation falls within the 95% confidence interval of the OLS estimates due to large standard errors, the differences in point estimates are economically significant.

Overall, we find that high functional obsolescence for condominiums can result in significantly high economic depreciation even if physical deterioration is comparable across different property types. Furthermore, carefully controlling for cohort effects reveals the variation in economic depreciation by age. Put differently, fine control of neighborhood effects by census tract fixed effects will not completely take care of cohort effects.

6. Conclusion

We use a unique data set of Las Vegas rental contracts and estimate rent depreciation, which is an essential input to the estimation of inflation rates. Rent depreciation is a form of economic depreciation that captures the physical deterioration and functional obsolescence of a residential structure. We demonstrate that rental depreciation rates are higher for newer structures than older ones and decrease non-linearly as they age. We also show that the rental depreciation rate increases with unit size and varies by location within a metropolitan area. Furthermore, the depreciation of condominium rents is significantly higher than the rates for single-family residences. Using an IE method to segment age, period, and cohort effects, we decompose the economic depreciation and find that single-family residences and condominiums have similar physical deterioration rates, whereas condominiums face a greater rate of functional obsolescence than single-family residences.

The variation in depreciation significantly impacts inflation rates because shelter is the largest component of the consumption basket. The BLS adjusts for an aging-bias in rent inflation by using the area average depreciation rate estimated following Lane et al. (1988). However, in contrast with our findings, their approach assumes that the depreciation rate is a linear function of age, the inclusion of structural and neighborhood characteristics eliminates cohort effects, and all hedonic characteristics are common for detached and non-detached housing. Under the BLS approach, rent depreciation rates for U.S. cities in the West range from 0.19% to 0.25%. We estimate a much greater average depreciation rate of 0.75% for single-family residences and 1.9% for condominiums in a metropolitan area that epitomizes growing cities in the West. The true rent depreciation rates may be even greater considering potential bias from the maintenance or survivorship of housing units in our sample.

Our results imply a downward bias in local rates for areas with a larger proportion of new and large properties. This bias would distort consumption choice, corporate investment, monetary policy, and social security related decisions. As the BLS considers changes in their current approaches to better address the issue of age-bias in the Housing Survey (Campbell, 2006), we demonstrate challenges with estimating rent deprecation rates and present a potential set of models that could be applied for aging-bias adjustments.

Credit author statement

Luis A. Lopez: Methodology; Formal analysis; Investigation; Resources; Data curation; Writing – original draft; Writing – review & editing. Jiro Yoshida: Conceptualization; Methodology; Formal analysis; Investigation; Writing – original draft; Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Impact of Rent Depreciation on Inflation Calculations

In principle, the rent and owners' equivalent indices provide constant-quality measures of the housing services component of the CPI. They are both constructed using data on observed rent changes over six month intervals of repeat observations of housing units from the Housing Survey (Bureau of Labor Statistics, 2018). For instance, the unadjusted rent inflation for a single location is captured by

$$r_t = \frac{\sum_i \omega_i R_{it}}{\sum_i \omega_i R_{it-6}} \quad \text{(A.1)}$$

where ω_i is the weight of housing unit i, R_{it} is the contract rent of the housing unit, and R_{it-6} is the contract rent of the same housing unit six months ago.

To avoid an aging bias from economic depreciation that occurs between time $(t-6)$ and (t), the BLS adjusts the current rent of each housing unit upwards using an aging-bias adjustment factor $D = \frac{1}{1-d}$ where d is the average semi-annual depreciation rate for the area of the housing units (Bureau of Labor Statistics, 2018).[19] Hence, the constant-quality growth rate (or inflation) of housing services at time t is

$$g_t^o = r_t \times D - 1 \quad \text{(A.2)}$$

where r_t is defined by equation (A.1). An increase in the depreciation rate (d), increases the aging-bias adjustment factor (D), and in turn, implies further growth in the price of housing services (g_t^o). As the CPI is a function of housing services, the CPI's growth would be higher, too.

The BLS estimates the depreciation rate d using the methodology proposed by Lane et al. (1988), who report an average rate of approximately 0.225%, ranging from 0.19% to 0.25% per year for cities in the West. By contrast, we estimate that the average depreciation rate for Las Vegas (which is in the West region) is 0.75% for single-family residences in the 11–15 years age group (Column 2, Table 3). The average depreciation estimate is larger if condominiums are included.

To examine how the CPI changes using an updated depreciation rate with a back-of-envelope approach, we measure a new service growth rate (g_t^n) as:

$$g_t^n = r_t \times D^n - 1 \quad \text{(A.3)}$$

[19] For further details, see https://www.bls.gov/opub/hom/cpi/pdf/cpi.pdf.

where $D^n = \frac{1}{1-d^n}$ and d^n is set to the new depreciation rate for the area.

We then adjust the growth rate of the CPI (g_t^{AdjCPI}) over rolling six-month intervals as:

$$g_t^{AdjCPI} = g_t^{CPI} - w_t g_t^o + w_t g_t^n \tag{A.4}$$

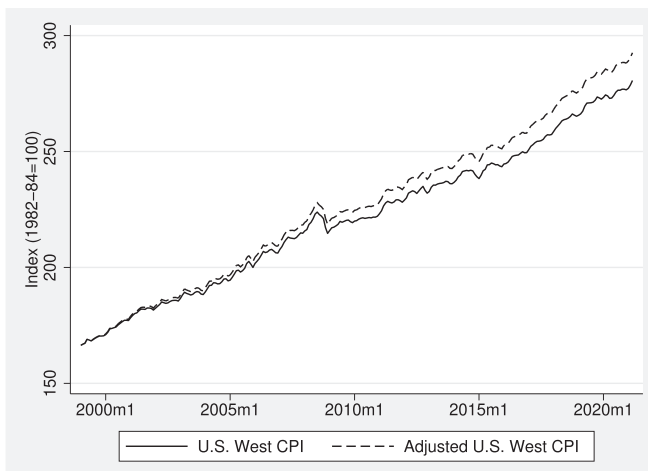
where w_t is the relative importance of the shelter component. Equation (A.4) simplifies to

$$g_t^{AdjCPI} = g_t^{CPI} + w_t(g_t^o + 1)\frac{d^n - d}{1 - d^n} \tag{A.5}$$

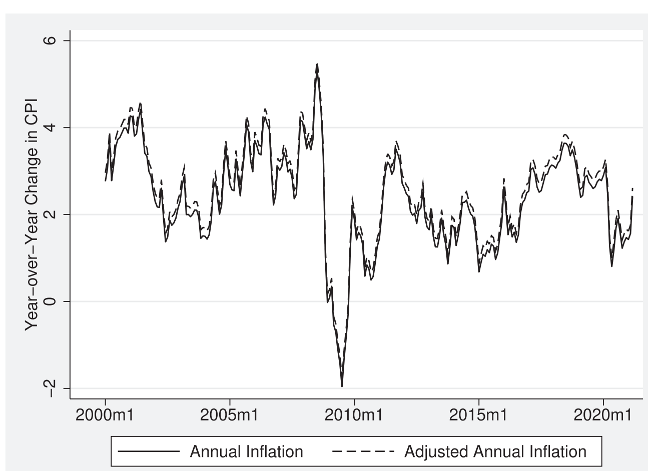
when using equations (A.2) and (A.3).

To compute equation (A.5), we calculate g_t^{CPI} using the CPI for all items in West Urban Cities (or *CPI_t*, CUUR0400SA0), and g_t^o using the corresponding shelter component of the West Urban CPI at month t (or CUUR0400SAH1). Moreover, we set d in D equal to the semi-annual average depreciation rate ($(1 + .00225)^{1/2} - 1$), and use our estimate of the average depreciation rate ($(1 + .0075)^{1/2} - 1$) from Table 3 for d^n. Lastly, we set the relative importance weight, w_t, to be a constant of 0.36 for the purpose of exposition, which is the most recent relative importance weight for shelter in the West.[20] We then construct the implied Adjusted West CPI in levels and compare it with the actual West CPI.

