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Total returns to single-family rentals

Andrew Demers | **Andrea L. Eisfeldt**

UCLA Anderson and NBER, Los Angeles, CA, USA

Correspondence
Andrea L. Eisfeldt, UCLA Anderson and NBER, Los Angeles, CA, USA.
Email: andrea.eisfeldt@anderson.ucla.edu

Abstract

The market value of U.S. single-family rental assets totals more than $2.3 trillion. We provide the first systematic analysis of total returns to single-family rentals in a long, broad, and granular panel. Total returns are approximately equalized across U.S. cities at 8.5%, similar to average equity returns. On average, net rental yields and house price appreciation each contribute half total returns. However, they are negatively correlated in the cross section of cities. High-price-tier cities accrued more capital gains, whereas low-price-tier cities had higher net rental yields. Within cities, lower-price-tier ZIP codes have higher total returns.

1 | INTRODUCTION

Single-family rentals (SFRs) represent 35% of all rented housing units in the United States, and have a market value of approximately $2.3 trillion.[1] Analogous to the dividend yields and capital gains that constitute total equity returns, total returns to SFR assets have two components: rental yields and house price appreciation. There are many important studies of either housing returns from house price appreciation, or of rent-to-price ratios in the literature; however, we believe that we are the first to consider total returns to single-family houses accounting for both rental yields net of expenses, and house price appreciation, in a broad and granular cross-section, and a long time series.[2] We construct a dataset containing rental yields and house price appreciation data

[1] Authors' calculations using the 2013 American Community Survey (ACS) data from the Census Bureau. The ACS reports 116M household/units and a homeownership rate of 63.5%. Of the approximately 42 million rental units, about 15 million are single-family detached homes. The average U.S. home is worth approximately $200,000, and our calculations indicate that the average rental home is worth 25% less.

[2] We will make our code and constructed gross and net yield data for 30 cities from 1986 to 2014, and for 1986–2019 for 15 cities, publicly available on Github. Due to privacy concerns, the Census changed their geographic disclosure to include only the top 15 cities starting in 2015. Our yield data can be combined with publicly available or proprietary data on house price appreciation to form a long time series of city-level total returns.

for SFR assets, and study the total returns to this large and understudied asset class over a long time period from 1986 to 2014, and in a broad and granular cross section across U.S. cities and ZIP codes.

Including both the capital gain and rental yield components of SFR returns is crucial to understanding the return properties of single-family housing assets. Each component contributes approximately equally to the aggregate U.S. portfolio of housing returns, so excluding one component excludes half of total returns on average. This may explain why prior studies, focusing either only on rental yields or house price appreciation alone, have reported low returns to U.S. housing assets. Moreover, we show that the cross-sectional correlation between these two components is strongly negative at the city level. High price tier city-years have lower rental yields, but higher capital gains, or house price appreciation (HPA). Low price tier city-years have higher rental yields and lower capital gains. Thus, each component paints the opposite picture for the ranking of returns in the cross section of cities. Within cities, across ZIP codes, both net rental yields and house price appreciation are higher in lower-price-tier ZIP codes. The dispersion within cities is smaller for house price appreciation, however, and total return variation within cities is driven mainly by yields. Finally, at both levels of aggregation, rental yields appear to be less volatile than house price appreciation, implying that SFR assets with a larger return contribution from rental yields have higher measured Sharpe ratios.

There is considerable interest in SFRs as an asset class. We show that which cities an investor should include in their portfolio depends on violations of capital structure and dividend policy irrelevance.[3] As houses are illiquid and indivisible, partial liquidations to replicate dividend payments, as used in the proof for dividend policy irrelevance in Miller and Modigliani (1961), are costly. The illiquidity cost makes it unlikely that variation in dividend yields for SFR assets is irrelevant for investors. Although cities do not vary widely in average total returns, there is large variation across cities in the contribution of yields versus house price appreciation to these total returns. Debt investors may favor cities with higher dividend yields, and therefore higher debt service coverage ratios. On the other hand, cities with higher house price appreciation may appeal to private equity investors seeking larger capital gains over a shorter investment horizon.

Up until very recently, almost all of the approximately 12 million SFR assets were owned by individuals or small investors. However, following the financial and housing crisis of 2008, investment by large investors increased substantially. More recently, three Real Estate Investment Trusts backed by SFR assets have had their Initial Public Offering, with a current total market capitalization of over \$18 billion.[4] Moreover, there are currently about over \$20 billion of SFR-backed bonds outstanding. A sign of current growth in the institutional SFR market is that Fannie Mae recently offered the first guarantee for an SFR securitization.[5] Our study provides the first comprehensive analysis of the total returns to a large asset class, with growing institutional interest.

Understanding the drivers of the returns to SFRs is important for housing economics more broadly. As the Great Financial Crisis, homeownership rates have steadily declined. The current low homeownership rate of 63.6% is a level not seen in the United States since the 1960s.[6] Institutional ownership of SFR properties may reduce the cost of capital through diversification and lower operating costs through economies of scale. However, whether institutional involvement in

[3] See Miller and Modigliani (1961) and Miller and Modigliani (1958).

[4] These are Invitation Homes (INVH), Starwood Waypoint Homes (SFR), and American Homes for Rent (AMH). As of October, 2017, these three operators own over 125,000 homes.

[5] http://www.fanniemae.com/syndicated/documents/mbs/remicsupp/2017-T01.pdf

[6] https://fred.stlouisfed.org/series/RHORUSQ156N

SFRs is sustainable depends on the characteristics of the returns to SFRs, and whether the returns are compatible in the long run with institutional investors' objectives and constraints. Our study describes how the returns to SFRs vary in the time series and cross section. The facts we present inform investors in real SFR assets, as well as in SFR asset-backed securities, about historical asset performance, and about variation in returns in the cross section of cities and ZIP codes. A historical perspective can also help to put into context how this asset class might be expected to perform, and to understand what challenges investors might face. Our study also aims to inform policy makers, who are concerned about the effect of institutional investment and securitization on housing markets by lending insight into how investors might analyze potential portfolios of homes. Finally, the stylized facts we develop about rental yields and house price appreciation in the cross section are also independently useful for informing theories of housing valuations across cities, ZIP codes, and price tiers. One caveat to interpreting our study is that we construct city and ZIP-code-level total return indices that abstract from any special characteristics of rental homes such as lower maintenance and selection into rental status.

We construct time series data describing city-level returns for the largest 30 cities from 1986 to 2014 using data from the American Housing Survey (AHS) from the Census Bureau to construct net rental yields, and Core Logic's House Price Index (HPI) data to compute house price appreciation. Beginning with the 2015 Census, the AHS data only consistently provide data for the top 15 metropolitan areas. We show that our main results are similar using the full time series from 1986 to 2019 using those 15 cities in the Internet Appendix. We combine the time series for net rental yields with the corresponding time series for annual house price appreciation in order to analyze what industry participants call "Total Returns," namely, the sum of net rental yields and capital gains.[7] Total Returns are a useful measure for considering institutional participation in SFRs, because they are analogous to total stock returns from dividends and capital gains. They represent the return reported by institutional investors in the SFR space.

Constructing net rental yields first requires the construction of gross rent-to-price ratios, and then subtracting costs. Because of the relatively low representation of single-family detached rentals in the AHS data, we use a hedonic model at the house level to construct our gross rental yield time series. In constructing city-level gross yields, we weight observations by the empirical density of rental units in different price deciles within each city to adjust for the fact that rental homes are more prevalent in lower-price tiers within cities. To construct net yields from gross yields, we use a formula that accounts for all renovation and operating costs as the appropriate fraction of either home value, size, or rent. We use time and state- or city-specific data for real estate taxes and vacancies. On average, we find that net yields are about 60% of gross yields, and this is consistent with house-level data from SFR bond annexes, as well as data from CoreLogic Rental Trends data.