Figure A.1(a) plots the actual and adjusted CPI for the West based on the existing and revised depreciation estimates, whereas Figure A.1(b) plots the implied year-over-year change of each CPI measure from July 1999 to March 2021. As Figure A.1 illustrates, an error of merely 0.525% in the depreciation rate will lead to a modest mismeasurement of rent inflation but accumulates into significant differences between the actual and observed CPI. For example, our results suggest that the CPI as of March 2021 would be underestimated by about 4.4%, and this error will incrementally grow every six months.



(a) CPI Index



(b) Inflation Estimates

Fig. A.1 Inflation Adjustment for Rent Depreciation.

[20] See https://www.bls.gov/cpi/tables/relative-importance/home.htm.

Appendix B. Relationship between Rent Depreciation and Value Depreciation

This section demonstrates the relationship between depreciation rates for rents and asset values. Developing a valuation model that incorporates depreciating cash flows is important to fully understand this relationship (Dixon et al., 1999). The valuation model is relevant for both commercial properties and housing because an owned house can be valued as the present value of owners' equivalent rents. Unlike Xu et al. (2018), we take depreciating structure rents as a primitive and derive property value depreciation rates.

We model aging effects on rents and prices after removing time trends and fluctuations. Thus, we consider a stationary urban economy with no real growth in income or city size in a discrete-time setting. We demonstrate a deterministic case because our focus is not on stochastic rent fluctuations. The introduction of stochastic rents will not change the intuition because stochastic rents can be analogously priced with the stochastic discount factor.

As DiPasquale and Wheaton (1995) conceptualize, housing rents comprise structure rents and land rents, which include both location and agricultural rents. In a stationary economy, land rents, C_L, are constant over time. The initial structure rent, C_{S1}, is subject to depreciation at a constant rate, d, because of physical deterioration and functional and technological obsolescence. The structure also has a finite life T (a *priori* assumption). The structure rent $C_S(t)$ at time $t = 1, \dots, T$ is:

$$C_S(t) = C_{S1}(1-d)^{t-1}. \tag{B.1}$$

The total housing rents $C(t)$ is the sum of structure and land rents: $C(t) = C_S(t) + C_L$. Then, the rent depreciation rate is defined as:

$$d_C = -\frac{d \ln C(t)}{dt}. \tag{B.2}$$

As land rent does not depreciate, we have $d_C < d$.

In this complete and stationary economy without a growth option, the land value L equals the present value of perpetual land rents:

$$\forall t : L(t) = \frac{C_L}{r} \equiv L, \tag{B.3}$$

where r denotes a constant discount rate under certainty.[21] Similarly, the initial structure value $S(0)$ equals the present discounted value of depreciating structure rents with a finite life T:

$$S(0) = C_{S1} \sum_{i=1}^{T} \frac{(1-d)^{i-1}}{(1+r)^i}. \tag{B.4}$$

Thus, the structure value at time t equals:

$$S(t) = \frac{C_{S1}(1-d)^t}{r+d}\left[1 - \left(\frac{1-d}{1+r}\right)^{T-t}\right]. \tag{B.5}$$

The property value equals $V(t) = S(t) + L$.

The structure value depreciation rate, d_S, is defined as:

$$d_S = -\frac{d \ln S(t)}{dt}, \tag{B.6}$$

and the property value depreciation rate is defined as:

$$d_V = -\frac{d \ln V(t)}{dt}. \tag{B.7}$$

Due to the non-depreciating land component, the property value depreciation rate is smaller than the structure value depreciation rate: $d_V < d_S$.

Figure B.1 depicts the graph of the rent depreciation rate (red dotted curve), the structure value depreciation rate (blue solid curve), and the property value depreciation rate (dashed green curve) for different values of structure rent depreciation rate. The depreciation rate is evaluated for a 10-year old structure that can operate until 50 years old. We set the initial proportion of land at 1/3. The parameter values are: $T = 50$, $t = 10$, $C_{S1} = 1$, $S(0)/L = 2$, and $r = 0.03$.

The model demonstrates two key results. First, the curve for the structure value depreciation (the blue solid curve) is located above the structure rent depreciation curve (the 45-degree line); that is, the structure value depreciation rate is always larger than the structure rent depreciation rate. This result holds regardless of parameter values. There are two reasons for this result. First, when structure rent depreciation is large, the current income is large relative to the present value of the remaining future rental income. Second, the structure value additionally decreases each period because of a shorter remaining life of the structure. This second effect is often observed as an increase in cap rates or cap rate creep (Bokhari and Geltner, 2018). The y-intercept represents the finite-life effect when structure rent depreciation is zero.

The second result is that the property value depreciation rate is larger than the rent depreciation rate for a reasonable range of structure rent depreciation. In Figure B.1, the property depreciation rate is 1.8% when the rent depreciation rate is 0.7%. This case is consistent with the results in existing studies (e.g., Himmelberg et al., 2005). In the right-hand side region where rent depreciation is large, the property value depreciation rate becomes smaller than the rent depreciation rate because the land value becomes dominant as the structure value quickly depreciates. This region corresponds to the estimation result in Xu et al. (2018) for the Beijing housing market, where both structure depreciation and land proportion are large.

[21] For a city with a growth option, the land value will be stochastic (Capozza and Helsley, 1990).

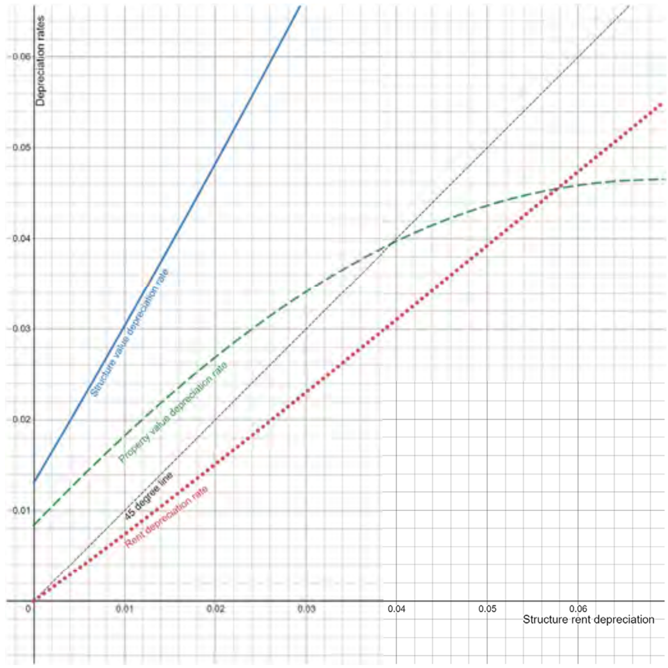


Fig. B.1 The relationship between rent depreciation rate and value depreciation rates.

This figure depicts the rates of rent depreciation (dotted red curve), structure value depreciation (solid blue curve), and property value depreciation (dashed green curve) for different values of structure rent depreciation rate. These curves are defined by equations (B.2), (B.6), and (B.7). The parameter values are: $T = 50$, $t = 10$, $C_{S1} = 1$, $S(0)/L = 2$, and $r = 0.03$.

Appendix C. Example of Functional Obsolescence and Cohort Effects

The following example illustrates how we estimate functional obsolescence from cohort effects. The example specifies how physical deterioration, functional obsolescence, and vintage premia determine age and cohort coefficients in regressions.

First, suppose that building technology and consumer tastes change over time. As fundamental building functions and styles cannot be easily updated, rents exhibit (latent) functional obsolescence for properties with outdated characteristics. For simplicity, suppose log rents are lower by 0.01 for a five-year earlier construction year; that is, relative to 1975, log rents are lower by 0.01 for the 1970 cohort and by 0.02 for the 1965 cohort, and so on. In addition, some vintages have mean-zero relative premia and discounts because of construction quality. Assume a 0.01 premium for 1960 and 1970 and a 0.01 discount for 1955 and 1965. Finally, physical deterioration causes log rents to depreciate by 0.03 every five years; that is, in a 1975 rental market, log rents are lower by 0.03 for 5-year-old buildings, 0.06 for 10-year old buildings, and so on. The following table illustrates the three effects relative to 1975.

Year	1955	1960	1965	1970	1975
Obsolescence	−0.04	−0.03	−0.02	−0.01	0
Vintage	−0.01	0.01	−0.01	0.01	0
Age	**20**	**15**	**10**	**5**	**0**
Deterioration	−0.12	−0.09	−0.06	−0.03	0

If we estimate a hedonic model without controlling for cohort effects, the age profile of log rents will reflect the sum of all three latent effects.

Age	20	15	10	5	0
Age coefficients	−0.17	−0.11	−0.09	−0.03	0

Now suppose we can correctly separate cohort effects from age effects. Then, as Francke and van de Minne (2017) suggest, the age coefficients will capture only physical deterioration, whereas cohort effects will capture both functional obsolescence and vintage effects.

Age	20	15	10	5	0
Age coefficients	−0.12	−0.09	−0.06	−0.03	0
Year	**1955**	**1960**	**1965**	**1970**	**1975**
Cohort effects	−0.05	−0.02	−0.03	0	0

Without knowing the true functional form for obsolescence, correctly identifying obsolescence and vintage effects is not possible. However, by imposing an assumption on the functional form, such as a log-linear form, we can estimate a constant rate of functional obsolescence. If the true function does not take a log-linear form, the constant rate can still be interpreted as the average rate. In this particular example, a linear regression of cohort effects on year gives a slope of approximately 0.01 for every five years. Thus, the estimated slope correctly identifies the constant rate of obsolescence. The sum of deterioration and obsolescence (0.04 per five years) represents economic depreciation, excluding vintage effects.

Appendix D. Dictionary of Variables

Table D.1
Dictionary of Variables

Variable	Definition
Market Outcomes	
Contract Rent ($)	Contractual rent on lease contract
Asking Rent ($)	Asking rent on listing
Service Characteristics	
Cable Available	1 if cable television is available, and 0 otherwise
Tenant Pays: Cable	1 if the tenant pays for cable, and 0 otherwise
Tenant Pays: Gas	1 if the tenant pays for gas, and 0 otherwise
Tenant Pays: Power	1 if the tenant pays for power, and 0 otherwise
Tenant Pays: Sewer	1 if the tenant pays for sewer, and 0 otherwise
Tenant Pays: Water	1 if the tenant pays for water, and 0 otherwise
Tenant Pays: Garbage	1 if the tenant pays for garbage pickup, and 0 otherwise
Tenant Pays: Other	1 if the tenant pays for other services, and 0 otherwise
Structure Characteristics	
Age	Building's age measured as the listing year less built year
Living Area (Size) Square-Footage	Square footage of non-garage floor space in property/unit
Lot Area Square-Footage	Square footage of property's lot
Bedrooms	Number of bedrooms
Bathrooms	Number of bathrooms
Fireplaces	Number of fireplaces
Private Pool	1 if the property has a private pool, and 0 otherwise
Private Spa	1 if the property has a private spa, and 0 otherwise
Garage Car Spaces	Number of car spaces in the garage
Heating Fuel: Electric	1 if the property uses only electric heating fuel, and 0 otherwise
Heating Fuel: Gas	1 if the property uses only gas fuel for heating, and 0 otherwise
Heating Fuel: Mixed	1 if the property uses electric/gas heating fuels, and 0 otherwise
Heating Fuel: Other	1 if the property uses other heating fuel type, and 0 otherwise
Cooling Fuel: Electric	1 if the property uses electric fuel for cooling, and 0 otherwise
Cooling Fuel: Gas	1 if the property uses gas fuel for cooling, and 0 otherwise
Cooling Fuel: Other	1 if the property uses other cooling fuel types, and 0 otherwise
Dishwasher	1 if the rental contract includes a dishwasher, and 0 otherwise
W/D: Washer and Dryer	1 if the rental contract includes both a washer and dryer, and 0 otherwise
W/D: Dryer Only	1 if the rental contract includes a dryer but not a washer, and 0 otherwise
W/D: Washer Only	1 if the rental contract includes a washer but not a dryer, and 0 otherwise
W/D: None	1 if the rental contract does not include a dryer or washer, and 0 otherwise
TH	1 if townhouse, triplex, or fourplex, and 0 otherwise
Neighborhood Characteristics	
Age Restriction	1 if the neighborhood has an age restriction, and 0 otherwise
Gated Community	1 if the neighborhood is gated, and 0 otherwise
Community Pool	1 if the neighborhood has a community pool, and 0 otherwise
Community Spa	1 if the neighborhood has a community spa, and 0 otherwise
Community Park	1 if the neighborhood has a community park, and 0 otherwise
Community Golf	1 if the neighborhood has a community golf course, and 0 otherwise
Community Basketball	1 if the neighborhood has a community basketball court, and 0 otherwise
Community Clubhouse	1 if the neighborhood has a community clubhouse, and 0 otherwise
Community Gym	1 if the neighborhood has a community gym, and 0 otherwise
Community Rules	1 if the neighborhood has community rules, and 0 otherwise
High School	Categorical variables for the high school assigned to neighborhood
Jr. High School	Categorical variables for the jr. high school assigned to neighborhood
ACS Census Tract Variables	
Home-ownership	Home-ownership rate in the census tract
Population 65+ share	Proportion of population that is 65 years or older in the census tract
Hispanic share	Proportion of population that is Hispanic in the census tract
Black share	Proportion of population that is non-Hispanic Black in the census tract
Asian share	Proportion of population that is non-Hispanic Asian in the census tract
Population density	Number of people per square mile in the census-tract
Median household income	Median household income in the census tract