Our city-level results for 1986–2014 uncover some striking stylized facts. First, we show that rental yields tend to be highest in the lowest-price-tier cities, and monotonically decline with price tier.[8] If rents were constant across price tiers, this would be a tautology, but high-quality houses should, all else equal, have both higher rents and higher purchase prices. Empirically, however, rental yields are substantially higher in lower-price-tier cities. On average, yields were 6.1% in the lowest price quintile across cities, and 2.4% in the highest price quintile over the period 1986–2014, a difference of nearly 4%. By contrast, higher-price-tier cities have experienced more

[7] See, for example, Shen and Mele (2014).

[8] We form price tiers each year using quintiles of prior year price levels using a procedure described in Section 3.3.

house price appreciation over the period we study.[9] Indeed, we find that city-level house price appreciation monotonically increases with price tier. From 1986 to 2014, house price appreciation in the lowest tier cities averaged 3.1%, whereas it averaged 5.5% in the highest tier. As a result, total returns are more equated in the cross section of cities than either individual component is.[10] Indeed, cities with higher rental yields have tended to have lower house price appreciation. The lowest-price-tier cities do display slightly higher total returns of 9.2%, as compared to 7.9% for the highest price tier. This is because there is more dispersion across price tiers in net rental yields than in house price appreciation, and this benefits the lower tiers. Note that including rental yields completely overturns the popular wisdom that investing in coastal cities, which tend to have high prices and high house price appreciation, dominates investing in interior, so-called "fly-over" cities. Also striking is the fact that the pooled time series cross-section averages of annual city-level net yields and house price appreciation are almost exactly equal, at 4.2% and 4.3%, respectively. House price appreciation appears to display higher time series volatility than rental yields do in our data, however. Thus, lower-price-tier cities, with a larger contribution to returns from rents, seem to have higher Sharpe ratios, with slightly higher average returns to the rest of the country, and lower return volatility.

We construct ZIP-code-level total returns at the monthly frequency from 2012 to 2016, the period for which we have ZIP-code level net yield data. We utilize a detailed new dataset from Core Logic, Rental Trends, which was developed in 2012 by Core Logic to support institutional investment in SFR strategies.[11] Rental Trends reports median net rental yields, or "cap rates" by ZIP code, property type, and number of bedrooms for 11 million rental units, or about 75% of SFR homes. Core Logic constructs net rental yields using proprietary data from Multiple Listing Service records, tax records, actual vacancies, tenant credit events, and Core Logic's home price index model. For our ZIP-code-level house price appreciation analysis, we utilize Core Logic's monthly ZIP-code-level HPI data.

We find that, similar to our results at the city level, ZIP-code-level net rental yields decline with price tier. However, in contrast to the city-level data, we do not find that house price appreciation increases with price tier at the ZIP code level. If anything, especially in recent data, house price appreciation has been higher in the *lower* price tier ZIP codes. This pattern is consistent with theories of gentrification, as well as theories of the effects of subprime finance. As a result of both net yields declining, and house price appreciation being flat or decreasing with house prices, total returns clearly decline with house price tier at the ZIP code level. Thus, our findings suggest that investors may find higher average returns from properties in the lower price tiers within cities. However, house price appreciation in the lower tier ZIP codes does tend to display higher betas on city-level house price appreciation, so these higher returns may be compensation for higher risk. Although most ZIP codes load heavily on their respective city-level house price appreciation factor, with 90% of loadings falling between 0.8 and 1.2 using monthly data from 1985 to the present, these loadings tend to be higher in the lower-price-tier ZIP codes. Vacancy and credit risk are likely to make rental yields similarly more risky in lower price tiers.

We also study the cross-section dispersion in returns across versus within cities. Consistent with our finding of high loadings of ZIP-code-level house price appreciation on city-level house

[9] This finding is consistent, for example, with the results in Gyourko et al. (2013) regarding the so-called "Superstar Cities".

[10] We show in the Internet Appendix that Internal Rates of Return (IRRs) on SFR investments are approximately linear in net yields and house price appreciation, with each element contributing approximately equally.

[11] We believe that ours is the first academic study to utilize this data.

price appreciation, we find that there is more cross-sectional variation in house price appreciation across cities than within cities. Each year, we compute the unconditional standard deviation of house price appreciation across ZIP codes, and find that the average standard deviation is 5.6%. By contrast, the time series average of the cross-section standard deviation of ZIP code house price appreciation in excess of their city-level means is only 3.4%. For rental yields, the dispersion is lower than that for house price appreciation at both levels of aggregation, and the ordering of dispersion is reversed. There is more dispersion in rental yields within cities than across cities. Over the shorter period for which we have ZIP-code-level net yield data, the average cross-section standard deviation of net yields is 1.3% across cities versus 2.2% within cities. The results on dispersion are interesting because while there is a strong city-level factor in house price appreciation, there appears to be more neighborhood-level variation in rental yields. This variation could be used in future research to better understand the drivers of prices versus rents.

The remainder of the paper proceeds as follows: In Section 2, we discuss the existing literature, which almost exclusively studies either house price appreciation, or price-to-rent ratios (the inverse of gross rental yields), but not both return components jointly. In Sections 3 and 4, we document the stylized facts describing net rental yields, house price appreciation, and total returns at the city and ZIP code level, respectively. Section 5 integrates the findings from these two levels of cross-section aggregation. Finally, Section 6 concludes.

2 | RELATED LITERATURE

The prior literature has primarily focused separately on either rent-to-price ratios (rental yields) or house price appreciation (capital gains). Our contribution is to combine and extend this literature in order to study total returns to SFR homes, a $2.3 trillion value asset class. To this aim, we advance the literature in several ways. First, we compute median city-level rental yields for the top 30 U.S. cities from 1986 to 2014 using a hedonic model, and the empirical distribution of rented units, to adjust for differences in the characteristics of rented and owned units. Second, we compute net rents for each city-year observation using data on gross rents along with actual data on vacancy and tax rates that vary over time and in the cross section, as well as accounting for credit losses, property management and leasing fees, Homeowners' Association (HOA) fees, insurance, repairs, and maintenance. Finally, we combine the data on net rental yields with data on house price appreciation to construct total return series at the city level from 1986 to 2014, and at the ZIP code level for the recent period from 2013 to the present.

The most closely related study to ours is the contemporaneous paper by Jorda et al. (2017), which documents the total returns to housing internationally, at the *country* level, for developed nations over a very long sample, back to 1870. The distinct contribution of our paper is to study variation in total returns within the United States, across cities and ZIP codes, rather than at the country level. Their finding that at the national level, both rental yields and house price appreciation are key inputs to total returns is consistent with our measurement and results. To our knowledge, the only other academic study of SFRs is the recent paper by Malloy et al. (2017).[12] That paper also focuses on SFRs as an asset class. However, an important distinction is that they do not study rental yields, but instead focus only on the capital gains component of returns from house price appreciation. Including rental yields is a major benefit of our study, because, for about half of

[12] See also the closely related working paper Malloy and Zarutskie (2013).

the cities in the United States, house price appreciation represents significantly less than half of the total return. The sample of focus in Malloy et al. (2017) is also distinct from ours. Rather than constructing returns over a long time period or broad cross section as we do, that paper instead focuses on the postcrisis period only, with a cross-section emphasis on locations with concentrated institutional investment. Thus, our study is distinct from, and complementary to theirs. Their paper presents convincing evidence that although institutional investor purchases of single-family homes were concentrated in geography and time, that their behavior was distinctly different from that of other housing investors. In particular, they show that SFR investors had longer holding periods. Our findings support their conclusion that the SFR business may not simply be a trade based on depressed housing prices following the financial crisis, but rather a sustainable asset class for institutional investors. This view is also supported by the performance of the Real Estate Investment Trusts based on SFR strategies that have gone public after the housing recovery.

In the housing literature, there are two broad ways of thinking about the price-to-rent ("P/R") ratio, which is the inverse of gross SFR yields. The first methodology considers price-to-rent ratios as implied by imposing indifference, or no arbitrage, between renting and owning. This method, following Poterba (1984), computes the "user cost" of owned housing, and equates the inverse of this cost to the price rent ratio.[13] Studies of the user cost of housing typically focus on the relative cost of renting versus buying, rather than on the total return to buying, and then renting, a single-family home. Himmelberg et al. (2005) provide a clear description and assessment of the P/R ratio implied by inverse user costs. They employ a user cost model to impute an annual rental cost to owned properties and to ask whether the early part of the millennium represented a bubble in house prices. The six inputs to their user cost model are: the risk-free rate, property taxes, mortgage interest deductions, depreciation, capital gains, and the housing risk premium. Davis et al. (2008) construct a quarterly aggregate time series for the price-to-rent ratio of the U.S. owner-occupied housing stock from 1960 to 1995. By contrast, we construct city-level time series for the price-to-rent ratio of SFR homes, and combine that with data on house price appreciation to construct city-level total return series.

The user cost framework has also been used to study the cross section of price-to-rent ratios. Garner and Verbrugge (2009) use Consumer Expenditure Survey data from 2004 to 2007 to reconcile user costs and monetary rents at the house level. Consistent with our findings, they report that monetary rents are much more stable than user costs implied by house prices, and that user costs may be negatively correlated with monetary rents. Hill and Syed (2016) emphasize variation in the cross section of price rent ratios within cities, and like our study, they use a hedonic model to correct for differences in the characteristics of owned versus rented homes using data from 73,000 houses in Sydney, Australia. Finally, Bracke (2015) uses data from homes in central London that were both rented and sold within 6 months between 2006 and 2012 to show that higher priced homes have lower rental yields. The findings in these three studies, using the CES data for the United States from 2004 to 2007, and from Sydney and London, respectively, largely corroborate our findings in the AHS for the United States from 1986 to 2014.

The second methodology treats housing analogously to more liquid financial assets, and argues that lower discount rates imply higher valuations, and that momentum traders can amplify house price movements in the short run, whereas rents are more stable. Following Campbell's (1991) decomposition of stock returns, Campbell et al. (2009) conduct a variance decomposition of the rent-to-price ratio using a dynamic Gordon growth model. They find that there is an important

[13] See also Hendershott and Slemrod (1982).

role for variation in housing risk premia in explaining house-price dynamics, and cyclical variation in the P/R ratio.

Rental yields in the time series and cross section may also be affected by financial constraints. Eisfeldt and Rampini (2009) identify the role of financial constraints in determining the equilibrium rental rate corporations pay to lease equipment and structures. Because leasing has a higher debt capacity due to stronger repossession rights, constrained firms are willing to pay a higher yield in order to relax their borrowing constraint. We document higher rental yields at lower price points both in the time series and in the cross section, which is consistent with a similar role for financial constraints driving rents higher in lower price tiers.

House price appreciation has been studied extensively in the forecasting literature. Although we do not forecast house price appreciation for the purposes of this paper, we follow the literature in conceptually considering city-level house price processes as best described by a two-stage error correction model in which house prices grow with income, but exhibit momentum and mean reversion. Malpezzi (1999) and Capozza et al. (2004) are classic references.[14] Realized house price appreciation has been shown to be highly correlated with the degree of physical constraints such as water and mountains (Saiz, 2010), as well as regulatory constraints such as zoning restrictions (Gyourko et al., 2008). Gyourko et al. (2013) document a positive correlation between house price appreciation and variation in amenities and productivity, and coined the term "superstar cities" to describe the growing inequality between cities.[15] Due to this and other variation in city characteristics, the first stage of house price appreciation forecasting models often includes either city fixed effects, or interactions of population or income with supply elasticity.[16] Second-stage momentum and mean reversion coefficients also vary significantly across cities. This is consistent with the idea that because housing pays a dividend in the form of a nontradable service, markets are local, as emphasized in the assignment model literature such as Määttänen and Terviö (2014) and Landvoigt et al. (2012) and in the sorting literature, such as Van Nieuwerburgh and Weill (2010). Van Nieuwerburgh and Weill (2010) develop an assignment model of income and housing to show how sorting of higher income consumers into higher productivity cities might explain recent cross-sectional patterns in city-level house price appreciation, and lead to superstar cities. Although city-specific effects are important, we note that recent work by Cotter et al. (2014) shows that, empirically, house price appreciation has become more correlated across cities in recent years.[17]

Finally, recent work has attempted to model house prices, and less often rents, in general equilibrium macroeconomic models. Davis and Nieuwerburgh (2014) and Piazzesi and Schneider (2016) review some of these recent advances. In particular, house price appreciation within cities has been studied in the context of different patterns of development and gentrification, as well as in the context of financial innovations such as subprime lending. Guerrieri et al. (2013) emphasize the role of geographical spillovers in a spatial equilibrium model of gentrification, and

[14] As found in Case and Shiller (1990), the persistence of excess returns is higher for housing than for stocks and bonds. This may be because houses are not as liquid as financial assets. More recently, Guren (2014) studies house price appreciation across cities with an autoregression and measures a decay rate of less than half, with the median city having an annual AR(1) coefficient of 0.60. Titman et al. (2014) argue that the serial correlation is highest at 1-year intervals and longer horizons display reversion.

[15] See also Davidoff (2014).

[16] See, for example, Shan and Stehn (2011).

[17] See also Giglio et al. (2015) and Giglio et al. (2016) for studies of very long-run housing discount rates using data freeholds versus leaseholds.

provide empirical evidence supporting the presence of such spillovers.[18] Using data from the 2000 to 2005 boom in San Diego house prices, along with an assignment model which incorporates financial constraints, Landvoigt et al. (2012) provide evidence of the effects of subprime lending on house prices at the lower end. To our knowledge, a theory of both rental yields and house price appreciation patterns in the cross section remains a gap in the literature.

3 | CITY-LEVEL TOTAL RETURNS

We focus on total returns from net rental yields and house price appreciation. These total returns are analogous to total stock returns from dividends and capital gains. We also note that total returns, unlike IRRs, are insensitive to the holding period, and total returns summarize returns that would be reported annually by institutional investors.[19] We begin by documenting gross and net rental yields, and house price appreciation, at the city level from 1986 to 2014 for the top 30 cities by number of AHS observations in 1985. We describe this data, our variable names, and empirical procedures in detail in the Internet Appendix. In the Internet Appendix, we describe results for 1986 to 2019 for which data for a smaller set of 15 Metropolitan Statistical Areas (MSAs) is available in the AHS.

At the city level, we construct total returns annually by summing net rental yields constructed using the AHS data, and annual realized house price appreciation constructed using Core Logic's monthly HPI data. We report yields and house price appreciation in nominal terms, as is typical in the finance literature. The timing is as follows, where for concreteness, we use 2008 as an example. The typical total annual return calculation for a stock j at $t = 2008$ is:

$$R_{j,2008} = \frac{P_{j,2008}}{P_{j,2007}} + \frac{D_{j,2007-2008}}{P_{j,2007}}. \tag{1}$$

We implement this calculation for total returns to SFRs in city j at time $t = 2008$, for example, using our two data sources as follows:

$$R^{\text{SFR}}_{j,2008} = \underbrace{\frac{\text{HPI}_{\text{j, CL June 2008}}}{\text{HPI}_{\text{j, CL June 2007}}}}_{\text{capital gain = HPA}} + \overbrace{\frac{\text{Net Rent}_{\text{j, AHS 2007}}}{\text{Price}_{\text{j, AHS 2007}}}}^{\text{dividend yield = net rental yield}} . \tag{2}$$

The AHS is conducted biannually, in odd-numbered years, between May and September. To match this timing, we compute annual house price appreciation each year from June to June using Core Logic's monthly HPI data. We use the rent reported in the beginning of period AHS survey, because this rent represents the dividend over the holding period. This measurement timing has the added benefit of using rent and price data from the same AHS survey, which avoids loss of data due to

[18] Kolko (2007) studies the empirical determinants of gentrification and argues that proximity to city center and the age of the housing stock are important observable drivers.