Appendix E. Additional Tables

Table E.1
Summary Statistics for Residential Leases

Variables	Single Family Residences (N = 188,219)					Condominiums (N = 89,324)				
	Mean	SD	Q25	Q50	Q75	Mean	SD	Q25	Q50	Q75
Market Outcomes										
Contract Rent ($)	1,392	507	1,100	1,292	1,500	1,024	545	750	895	1,100
Asking Rent ($)	1,397	509	1,100	1,295	1,500	1,032	666	750	895	1,100
Service Characteristics										
Cable Available^d	0.91	0.29	1.00	1.00	1.00	0.94	0.24	1.00	1.00	1.00
Tenant Pays: Cable^d	0.81	0.40	1.00	1.00	1.00	0.79	0.41	1.00	1.00	1.00
Tenant Pays: Gas^d	0.97	0.16	1.00	1.00	1.00	0.76	0.43	1.00	1.00	1.00
Tenant Pays: Power^d	0.99	0.10	1.00	1.00	1.00	0.97	0.16	1.00	1.00	1.00
Tenant Pays: Sewer^d	0.68	0.47	0.00	1.00	1.00	0.26	0.44	0.00	0.00	1.00
Tenant Pays: Water^d	0.95	0.21	1.00	1.00	1.00	0.38	0.49	0.00	0.00	1.00
Tenant Pays: Garbage Pickup^d	0.78	0.41	1.00	1.00	1.00	0.27	0.44	0.00	0.00	1.00
Tenant Pays: Other Services^d	0.79	0.41	1.00	1.00	1.00	0.27	0.44	0.00	0.00	1.00
Structure Characteristics										
Age	14.8	10.2	8.0	12.0	19.0	17.7	10.4	10.0	15.0	24.0
Living Area (Size) Square Footage	1,908	645	1,478	1,754	2,168	1,200	514	937	1,108	1,308
Lot Area Square-Footage	5,344	2,982	3,920	4,792	6,510	846	1,977	0	0	871
Bedrooms	3.4	0.7	3.0	3.0	4.0	2.0	0.7	2.0	2.0	2.0
Bathrooms	2.7	0.6	2.0	3.0	3.0	2.0	0.6	2.0	2.0	2.0
Fireplaces	0.50	0.61	0.00	0.00	1.00	0.37	0.51	0.00	0.00	1.00
Private Pool^d	0.13	0.33	0.00	0.00	0.00	0.00	0.07	0.00	0.00	0.00
Private Spa^d	0.09	0.28	0.00	0.00	0.00	0.02	0.13	0.00	0.00	0.00
Garage Car Spaces	2.05	0.58	2.00	2.00	2.00	0.65	0.80	0.00	0.00	1.00
Heating Fuel: Electric^d	0.04	0.19	0.00	0.00	0.00	0.28	0.45	0.00	0.00	1.00
Heating Fuel: Gas^d	0.96	0.20	1.00	1.00	1.00	0.71	0.45	0.00	1.00	1.00
Heating Fuel: Mixed^d	0.00	0.05	0.00	0.00	0.00	0.00	0.05	0.00	0.00	0.00
Heating Fuel: Other^d	0.00	0.03	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00
Cooling Fuel: Electric^d	0.99	0.12	1.00	1.00	1.00	0.99	0.11	1.00	1.00	1.00
Cooling Fuel: Gas^d	0.02	0.12	0.00	0.00	0.00	0.01	0.11	0.00	0.00	0.00
Cooling Fuel: Other^d	0.00	0.02	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.00
Dishwasher^d	0.98	0.13	1.00	1.00	1.00	0.97	0.16	1.00	1.00	1.00
W/D: Washer and Dryer^d	0.84	0.37	1.00	1.00	1.00	0.93	0.25	1.00	1.00	1.00
W/D: Dryer Only^d	0.00	0.05	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00
W/D: None^d	0.16	0.37	0.00	0.00	0.00	0.06	0.24	0.00	0.00	0.00
W/D: Washer Only^d	0.00	0.04	0.00	0.00	0.00	0.00	0.04	0.00	0.00	0.00
TH^d	.	.	.	.	.	0.28	0.45	0.00	0.00	1.00
Neighborhood Characteristics										
Age Restriction^d	0.05	0.23	0.00	0.00	0.00	0.05	0.23	0.00	0.00	0.00
Gated Community^d	0.19	0.39	0.00	0.00	0.00	0.54	0.50	0.00	1.00	1.00
Community Pool^d	0.13	0.34	0.00	0.00	0.00	0.82	0.38	1.00	1.00	1.00
Community Spa^d	0.05	0.22	0.00	0.00	0.00	0.48	0.50	0.00	0.00	1.00
Community Park^d	0.04	0.18	0.00	0.00	0.00	0.13	0.33	0.00	0.00	0.00
Community Golf^d	0.04	0.20	0.00	0.00	0.00	0.02	0.15	0.00	0.00	0.00
Community Basketball^d	0.02	0.15	0.00	0.00	0.00	0.03	0.18	0.00	0.00	0.00
Community Clubhouse^d	0.06	0.24	0.00	0.00	0.00	0.35	0.48	0.00	0.00	1.00
Community Gym^d	0.03	0.17	0.00	0.00	0.00	0.34	0.47	0.00	0.00	1.00
Community Rules^d (HOA)	0.73	0.45	0.00	1.00	1.00	0.79	0.40	1.00	1.00	1.00

This table reports the mean, standard deviation (SD), 25th percentile (Q25), 50th percentile (Q50), and 75th percentile (Q75) of property characteristics by property type. The sample includes leased properties advertised for rent on the MLS in Clark County, NV between 2009Q1 and 2019Q1. Table D.1 in the appendix provides definitions for each variable. The *d* superscript denotes dummy variable. The mean of dummy variables can be interpreted as the share of the sample where the dummy variable equals 1.

Table E.2
Payment of Operating Expenses by Age Group

Age Group	Gas	Power	Water	Sewer	Disposal	Cable	Other
Panel A: Single-Family Residences							
G(0 yr)	0.98	0.99	0.96	0.70	0.80	0.80	0.77
G(1–10 yr)	0.98	0.99	0.95	0.66	0.78	0.78	0.82
G(11–20 yr)	0.99	0.99	0.96	0.70	0.80	0.81	0.81
G(21–30 yr)	0.97	0.99	0.95	0.68	0.78	0.79	0.80
G(31–40 yr)	0.92	0.99	0.95	0.65	0.76	0.78	0.79
G(41–50 yr)	0.81	0.98	0.93	0.62	0.71	0.74	0.80
G(51–60 yr)	0.80	0.98	0.93	0.61	0.72	0.73	0.76
Panel B: Condominiums							
G(0 yr)	0.85	0.95	0.65	0.47	0.61	0.61	0.80
G(1–10 yr)	0.74	0.97	0.34	0.22	0.25	0.26	0.80
G(11–20 yr)	0.85	0.97	0.39	0.27	0.29	0.29	0.79
G(21–30 yr)	0.71	0.97	0.34	0.25	0.22	0.22	0.79
G(31–40 yr)	0.64	0.98	0.50	0.34	0.32	0.32	0.77
G(41–50 yr)	0.57	0.98	0.57	0.32	0.35	0.35	0.76
G(51–60 yr)	0.35	0.97	0.31	0.21	0.20	0.20	0.66

This table reports the share of lease contracts (by property type and age groups) that require the tenant to pay for the named operating expense. The operating expenses are specified in the column headers. Panel A summarizes lease contracts of single-family homes, while Panel B summarizes those of condominiums.

Table E.3
Suppressed Coefficients from Table III - Annual Rent Depreciation Rates

Dep. Var.: ln(Rent) Sample:	(1) SFR	(2) SFR	(3) COND	(4) COND
ln(Size)^{dm}	0.45***	0.45***	0.54***	0.53***
	(0.01)	(0.01)	(0.09)	(0.09)
ln(Lot Area)	0.11***	0.11***	−0.00	−0.00
	(0.01)	(0.01)	(0.00)	(0.00)
Bedrooms	0.02***	0.02***	0.05***	0.05***
	(0.00)	(0.00)	(0.01)	(0.01)
Bathrooms	0.02***	0.02***	0.06***	0.06***
	(0.00)	(0.00)	(0.01)	(0.01)
Fireplaces	0.03***	0.02***	0.00	0.00
	(0.00)	(0.00)	(0.01)	(0.01)
Garage Car Spaces	0.04***	0.03***	0.05***	0.05***
	(0.00)	(0.00)	(0.01)	(0.01)
Private Pool^{d}	0.15***	0.15***	0.08***	0.07***
	(0.00)	(0.00)	(0.02)	(0.02)
Private Spa^{d}	0.05***	0.05***	0.02*	0.02*
	(0.00)	(0.00)	(0.01)	(0.01)
Heating Fuel: Electric^{d}	−0.00	−0.00	−0.01	−0.01
	(0.00)	(0.00)	(0.01)	(0.01)
Heating Fuel: Mixed^{d}	0.03***	0.03***	0.02*	0.02*
	(0.01)	(0.01)	(0.01)	(0.01)
Heating Fuel: Other^{d}	0.00	0.00	−0.04	−0.04
	(0.01)	(0.01)	(0.03)	(0.03)
Cooling Fuel: Gas^{d}	0.00	0.00	0.02**	0.02**
	(0.00)	(0.00)	(0.01)	(0.01)
Cooling Fuel: Other^{d}	−0.03	−0.03	0.04	0.04
	(0.02)	(0.02)	(0.03)	(0.03)
Dishwasher^{d}	0.02***	0.02***	0.05***	0.05***
	(0.00)	(0.00)	(0.01)	(0.01)
W/D: Dryer Only^{d}	−0.01***	−0.01***	0.01	0.00
	(0.01)	(0.01)	(0.02)	(0.02)
W/D: None^{d}	−0.01***	−0.01***	−0.01	−0.01
	(0.00)	(0.00)	(0.01)	(0.01)
W/D: Washer Only^{d}	−0.01*	−0.01*	0.02	0.03
	(0.01)	(0.01)	(0.02)	(0.02)
Cable Available^{d}	0.01***	0.01***	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Tenant Pays: Cable^{d}	0.00***	0.00***	−0.00	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)