[19] We demonstrate the relationship between total returns and IRRs in the Internet Appendix, where we also show that IRRs are nearly exactly linear in net yields and house price appreciation.

the sample varying over time.[20] Our resulting total return series thus covers 1986–2014, using Core Logic's HPI data from June 1985 to June 2014, and data on prices and rents from the 1985–2013 AHS surveys.

3.1 | City-level net rental yields

We begin with a detailed description of our measurement of the second term, representing net rental yields biannually by city. Our first step is to compute gross rental yields on single-family homes by city using the AHS data. Although there are about 12 million SFR homes in the United States, these homes constitute only a small fraction of the AHS sample. Thus, to construct a city-level rental yield for single-family homes (as opposed to multifamily dwellings), we begin by estimating rental yields for *owned* single-family homes, which constitute the vast majority of the single-family sample, in the AHS using a hedonic model.[21] We index time by t, city by j, and house observation by i. First, we estimate a hedonic regression using all rented housing units in the AHS for the largest 30 cities to come up with rental prices for key housing characteristics as follows:

$$\begin{aligned} \ln(\text{MonthlyRent}_i) = \beta_{0,j} + \beta_{0,t} + \beta_1 \text{Rooms}_i + \beta_2 \text{Beds}_i + \beta_3 \text{Baths}_i \\ + \beta_4 \text{AirSys}_i + \beta_5 \text{UnitType}_i + \beta_6 \text{Age}_i + \beta_7 \text{Ln(SqFt)} + \epsilon_i . \end{aligned} \tag{3}$$

We include city fixed effects and year fixed effects, as captured by $\beta_{0,j}$ and $\beta_{0,t}$. MSA is a dummy variable for each of the cities, Beds is the number of bedrooms, Baths is the number of bathrooms, AirSys is 1 if the unit has a central air conditioning system and 0 otherwise, UnitType is either attached condo or detached home (with detached condos and attached homes being the excluded categories), Age is a categorical variable corresponding to the decade of construction, and Ln(SqFt) is the natural log of square footage. Once we have our coefficient estimates using the rented subset of the AHS sample, we then use these coefficients, along with the observed characteristics of owned single-family units, to construct estimated rents for each observation of the owner-occupied subset.[22] To correct for the log transformation, we apply the Goldberger (1968) correction, as used by Malpezzi et al. (1998) in the context of house price indices. The end result is a dataset of both prices and an estimated rent for each owner-occupied unit in the AHS.[23]

A key consideration in constructing representative total returns for SFR assets is the higher prevalence of rental units in lower price tiers.[24] Therefore, to construct our city-level gross rental yields, we weight each house-level observation according to the empirical price distribution of

[20] Rental contracts are typically at least annual, and, moreover, rents are slow moving. Thus, we argue that it is reasonable to use rents reported in June of 2007 as covering the period June 2007–June 2008. Note that this method also ensures that synchronous measurement of the denominator of each return component.

[21] We show that our main conclusions hold under the alternative method of using actual rents from the much smaller sample of rental homes, and hedonically estimated prices, in the Internet Appendix.

[22] The regression results appear in the Internet Appendix.

[23] Although self-reported values may be inflated slightly, Kiel and Zabel (1999) document the accuracy of owner provided home values in the AHS data, and report that estimates are only slightly biased upwards, on the order of magnitude of about 5%. They further argue that "the use of the owners' valuations will result in accurate estimates of HPIs and will provide reliable estimates of the prices of house and neighborhood characteristics."

[24] Our finding of higher rental yields in lower price tiers for the United States is consistent with that of Bracke (2015) for London.

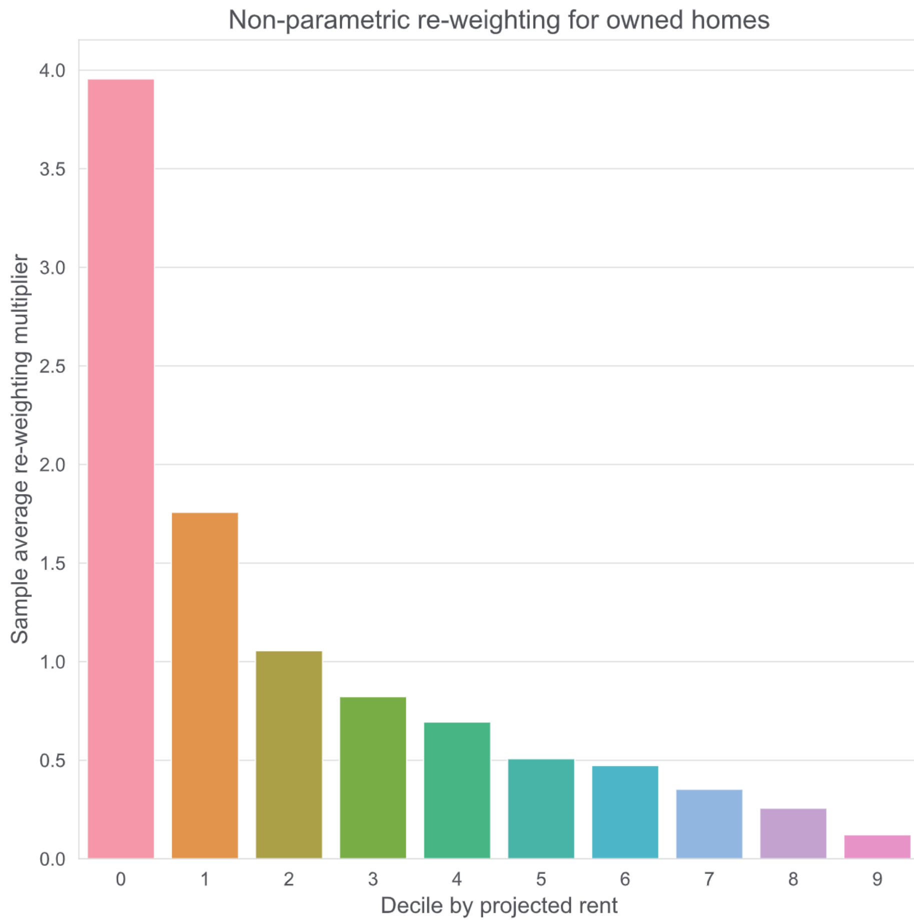

FIGURE 1 Plot of average ratio of rental to owned densities of housing units by rent tier within cities. We nonparametrically reweight homes within cities to adjust weighted median net rental yields. The reweighted distribution more accurately represents the actual distribution of rented homes across the distribution of rent levels [Color figure can be viewed at wileyonlinelibrary.com]

rented units using the following method. First, we apply the hedonic model to each house to predict its rent. We then order observations in increasing order of their predicted rent. We bin all homes (owned and rented) into deciles. This gives us an empirical density for each of rented and owned homes. The density for rented homes is decreasing in predicted rent, whereas the density for owned homes is increasing. The ratio of rented-to-owned densities is therefore decreasing in predicted rent. This ratio is applied to the owned home sample to calculate the weighted median rent-to-price ratio. The reason we apply the rented-to-owned densities to the owned home sample instead of applying the rented-to-total densities to the whole sample to calculate the median rent-to-price ratio is that house price data for rented homes are not reported in the AHS. We perform this procedure for each city-year cell. The average rented-to-owned density ratio across all city-year cells is plotted in Figure 1. Note that relative to an unweighted median, this nonparametric procedure reduces the weight on expensive homes. These expensive homes are the same homes for which the hedonic model has the largest errors because it is estimated upon rental homes, which are likely to be less expensive and smaller homes. In the Internet Appendix, we present scatter plots of our estimates versus Zillow's and CoreLogic's. The figures show that our yield estimates using AHS data, which we can construct over a long sample, are consistent with Zillow and Core Logic data which cover only recent years.

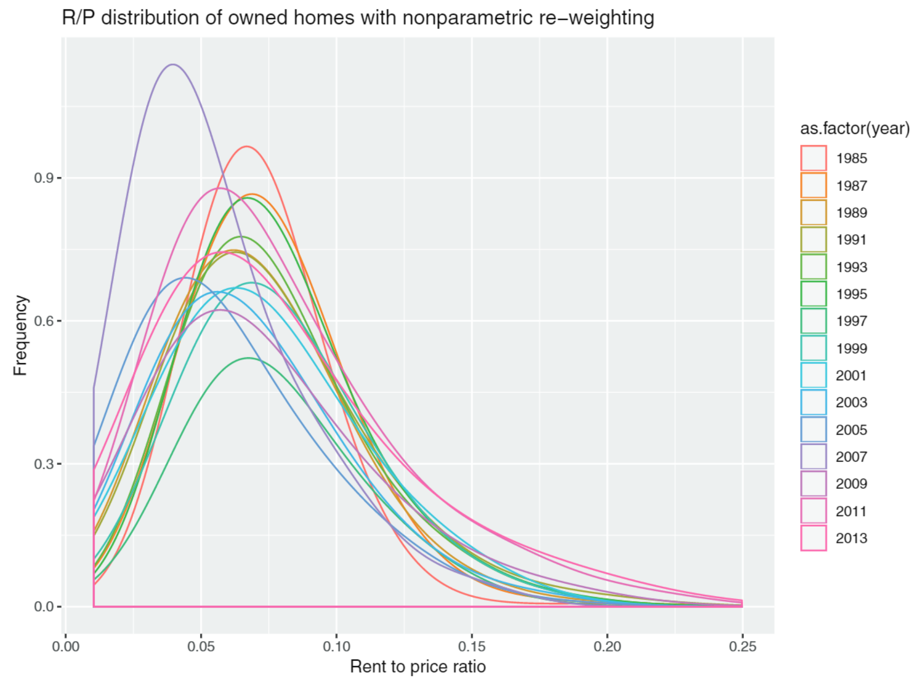

FIGURE 2 Price-to-rent ratios, owned homes: AHS data and hedonic model 1985–2013 [Color figure can be viewed at wileyonlinelibrary.com]

Figure 2 plots the house-level distribution of price to gross rent ratios for each AHS year from 1985 to 2013. We plot P/R because it makes it easy to see the clear cycle of prices relative to rents as prices increased and fell dramatically during this period, whereas rents grew at a fairly steady rate. One can clearly see the rightward shift in the P/R distribution in 2005 and 2007 relative to both the pre- and posthousing price peaks. It was popularly stated that in 2011, home prices were back to 2003 levels and, consistent with this, our estimates show that the distribution of P/R in 2011 closely resembles that from 2003.

To compute net yields, we use calibrated expense ratios, as well as detailed data on actual expenses. We use city- and time-specific data on vacancy rates from the AHS survey. We collect property tax rates by state from Emrath (2002), who reports Census implied tax rates for 1990 and 2000, and from the National Association of Home Builders (NAHB), who report tax rates implied by ACS data for 2005–2012. We also net out insurance and maintenance and repairs using assumed percentages of house price, and property management fees and credit losses as assumed percentages of rent. We base the assumed percentages on data from Tirupattur (2013) and Bernanke (2012), and confirm that the implied expense ratios are consistent with data we hand collected from SFR-backed bond annexes, as discussed in the Internet Appendix. The contained Appendix contains further details on expense assumptions. In the Internet Appendix, we also provide a sensitivity analysis to our main cost assumptions. In particular, we show that increasing the two largest costs for which we use ratio assumptions, namely, repairs and maintenance (% of house price) and management fees (% of rent), by 25% each, reduces yields by 0.25% on average. The yield reduction is very slightly higher for more expensive homes, 0.28% in the highest price tier, versus 0.22% in the lowest price tier.

Figure 3 plots the average gross and net rental yields using the baseline expense assumptions and data, as well as the contribution of net yields and expenses to gross yields over time at a national level, by weighting our city-level estimates by population. Gross yields averaged 7.5% over the sample, reached their highest level of 8.7% in 1998, and bottomed out at 5.7% in 2008.

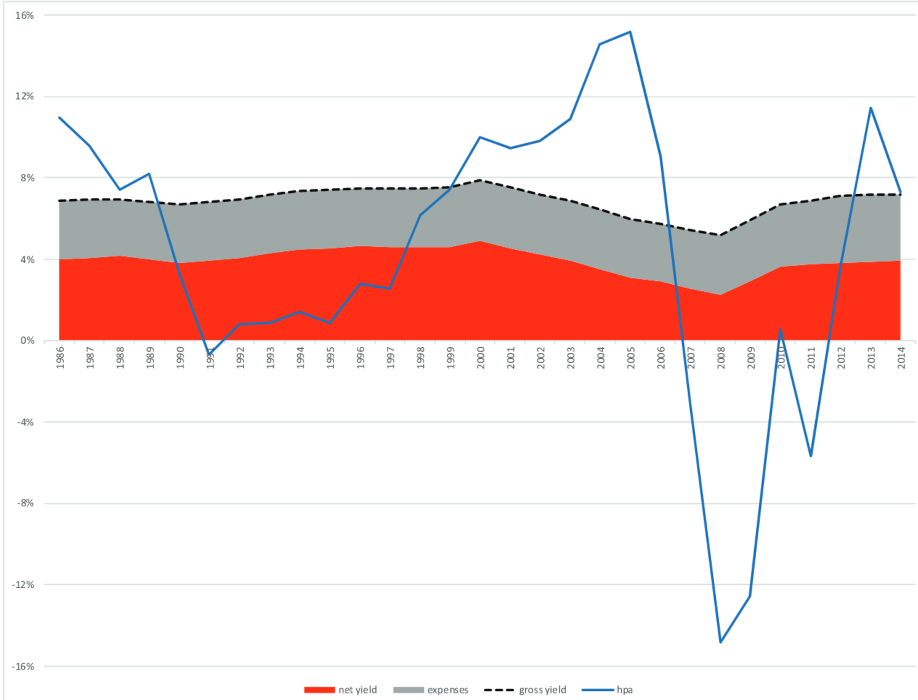

FIGURE 3 Gross yields, net yields, and expense rates versus House Price Appreciation, national averages 1986–2014. National net rental yields are computed as by taking a city population-weighted average of the city-level weighted medians of gross yields, net yields, and expense rates from 1986 to 2014. House price appreciation is June$_{t+1}$ on June$_t$, recorded at June$_{t+1}$. See Equation (2) for timing details [Color figure can be viewed at wileyonlinelibrary.com]

Figure 3 also plots the contribution of net yields, and the contribution of expenses, to gross yields. On average, the contribution of expenses to gross yields is 40%, and this is broadly consistent with data from bond annexes for SFR-collateralized securities. Expenses that are likely to vary with home prices rather than gross rents are over four times as large in magnitude as expenses that are likely to be computed as percentages of gross rents. The largest two expenses, real estate taxes and repairs and maintenance, both vary with home prices. These costs, which are essentially fixed costs from the perspective of moving from gross to net yields, rose in importance as prices increased relative to rents. As a result, expenses peaked at 52% of gross yields in 2008, and reached a low of 36% of gross yields in 1997. Finally, national average net yields averaged 4.5% over our sample, peaking at 5.6% in 1999 and reaching a low of 2.7% in 2008.