(*continued on next page*)

Table E.3 *(continued)*

Dep. Var.: ln(Rent) Sample:	(1) SFR	(2) SFR	(3) COND	(4) COND
Tenant Pays: Gas[d]	−0.01***	−0.01***	−0.02***	−0.02***
	(0.00)	(0.00)	(0.01)	(0.01)
Tenant Pays: Power[d]	−0.02***	−0.02***	−0.11***	−0.11***
	(0.00)	(0.00)	(0.01)	(0.01)
Tenant Pays: Sewer[d]	−0.00***	−0.00***	−0.00	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Tenant Pays: Water[d]	−0.01***	−0.01***	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Tenant Pays: Garbage Pickup[d]	−0.01***	−0.01**	−0.01	−0.01
	(0.00)	(0.00)	(0.02)	(0.02)
Tenant Pays: Service[d]	−0.00	−0.00	0.01	0.01
	(0.00)	(0.00)	(0.02)	(0.02)
Age Restriction[d]	0.01	0.01	0.01**	0.01**
	(0.00)	(0.00)	(0.00)	(0.00)
Gated Community[d]	0.03***	0.03***	0.01	0.01
	(0.00)	(0.00)	(0.01)	(0.01)
Community Pool[d]	0.01*	0.00	0.01*	0.01*
	(0.00)	(0.00)	(0.00)	(0.00)
Community Spa[d]	0.00	0.00	0.01***	0.01***
	(0.00)	(0.00)	(0.00)	(0.00)
Community Park[d]	0.01***	0.01***	0.02***	0.02***
	(0.00)	(0.00)	(0.00)	(0.00)
Community Golf[d]	0.03***	0.03***	0.03*	0.03*
	(0.01)	(0.01)	(0.02)	(0.01)
Community Basketball[d]	0.02***	0.02***	0.00	0.00
	(0.00)	(0.00)	(0.01)	(0.01)
Community Clubhouse[d]	0.03***	0.03***	−0.01	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)
Community Gym[d]	0.02***	0.02***	0.03***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
Community Rules[d]	−0.01***	−0.01***	−0.00	−0.00
	(0.00)	(0.00)	(0.00)	(0.00)
TH[d]			−0.18***	−0.19***
			(0.05)	(0.05)
Observations	188,216	188,216	89,318	89,318
Adjusted R^2	0.88	0.89	0.86	0.86
Age Function	Quadratic	Spline	Quadratic	Spline
High/Middle School	✓	✓	✓	✓

This table reports the OLS coefficient estimates that were suppressed in Table 3. Additional controls not reported include high school and middle school categories. Robust standard errors are in parentheses and clustered by census tract. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table E.4
Annual Rent Depreciation Rates with FAR Interaction

Dep. Var.: ln(Rent)	(1)	(2)
Sample:	SFR	SFR
Age/100	−1.25***	
	(0.07)	
Age/1000	0.19***	
	(0.01)	
G(1–5 yrs) × (Age/100)		−1.27***
		(0.10)
G(6–10 yrs) × (Age/100)		−1.19***
		(0.07)
G(11–15 yrs) × (Age/100)		−1.05***
		(0.06)
G(16–20 yrs) × (Age/100)		−0.94***
		(0.05)
G(21–25 yrs) × (Age/100)		−0.82***
		(0.05)
G(26–30 yrs) × (Age/100)		−0.73***
		(0.04)
G(31–35 yrs) × (Age/100)		−0.58***
		(0.04)
G(36–40 yrs) × (Age/100)		−0.48***
		(0.04)
G(41–45 yrs) × (Age/100)		−0.41***
		(0.04)
G(46–50 yrs) × (Age/100)		−0.35***
		(0.03)
G(51–55 yrs) × (Age/100)		−0.31***
		(0.04)
G(56–60 yrs) × (Age/100)		−0.22***
		(0.04)
(Age/100) × FAR^{dm}	0.04	0.08
	(0.12)	(0.12)
Observations	188,203	188,203
Adjusted R^2	0.82	0.82
Structural	✓	✓
Neighborhood	✓	✓
Services	✓	✓
Year-Quarter FE	✓	✓
Census Tract FE	✓	✓

This table reports the OLS estimates of the hedonic model specified by equation (1) for single-family residence rentals. The dependent variable is log contract rents. $G(\cdot)$ denotes an indicator function for each age group. Variables with the *dm* superscript are demeaned. FAR is the natural log of the floor area to lot size square-footage. Structure controls include log unit size to lot area ratio (FAR), bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel, cooling fuel, dishwasher, and washer/dryer. Service controls include indicators of tenant payments for cable, gas, power, sewer, water, garbage pickup, and other services. Neighborhood controls include age restriction, gated community, and community amenities such as pool, clubhouse, schools. All regressions have a constant. Table D.1 in the appendix provides definitions for each variable. The properties were advertised for rent on the MLS in Clark County, NV between 2009Q1 and 2019Q1. Robust standard errors are in parentheses and clustered by census tract. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table E.5
Annual Rent Depreciation Rates using Asking Rents

Dep. Var.: ln(Asking Rent)	(1)	(2)	(3)	(4)
Sample:	SFR	SFR	COND	COND
Age/100	−0.82***		−2.30***	
	(0.05)		(0.43)	
Age^2/1000	0.08***		0.15***	
	(0.01)			
			(0.06)	
G(1–5 yrs) × (Age/100)		−0.95***		−1.60***
		(0.07)		(0.32)
G(6–10 yrs) × (Age/100)		−0.90***		−1.88***
		(0.04)		(0.24)
G(11–15 yrs) × (Age/100)		−0.78***		−2.04***
		(0.04)		(0.27)
G(16–20 yrs) × (Age/100)		−0.70***		−1.96***
		(0.03)		(0.28)
G(21–25 yrs) × (Age/100)		−0.62***		−1.88***
		(0.03)		(0.29)
G(26–30 yrs) × (Age/100)		−0.58***		−1.75***
		(0.03)		(0.25)
G(31–35 yrs) × (Age/100)		−0.55***		−1.67***
		(0.03)		(0.21)
G(36–40 yrs) × (Age/100)		−0.50***		−1.59***
		(0.03)		(0.18)
G(41–45 yrs) × (Age/100)		−0.47***		−1.60***
		(0.03)		(0.17)
G(46–50 yrs) × (Age/100)		−0.46***		−1.58***
		(0.02)		(0.17)
G(51–55 yrs) × (Age/100)		−0.42***		−1.58***
		(0.03)		(0.18)
G(56–60 yrs) × (Age/100)		−0.38***		−1.41***
		(0.03)		(0.16)
(Age/100) × $\ln(\text{Size})^{dm}$	−0.40***	−0.40***	−1.40***	−1.39***
	(0.04)	(0.04)	(0.22)	(0.22)
(Age/100) × TH			0.85***	0.85***
			(0.16)	(0.15)
Observations	217,308	217,308	105,372	105,372
Adjusted R^2	0.88	0.88	0.86	0.86
Property controls	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Census Tract FE	✓	✓	✓	✓

This table reports the OLS estimates of the hedonic model specified by equation (1) using equation (3) for the age function in columns (1) and (3), and equation (4) in columns (2) and (4). The dependent variable is the log of the contract rent. $G(\cdot)$ represents for an indicator function for each age group (1–5 years, 6–10 years, and so on) where the reference groups are properties under 1 year of age. Age is divided by 100, Age^2 is divided by 1,000, and *dm* implies demeaned. Property controls include log size square footage demeaned, log lot area square footage, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel, cooling fuel, dishwasher, washer/dryer, cable availability, tenant pay indicators (i.e., cable, gas, power, sewer, water, garbage pickup, other services), age restriction, gated community, community amenities (pool, spa, park, golf, basketball, clubhouse, gym, rules), high school, middle school, a townhouse/duplex/triplex flag (TH, for the condominium sample), and a constant. Table D.1 in the appendix provides definitions for each variable. The sample in columns (1)–(2) comprises rental listings for single-family residences, whereas the sample in columns (3)–(4) comprises rental listings for condominiums. The sample includes properties advertised for rent on the MLS in Clark County, NV between 2009Q1 and 2019Q1, even if the property was not leased (i.e., the listing was "withdrawn" or "expired"). Robust standard errors are in parentheses and clustered by census tract. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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Table E.6
Annual Rent Depreciation Rates using Granular Location FEs

Dep. Var.: ln(Rent) Sample:	(1) SFR	(2) SFR	(3) COND	(4) COND
G(1–5 yrs) × (Age/100)	−0.50***	−0.57***	−1.62***	−2.05***
	(0.06)	(0.05)	(0.34)	(0.23)
G(6–10 yrs) × (Age/100)	−0.47***	−0.57***	−1.94***	−2.16***
	(0.05)	(0.04)	(0.32)	(0.21)
G(11–15 yrs) × (Age/100)	−0.42***	−0.50***	−2.19***	−2.27***
	(0.05)	(0.04)	(0.37)	(0.24)
G(16–20 yrs) × (Age/100)	−0.38***	−0.46***	−2.06***	−2.21***
	(0.05)	(0.04)	(0.36)	(0.24)
G(21–25 yrs) × (Age/100)	−0.36***	−0.41***	−1.95***	−2.08***
	(0.05)	(0.04)	(0.37)	(0.22)
G(26–30 yrs) × (Age/100)	−0.35***	−0.38***	−1.79***	−2.02***
	(0.04)	(0.04)	(0.30)	(0.20)
G(31–35 yrs) × (Age/100)	−0.34***	−0.38***	−1.67***	−2.00***
	(0.04)	(0.04)	(0.24)	(0.19)
G(36–40 yrs) × (Age/100)	−0.35***	−0.38***	−1.58***	−1.97***
	(0.05)	(0.04)	(0.20)	(0.18)
G(41–45 yrs) × (Age/100)	−0.33***	−0.39***	−1.57***	−1.96***
	(0.05)	(0.04)	(0.18)	(0.19)
G(46–50 yrs) × (Age/100)	−0.35***	−0.41***	−1.62***	−1.82***
	(0.04)	(0.04)	(0.19)	(0.17)
G(51–55 yrs) × (Age/100)	−0.34***	−0.38***	−1.68***	−1.70***
	(0.04)	(0.03)	(0.19)	(0.17)
G(56–60 yrs) × (Age/100)	−0.30***	−0.34***	−1.45***	−1.56***
	(0.04)	(0.04)	(0.16)	(0.14)
(Age/100) × $\ln(\text{Size})^{dm}$	−0.37***	−0.34***	−1.36***	−1.31***
	(0.03)	(0.03)	(0.22)	(0.20)
(Age/100) × TH			0.83***	0.64***
			(0.16)	(0.12)
Observations	181,696	183,342	87,749	88,537
Adjusted R^2	0.92	0.92	0.87	0.89
Property controls	✓	✓	✓	✓
Year-Quarter FE		✓		✓
Census Tract × Year-Quarter FE	✓		✓	
Street Name FE		✓		✓

This table reports the OLS estimates of the hedonic model specified by equation (1) using equation (4) for the age function. The dependent variable is the log of the contract rent. $G(\cdot)$ represents for an indicator function for each age group (1–5 years, 6–10 years, and so on) where the reference groups are properties under 1 year of age. Age is divided by 100, and *dm* implies demeaned. Property controls include log size square footage demeaned, log lot area square footage, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel, cooling fuel, dishwasher, washer/dryer, cable availability, tenant pay indicators (i.e., cable, gas, power, sewer, water, garbage pickup, other services), age restriction, gated community, community amenities (pool, spa, park, golf, basketball, clubhouse, gym, rules), high school, middle school, a townhouse/duplex/triplex flag (TH, for the condominium sample), and a constant. Table D.1 in the appendix provides definitions for each variable. The sample in columns (1)–(2) comprises leases for single-family residences, whereas the sample in columns (3)–(4) comprises leases for condominiums. The properties were advertised for rent on the MLS in Clark County, NV between 2009Q1 and 2019Q1. Robust standard errors are in parentheses and clustered by census tract. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table E.7
Hausman Tests on inclusion of Neighborhood Controls

	SFR		COND	
	Linear	Non-Linear	Linear	Non-Linear
Chi-squared	11,684.49	15,692.38	1,017.59	5,695.14
P-value	0.000	0.000	0.000	0.000

This table reports the Chi-squared and p-value of the Chi-squared statistic for multiple Hausman tests that compare the age function coefficients between a random and fixed effects model. The tests are executed by property type and age function. The null hypothesis is that there are no systematic differences in the age function coefficients.

Table E.8
Annual Rent Depreciation Rates with Tests—Single Family Residences

Dep. Var.: ln(Rent) Sample:	(1) SFR	(2) SFR	(3) SFR	(4) SFR
Age/100	−0.90***	−1.16***	−0.87***	−0.82***
	(0.07)	(0.10)	(0.07)	(0.08)
G(6–10) × (Age/100)	0.04	0.30***	0.04	0.02
	(0.04)	(0.06)	(0.04)	(0.04)
G(11–15) × (Age/100)	0.15***	0.55***	0.14***	0.11**
	(0.05)	(0.08)	(0.05)	(0.05)
G(16–20) × (Age/100)	0.22***	0.60***	0.21***	0.17***
	(0.05)	(0.09)	(0.05)	(0.05)
G(21–25) × (Age/100)	0.30***	0.62***	0.27***	0.23***
	(0.06)	(0.09)	(0.06)	(0.06)
G(26–30) × (Age/100)	0.33***	0.62***	0.30***	0.26***
	(0.06)	(0.10)	(0.06)	(0.06)
G(31–35) × (Age/100)	0.36***	0.60***	0.32***	0.31***
	(0.06)	(0.10)	(0.06)	(0.06)
G(36–40) × (Age/100)	0.40***	0.64***	0.36***	0.34***
	(0.06)	(0.10)	(0.06)	(0.06)
G(41–45) × (Age/100)	0.43***	0.66***	0.38***	0.36***
	(0.06)	(0.10)	(0.06)	(0.06)
G(46–50) × (Age/100)	0.44***	0.66***	0.39***	0.34***
	(0.06)	(0.10)	(0.07)	(0.07)
G(51–55) × (Age/100)	0.46***	0.69***	0.41***	0.35***
	(0.06)	(0.10)	(0.07)	(0.07)
G(56–60) × (Age/100)	0.52***	0.76***	0.47***	0.41***
	(0.07)	(0.10)	(0.07)	(0.07)
(Age/100) × ln(Size)^{dm}	−0.42***	−0.37***	−0.41***	−0.40***
	(0.04)	(0.07)	(0.04)	(0.04)
(Age/100) × Home-ownership^{dm}			0.01	
			(0.13)	
(Age/100) × Population 65+ share^{dm}			0.56*	
			(0.30)	
(Age/100) × Hispanic share^{dm}			0.34**	
			(0.14)	
(Age/100) × Black share^{dm}			0.19	
			(0.17)	
(Age/100) × Asian share^{dm}			−0.20	
			(0.18)	
(Age/100) × ln(Population density)^{dm}			0.01	
			(0.02)	
(Age/100) × ln(Median household income)^{dm}			0.08	
			(0.11)	
Observations	188,216	188,219	188,216	188,216
Adjusted R^2	0.89	0.80	0.89	0.89
F-stat (age group interactions)	14.705	7.243	8.726	7.248
P-value (age group interactions)	0.000	0.000	0.000	0.000
F-stat (census tract interactions)	.	.	1.71	2.1e+05
P-value (census tract interactions)	.	.	0.105	0.000
Structural	✓	✓	✓	✓
Neighborhood	✓		✓	✓
Services	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Census Tract FE	✓		✓	✓
Census Tract FE × Age				✓