3.2 | City-level house price appreciation

Having carefully described the drivers of gross and net rental yields, we now turn to the results for house price appreciation. We compute annualized realized house price appreciation at the city level using Core Logic's HPI data, which is available at a monthly frequency from 1976 to the present. To account for the higher representation of rental homes in lower price tiers within cities, we use Core Logic's tier 2 price index, which covers homes with price levels between 75% and 100% of the city-level median house price. However, our results are very similar using Core Logic's tier 11 index, which covers all price levels, as we show in the Internet Appendix. This is because, as we will show in Section 4, whereas net rental yields vary substantially across price tiers, the relation

TABLE 1 Average net rental yields, house price appreciation, and total returns by pooled time series, cross-section annual city price quintile from 1986 to 2014

Price quintile	Net rental yield	House price appreciation	Total return
1	6.1%	3.1%	9.2%
2	5.3%	3.5%	8.7%
3	4.2%	4.2%	8.4%
4	3.1%	5.2%	8.4%
5	2.4%	5.5%	7.9%

between house price appreciation and price tier is fairly weak. To approximately match the timing of the AHS survey, which is computed between May and September, we compute house price appreciation from June to June each year, and report, for example, 2008 house price appreciation as the realized house price appreciation from June 2007 to June 2008. Figure 3 plots the time series of national realized house price appreciation along with net rental yields. The much larger variation in house price appreciation is clear from the graph. Although the average house price appreciation of 4.4% is very close to the average net yield of 4.5% over the period 1986–2014, the time series standard deviation of house price appreciation is 7.2%, as compared to 0.7% (an order of magnitude lower) for net rental yields.

3.3 | City-level total returns

Next, we examine total returns at the city level, namely, the sum of house price appreciation and net rental yields. The contribution to total returns from net yields and house price appreciation differs across high- and low-price tier cities. Lower-price-tier cities tend to have higher rental yields and lower house price appreciation. By contrast, higher-price-tier cities tend to have lower rental yields and higher house price appreciation. To construct price tiers each year, we first match the HPI from CoreLogic in June 2014 with the Zillow Home Value Index from June 2014. We then construct the price level for each city-year pair from 1985 to 2014 by appropriately deflating the Zillow price levels using the Core Logic HPI.[25] Then, each year, we sort cities into quintiles according to their concurrent price level. Finally, we compute house price appreciation and rental yields in the following year for each quintile, and average across years within each quintile.

Figure 5 plots average annualized house price appreciation, average net rental yields, and total returns from 1986 to 2014 by price quintile, from lowest to highest, and clearly illustrates that rental yields decline in price whereas house price appreciation increases with price. Table 1 presents the underlying data. Of course, if rents were constant, this would be a tautology; however, all else equal, both rents and prices should be higher for more attractive housing units. In the Internet Appendix, we show that the patterns for yields (declining with price tier), house price appreciation (increasing with price tier), and total returns (flat across price tiers) hold for most subsamples. The one exception is the recent period from 2008 to 2014. During this period, yields declined as usual with price tier; however, house price appreciation was relatively flat.

Figure 4 shows that a similar pattern holds without aggregating by price tier. This figure presents a scatter plot of the time series averages of city-level annualized house price appreciation versus the time series average of city-level net rental yields from 1986 to 2014. Clearly, there is

[25] See the Internet Appendix for further details on price tier formation and transition probabilities.

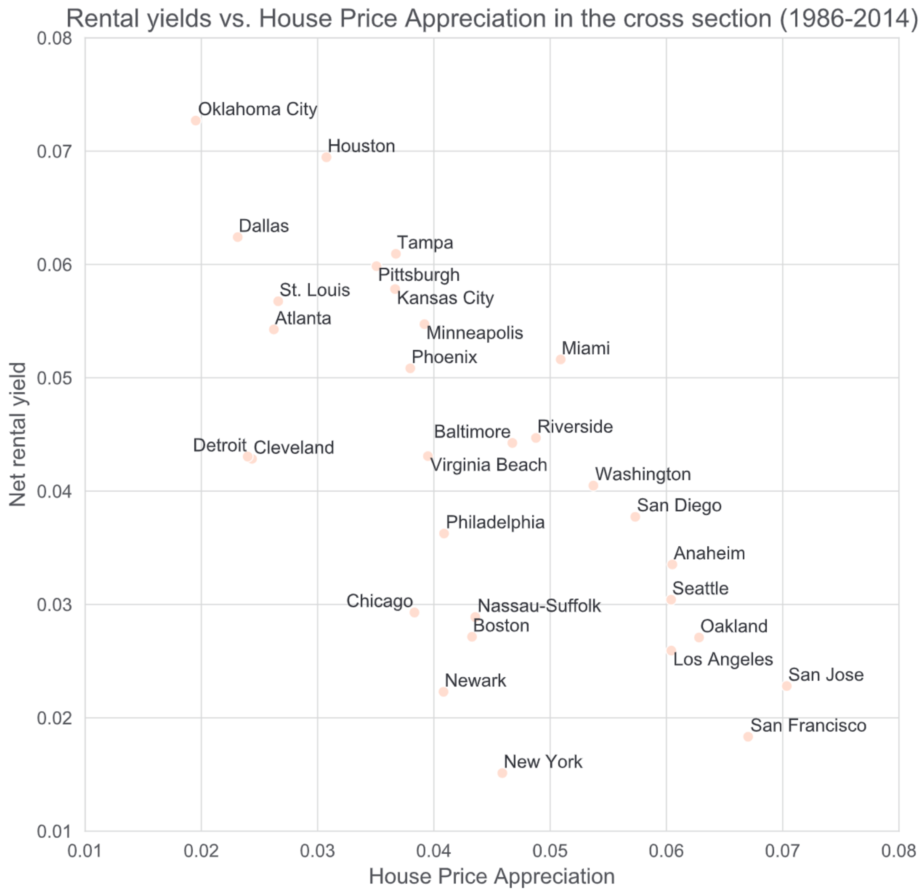

FIGURE 4 Annualized average city-level house price appreciation versus net rental yields 1986–2014 [Color figure can be viewed at wileyonlinelibrary.com]