This table reports the OLS estimates of the hedonic model specified by equation (1) for single-family residence rentals. The dependent variable is log contract rents. $G(\cdot)$ denotes an indicator function for each age group. Variables with the *dm* superscript are demeaned. Structure controls include log unit size, log lot area, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel, cooling fuel, dishwasher, and washer/dryer. Service controls include indicators of tenant payments for cable, gas, power, sewer, water, garbage pickup, and other services. Neighborhood controls include age restriction, gated community, community amenities such as pool, clubhouse, schools, and a townhouse/duplex/triplex flag (TH). All regressions have a constant. Table D.1 in the appendix provides definitions for each variable. The properties were advertised for rent on the MLS in Clark County, NV between 2009Q1 and 2019Q1. Robust standard errors are in parentheses and clustered by census tract. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table E.9
Annual Rent Depreciation Rates with Tests—Condominiums

Dep. Var.: ln(Rent)	(1)	(2)	(3)	(4)
Sample:	COND	COND	COND	COND
Age/100	−1.50***	−1.52***	−1.23***	−1.42***
	(0.31)	(0.46)	(0.25)	(0.36)
G(6–10) × (Age/100)	−0.25*	−0.48	−0.12	0.22
	(0.15)	(0.29)	(0.17)	(0.15)
G(11–15) × (Age/100)	−0.41***	−0.81***	−0.30**	0.02
	(0.15)	(0.28)	(0.15)	(0.13)
G(16–20) × (Age/100)	−0.34**	−0.40	−0.28*	0.02
	(0.15)	(0.33)	(0.15)	(0.11)
G(21–25) × (Age/100)	−0.25	−0.17	−0.23	0.09
	(0.16)	(0.39)	(0.15)	(0.11)
G(26–30) × (Age/100)	−0.14	−0.33	−0.18	0.14
	(0.16)	(0.32)	(0.16)	(0.12)
G(31–35) × (Age/100)	−0.06	−0.33	−0.11	0.20*
	(0.17)	(0.30)	(0.17)	(0.12)
G(36–40) × (Age/100)	−0.01	−0.04	−0.04	0.25**
	(0.18)	(0.31)	(0.18)	(0.12)
G(41–45) × (Age/100)	−0.02	0.07	−0.06	0.24**
	(0.20)	(0.31)	(0.18)	(0.12)
G(46–50) × (Age/100)	0.01	−0.05	−0.05	0.26**
	(0.21)	(0.31)	(0.19)	(0.13)
G(51–55) × (Age/100)	0.01	−0.12	0.01	0.34**
	(0.22)	(0.32)	(0.20)	(0.15)
G(56–60) × (Age/100)	0.15	0.12	0.20	0.45***
	(0.22)	(0.33)	(0.21)	(0.17)
(Age/100) × ln(Size)^{dm}	−1.30***	−2.01***	−1.35***	−1.36***
	(0.21)	(0.28)	(0.21)	(0.21)
(Age/100) × TH	0.81***	1.06***	0.58***	0.50***
	(0.15)	(0.19)	(0.14)	(0.15)
(Age/100) × Home-ownership^{dm}			2.86***	
			(0.64)	
(Age/100) × Population 65+ share^{dm}			−0.61	
			(1.18)	
(Age/100) × Hispanic share^{dm}			0.27	
			(0.71)	
(Age/100) × Black share^{dm}			−0.96	
			(1.04)	
(Age/100) × Asian share^{dm}			−4.02***	
			(1.50)	
(Age/100) × ln(Population density)^{dm}			0.35***	
			(0.13)	
(Age/100) × ln(Median household income)^{dm}			−0.38	
			(0.45)	
Observations	89,318	89,323	89,318	89,318
Adjusted R^2	0.86	0.56	0.87	0.88
F-stat (age group interactions)	2.342	1.975	2.59	2.134
P-stat (age group interactions)	0.009	0.03	0.004	0.018
F-stat (census tract interactions)	.	.	7.91	2.3e+05
P-stat (census tract interactions)	.	.	0.000	0.000
Structural	✓	✓	✓	✓
Neighborhood	✓		✓	✓
Services	✓	✓	✓	✓
Year-Quarter FE	✓	✓	✓	✓
Census Tract FE	✓		✓	✓
Census Tract FE × Age				✓

This table reports the OLS estimates of the hedonic model specified by equation (1) for condominium rentals. The dependent variable is log contract rents. $G(\cdot)$ denotes an indicator function for each age group. Variables with the *dm* superscript are demeaned. Structure controls include log unit size, log lot area, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel, cooling fuel, dishwasher, and washer/dryer. Service controls include indicators of tenant payments for cable, gas, power, sewer, water, garbage pickup, and other services. Neighborhood controls include age restriction, gated community, and community amenities such as pool, clubhouse, schools. All regressions have a constant. Table D.1 in the appendix provides definitions for each variable. The properties were advertised for rent on the MLS in Clark County, NV between 2009Q1 and 2019Q1. Robust standard errors are in parentheses and clustered by census tract. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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Table E.10
Intrinsic Estimators with Location × Age Effects