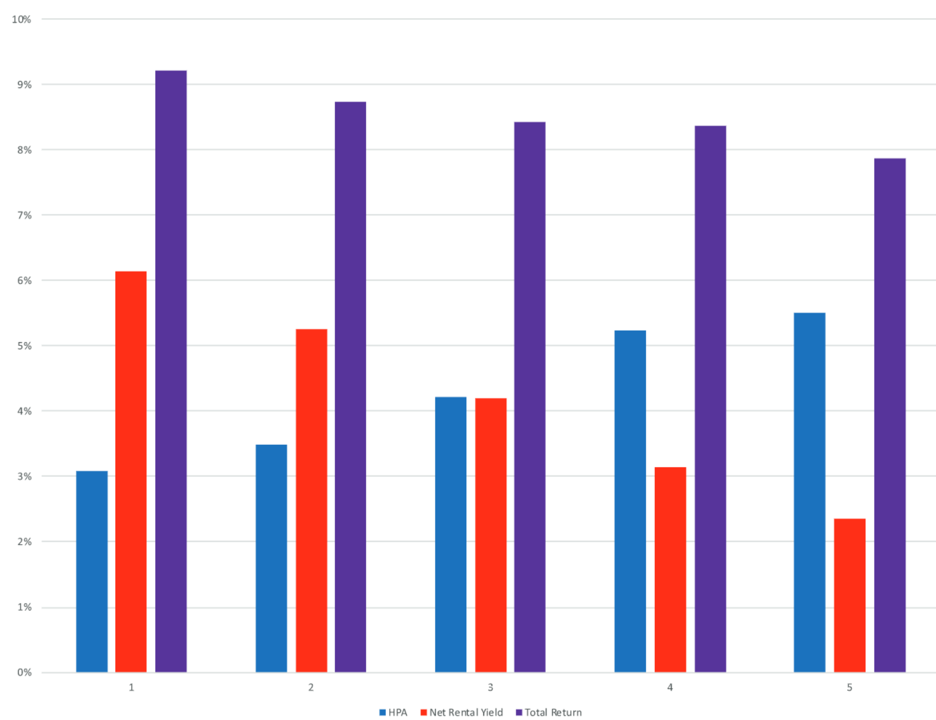

FIGURE 5 Annualized average city-level house price appreciation, net rental yields, and total returns 1986-2014 by house price quintile, lowest (1) to highest (5) [Color figure can be viewed at wileyonlinelibrary.com]

a strong, negative relationship. The (typically more expensive) cities in the bottom right quadrant of the figure have the lowest net rental yields, but tended to experience higher annual house price appreciation. Accordingly, the correlation between average net yields and house price appreciation across cities is −0.65. We noted above that on average over this long time series, net rental yields and house price appreciation contributed roughly equally to total returns. Although house price appreciation varied in the time series by a much larger amount, in the cross section, house price appreciation and net rental yields display about the same amount of variation. The cross-section standard deviation of the time series averages of city-level net rental yields and house price appreciation are 1.6% and 1.4%, respectively.

The negative relationship between net yields and house price appreciation across cities implies that the cross-sectional dispersion in long-run averages of total returns is relatively low (1.2%). The approximate equality of total returns across cities in the long run can be understood in the context of the user cost model described in Himmelberg et al. (2005). That paper presents a user cost model that implies that rents will be lower in locations in which expected capital gains are higher. If consumers could forecast that low supply elasticity, high amenity cities would have higher house price appreciation, and then buying may have been perceived as an important hedge against future price increases. The role of home buying as a hedge against future *rent* increases is modeled and emphasized in Sinai and Souleles (2005). Another explanation for high rental yields in low-price tiers is that consumers in these tiers are more credit constrained. The negative relationship between price levels and rental yields would then naturally arise from differences in the convenience yields rents provide by increasing renter versus owner borrowing capacity as in Eisfeldt and Rampini (2009).

Finally, we discuss the implications of these results for portfolio formation. We start with a traditional measure of the risk return trade-off, the Sharpe (1966) ratio. Table 2 presents the city-level data, sorted in decreasing order by average total returns divided by annualized total return volatility 1986–2014, as displayed in the last column. Volatility is computed using biannual data on annualized total returns. In the Internet Appendix, we present several robustness checks, including using annual house price appreciation data, and show that results are very similar and the conclusions are unchanged. Although total returns are approximately equated in the cross section, Table 2 clearly shows that cities for which rental yields contribute more to total returns have lower volatility, and hence higher Sharpe ratios. Indeed, a univariate regression of city-level Sharpe ratios on the fraction of total returns from net yields generates an adjusted R^2 of 26% and a slope coefficient of 2.4 that is significant at the 1% level. Dropping the outlier of Pittsburgh generates an adjusted R^2 of 51% and a slope coefficient of 1.8 that is significant at the 1% level.

One concern with Sharpe ratios estimated with AHS data is that Davis and Quintin (2017) show that survey respondents tended to report lower house prices during the boom, and higher house prices during the bust. Smoothing of house price estimates reduces the volatility of the denominator of rental yields. This same bias should not affect the numerator, however. This is because the AHS only reports rents for rented units, for which rents should reflect contractual income. Our finding is consistent with the findings in Campbell et al. (2009), namely, that variation in housing risk premia explain most of the variation in price-to-rent ratios, and that the covariance between expected future housing risk premia and rents is positive in most markets. In particular, their finding of positive covariance between expected future housing risk premia and rents implies lower volatility in rental yields versus house prices.

Next, we examine a simple portfolio objective that might be appealing to investors, namely, an objective that selects cities with higher total returns. Table 2 displays cities' house price appreciation in column (2). Finally, we consider that institutional investors may also seek portfolios that

TABLE 2 Average net rental yields, house price appreciation, and total returns by city from 1986 to 2014, sorted in declining order by observed biannual Sharpe ratio

City name	Net yield	House price appreciation	Total return	% of total return from net yield	Standard deviation	Sharpe ratio
Pittsburgh	6.0%	3.5%	9.5%	63.1%	2.2%	4.29
St. Louis	5.7%	2.7%	8.3%	68.1%	4.1%	2.02
Dallas	6.2%	2.3%	8.6%	73.0%	4.5%	1.88
Houston	6.9%	3.1%	10.0%	69.3%	5.8%	1.72
Oklahoma City	7.3%	2.0%	9.2%	78.8%	5.6%	1.64
Kansas City	5.8%	3.7%	9.4%	61.2%	6.7%	1.42
Cleveland	4.3%	2.4%	6.7%	63.8%	4.8%	1.4
Minneapolis	5.5%	3.9%	9.4%	58.3%	7.2%	1.31
Philadelphia	3.6%	4.1%	7.7%	47.0%	6.4%	1.2
Atlanta	5.4%	2.6%	8.1%	67.4%	6.8%	1.19
Baltimore	4.4%	4.7%	9.1%	48.6%	7.7%	1.18
Virginia Beach	4.3%	3.9%	8.3%	52.2%	7.2%	1.15
Seattle	3.0%	6.0%	9.1%	33.5%	9.2%	0.99
Washington DC	4.0%	5.4%	9.4%	43.0%	10.0%	0.94
Tampa	6.1%	3.7%	9.8%	62.4%	10.5%	0.93
Chicago	2.9%	3.8%	6.8%	43.3%	7.4%	0.91

(Continues)

TABLE 2 (Continued)

City name	Net yield	House price appreciation	Total return	% of total return from net yield	Standard deviation	Sharpe ratio
Nassau-Suffolk	2.9%	4.4%	7.2%	39.9%	8.4%	0.86
Boston	2.7%	4.3%	7.0%	38.6%	8.4%	0.84
San Francisco	1.8%	6.7%	8.5%	21.5%	10.5%	0.82
San Diego	3.8%	5.7%	9.5%	39.7%	11.7%	0.81
Miami	5.2%	5.1%	10.3%	50.3%	13.1%	0.78
Anaheim	3.4%	6.1%	9.4%	35.7%	12.3%	0.77
San Jose	2.3%	7.0%	9.3%	24.5%	12.5%	0.74
Phoenix	5.1%	3.8%	8.9%	57.2%	13.4%	0.66
Detroit	4.3%	2.4%	6.7%	64.2%	10.3%	0.65
Oakland	2.7%	6.3%	9.0%	30.1%	13.8%	0.65
New York	1.5%	4.6%	6.1%	24.8%	9.4%	0.65
Newark	2.2%	4.1%	6.3%	35.3%	9.8%	0.65
Los Angeles	2.6%	6.0%	8.6%	30.0%	13.4%	0.64
Riverside	4.5%	4.9%	9.3%	47.8%	15.4%	0.61
Average	4.2%	4.3%	8.5%	49.1%	8.9%	1.14
Stddev	1.56%	1.40%	1.17%	15.91%	3.30%	0.71

enable high leverage. Under current conditions of high and rising price levels, leverage is most constrained by the minimum debt service coverage ratio on net rental yields relative to interest payments. The debt service coverage ratio required to receive a bond rating is about 1.2. According to bond annex data from SFR securitizations, most loan-to-value ratios range between 60% and 70%. At a 60% loan-to-value ratio, and at a 6% rate of interest, which falls between individual borrower rates and single borrower securitization rates, a yield of 4.35% is required to satisfy a typical debt service coverage ratio (DSCR) of 1.2. In the current environment, investors may prefer higher yield assets. These assets are more prevalent in lower-price-tier cities.