Dep. Var.: ln(Rent) Sample:	(1) SFR	(2) CONDO	Continued	(1) SFR	(2) CONDO	Continued	(1) SFR	(2) CONDO
Age: 0–4 yrs	0.02**	−0.06***	Cohort: 1945–1949	0.19***	0.15	Homeownership	−0.06***	−0.85***
	(0.01)	(0.02)		(0.05)	(0.15)		(0.00)	(0.01)
Age: 5–9 yrs	−0.03***	−0.09***	Cohort: 1950–1954	−0.01	0.05	Population 65+ share	−0.02**	1.01***
	(0.01)	(0.02)		(0.01)	(0.05)		(0.01)	(0.02)
Age: 10–14 yrs	−0.04***	−0.11***	Cohort: 1955–1959	−0.05***	0.02	Hispanic share	−0.23***	−0.19***
	(0.01)	(0.01)		(0.01)	(0.04)		(0.01)	(0.02)
Age: 15–19 yrs	−0.05***	−0.11***	Cohort: 1960–1964	−0.02*	0.04	Black share	−0.18***	−0.23***
	(0.00)	(0.01)		(0.01)	(0.03)		(0.01)	(0.03)
Age: 20–24 yrs	−0.03***	−0.08***	Cohort: 1965–1969	−0.05***	−0.01	Asian share	−0.17***	−0.07**
	(0.00)	(0.01)		(0.01)	(0.03)		(0.01)	(0.03)
Age: 25–29 yrs	−0.02***	−0.04***	Cohort: 1970–1974	−0.01*	0.09***	ln(Population density)	0.01***	−0.06***
	(0.00)	(0.01)		(0.01)	(0.02)		(0.00)	(0.00)
Age: 30–34 yrs	−0.00	−0.02***	Cohort: 1975–1979	−0.01*	0.05**	ln(Median household	0.10***	0.27***
	(0.00)	(0.01)		(0.01)	(0.02)	income)	(0.00)	(0.00)
Age: 35–39 yrs	−0.00	0.00	Cohort: 1980–1984	−0.02***	−0.00	Homeownership ×	−0.11***	3.06***
	(0.00)	(0.01)		(0.01)	(0.02)	(Age/100)	(0.02)	(0.05)
Age: 40–44 yrs	0.01	0.02	Cohort: 1985–1989	0.00	−0.04***	Population 65+ share ×	0.09**	−3.55***
	(0.01)	(0.01)		(0.00)	(0.01)	(Age/100)	(0.04)	(0.12)
Age: 45–49 yrs	0.02***	0.05***	Cohort: 1990–1994	−0.00	−0.05***	Hispanic share ×	0.35***	−0.83***
	(0.01)	(0.02)		(0.00)	(0.01)	(Age/100)	(0.02)	(0.07)
Age: 50–54 yrs	0.01*	−0.01	Cohort: 1995–1999	0.01***	−0.04***	Black share × (Age/100)	0.52***	0.16
	(0.01)	(0.02)		(0.00)	(0.01)		(0.04)	(0.10)
Age: 55–59 yrs	0.07***	0.16***	Cohort: 2000–2004	0.01***	−0.06***	Asian share × (Age/100)	0.24***	−1.95***
	(0.01)	(0.02)		(0.00)	(0.00)		(0.05)	(0.15)
Age: 60–64 yrs	0.04***	0.29***	Cohort: 2005–2009	−0.01**	−0.02**	ln(Population density) ×	−0.05***	0.19***
	(0.01)	(0.05)		(0.00)	(0.01)	(Age/100)	(0.00)	(0.01)
Period: 2005–2009	−0.04***	−0.08***	Cohort: 2010–2014	−0.03***	−0.04***	ln(Median household	−0.00	−0.31***
	(0.00)	(0.00)		(0.00)	(0.01)	income) × (Age/100)	(0.00)	(0.01)
Period: 2010–2014	−0.05***	−0.07***	Cohort: 2015–2019	0.00	−0.13***			
	(0.00)	(0.00)		(0.01)	(0.02)			
Period: 2015–2019	0.09***	0.14***						
	(0.00)	(0.00)						
Observations	188,166	89,194						
Constant	✓	✓						
Property controls	✓	✓						

This table reports the age, period, and cohort effects on the natural log of the contract rate based on the IE method. The sample in column 1 (2) comprises leases for single-family residences (condominiums). The properties were advertised for rent on the MLS in Clark County, NV between 2009Q1 and 2019Q1. Age, period, and cohort flag the structure age group, rent lease listing date, and the structure year-built group, respectively. Property controls include log size square footage, log lot area square footage, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel, cooling fuel, dishwasher, washer/dryer, cable availability, tenant pay indicators (i.e., cable, gas, power, sewer, water, garbage pickup, other services), age restriction, gated community, community amenities (pool, spa, park, golf, basketball, clubhouse, gym, rules), high school, middle school, a townhouse/duplex/triplex flag (TH, for the condominium sample), and a constant. Table D.1 in the appendix provides definitions for each variable. Standard errors are in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

Table E.11
Supplemental Rent Regressions

Dep. Var.: ln(Rent) Sample:	(1) SFR	(2) CONDO
G(0–4 yrs) × (Age/100)	−0.95***	−1.26***
	(0.08)	(0.33)
G(5–9 yrs) × (Age/100)	−0.95***	−1.53***
	(0.05)	(0.23)
G(10–14 yrs) × (Age/100)	−0.82***	−1.77***
	(0.04)	(0.27)
G(15–19 yrs) × (Age/100)	−0.73***	−1.73***
	(0.04)	(0.28)
G(20–24 yrs) × (Age/100)	−0.64***	−1.61***
	(0.03)	(0.29)
G(25–29 yrs) × (Age/100)	−0.58***	−1.48***
	(0.03)	(0.26)
G(30–34 yrs) × (Age/100)	−0.53***	−1.34***
	(0.03)	(0.22)
G(35–39 yrs) × (Age/100)	−0.49***	−1.26***
	(0.03)	(0.20)
G(40–44 yrs) × (Age/100)	−0.45***	−1.21***
	(0.03)	(0.19)
G(45–49 yrs) × (Age/100)	−0.42***	−1.17***
	(0.02)	(0.19)
G(50–54 yrs) × (Age/100)	−0.39***	−1.30***
	(0.02)	(0.17)
G(55–59 yrs) × (Age/100)	−0.31***	−1.08***
	(0.03)	(0.16)
G(60–64 yrs) × (Age/100)	−0.29***	−0.81***
	(0.04)	(0.23)
Observations	188,163	89,190
R^2	0.88	0.85
Constant	✓	✓
Property controls	✓	✓
Year-Quarter FE	✓	✓
Census Tract FE	✓	✓

This table reports the OLS estimates of the hedonic model specified by equation (1) using equation (4)—but without an age interaction with size or TH—for the age function. The dependent variable is the log of the contract rent. $G(\cdot)$ stands for an indicator function for each age group (0–4 years, 5–9 years, 10–14 years, and so on); the 0–4 years age group is set as the reference group. Property controls include log size square footage demeaned, log lot area square footage, bedrooms, bathrooms, fireplaces, private pool, private spa, garage car spaces, heating fuel, cooling fuel, dishwasher, washer/dryer, cable availability, tenant pay indicators (i.e., cable, gas, power, sewer, water, garbage pickup, other services), age restriction, gated community, community amenities (pool, spa, park, golf, basketball, clubhouse, gym, rules), high school, middle school, a townhouse/duplex/triplex flag (TH, for the condominium sample), and a constant. Table D.1 in the appendix provides definitions for each variable. The sample in column 1 comprises leases for single-family residences, whereas the sample in column 2 comprises leases for condominiums. The properties were advertised for rent on the MLS in Clark County, NV between 2009Q1 and 2019Q1. Robust standard errors are in parentheses and clustered by census tract. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

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Appendix F. Additional Figures

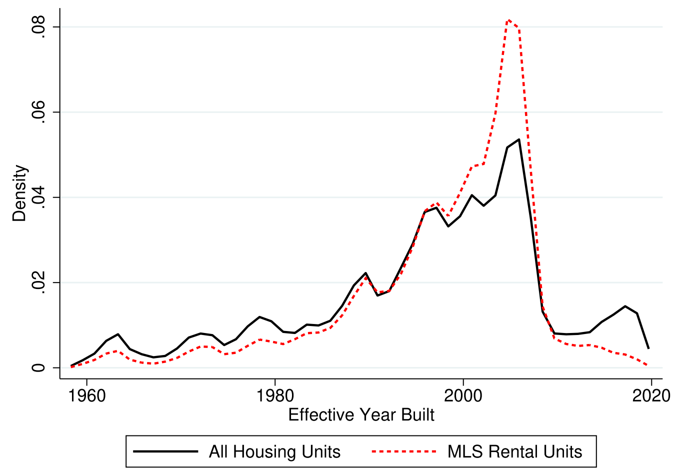

Fig. F.1 Kernel Distribution of Year-Built.

This figure displays the kernel density plot of the effective year built for the entire population of residential properties in Clark County as of 2019Q1 (All Housing Units) and the population of unique residential properties in the MLS sample (MLS Rental Units).

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