City-level stylized facts
To summarize, the city-level stylized facts describing total returns and their components in U.S. data from 1986 to 2014 are as follows:

1. Gross and net rental yields tend to decline with price.
2. Conversely, realized house price appreciation was higher in higher price tiers.
3. Together, these results imply that there is less cross-sectional dispersion in total returns than in either of its components.
4. House price appreciation appears to be more volatile in time series data than are rental yields. As a result, measured Sharpe ratios are higher for cities with higher contributions to returns from rental yields.

4 | ZIP-CODE-LEVEL TOTAL RETURNS

Next, we study variation in total returns to SFRs within cities, across ZIP codes. We use Core Logic's Rental Trends dataset to examine net rental yields at the ZIP code level at the monthly frequency from 2013 to 2017, with the same timing convention as at the city level, as described in Equation (2). This data contain property-level net yields (also known as "capitalization" or "cap" rates) for 11 million units, or about 75% of SFR homes.[26] We use Core Logic's HPI data at a monthly frequency to compute ZIP-code-level house price appreciation annually from June to June, to match the timing of the city-level analysis using AHS data. Similarly, we use the June snapshot of net yields from Rental Trends. Our ZIP-code-level sample includes 2,133 ZIP codes across the 30 largest cities. Although the sample is shorter than the AHS sample, the advantage of the Core Logic data is the ability to compare yields within cities, across ZIP codes.[27]

4.1 | ZIP code-level net rental yields

To get an idea of how much optimization of locations within a city might improve SFR asset performance, we first discuss the relative amount of cross-sectional variation in net yields within

[26] See http://www.corelogic.com/downloadable-docs/capital-markets-rentaltrends.pdf and the Appendix for further details on the Rental Trends data.

[27] Zillow gross yield data are also available at the ZIP code level for the recent time period, but Zillow does not have data on expenses or net yields. Moreover, Core Logic claims to have the largest dataset of MLS rents, which they supplement with local electronic listings.

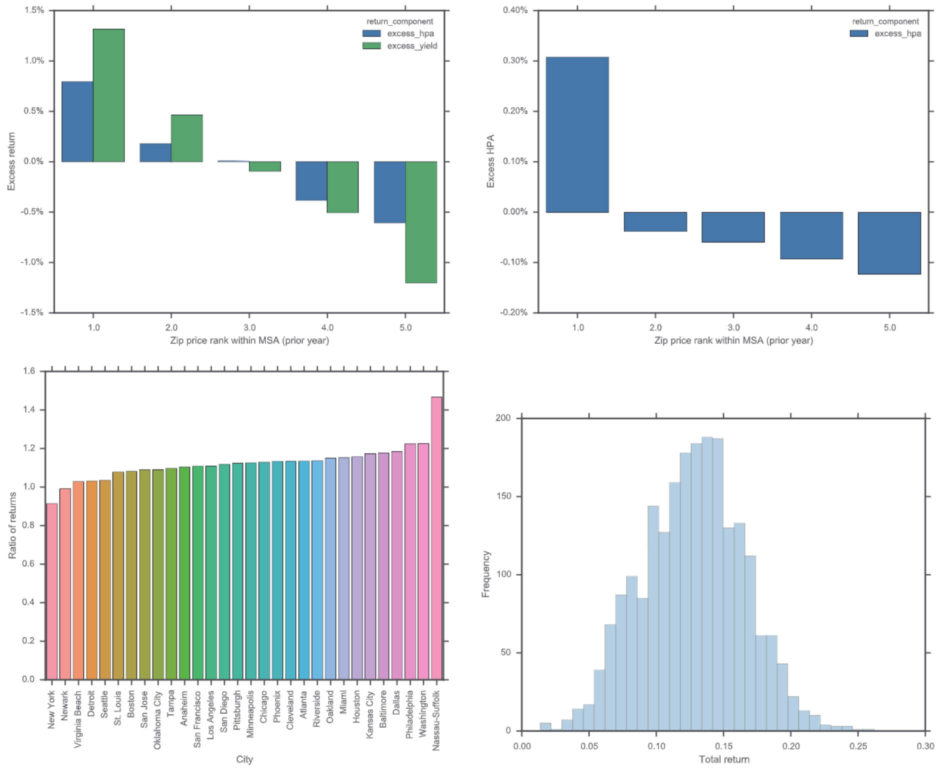

FIGURE 6 ZIP-code-level rental yields and HPA. Top Left: ZIP-code-level net yields and house price appreciation relative to city-level averages, from 2013 to 2017, by house price quintile. Top Right: ZIP-code-level house price appreciation relative to city-level average, from 1986 to 2016, by house price quintile. Bottom Left: ZIP-code-level distribution of total returns from 2013 to 2017. Bottom Right: Average of the lowest two price quintile total returns to overall city-level average 2013–2017 [Color figure can be viewed at wileyonlinelibrary.com]

cities, across ZIP codes, versus across cities. On average from 2013 to 2017, the cross-sectional standard deviation in net yields across ZIP codes, within cities, was 1.3%, which is slightly lower than the 1.6% dispersion across cities in the city-level data we construct using the AHS data from 1986 to 2014.[28]

Within cities, rental yields decline with ZIP-code price tier, which mimics the pattern found across city-level price tiers. The top left panel of Figure 6 plots average ZIP-code-level excess yields over their respective city-level average, by house price quintile, for the period from 2013 to 2017 over which we have overlapping Core Logic data on both components of total returns. The declining pattern of net yields with price tier is clearly apparent in the figure.

In sum, there is about as much dispersion in net yields within cities as across cities, and the pattern of rental yields across ZIP codes within cities is declining with ZIP-code price tier.

4.2 | ZIP-code-level house price appreciation

We find that although net rental yields decline with price tier within cities, as they do across cities, house price appreciation appears to also decline with price tier within cities. This is in stark

[28] Average dispersion in city-level yields in the data constructed using AHS data is 2.2% for the shorter time period 2013–2014 for which the city and ZIP-level data overlap. The standard deviation in net yields across cities in Core Logic's net yield data from 2013 to 2017 was 1.3% on average, equal to the average within city dispersion estimate.

contrast to the pattern of increasing house price appreciation across city-level price tiers. As rental yields and house price appreciation both decline with price tiers within cities, there appear to be opportunities for substantially larger total returns in the lower-price-tier ZIP codes within U.S. cities. This is in contrast to the city-level data, in which the negative correlation between rental yields and house price appreciation implies a more flat total return distribution across cities. The top left panel of Figure 6 plots average excess house price appreciation over the respective city-level average, by house price quintile, for the period from 2013 to 2017 over which we have overlapping Core Logic data on both components of total returns. The figure shows that the lower price quintiles had higher house price appreciation over this period. To get a longer term perspective on ZIP-code-level variation in house price appreciation, the top right panel of Figure 6 plots average excess house price appreciation over the city-level average by ZIP-code-level house price quintile for the longer period from 1986 to 2014. This figure shows that there is much less dispersion in house price appreciation over longer horizons; however, the declining pattern across price tiers is still present.

ZIP-code-level house price appreciation loads heavily on city-level appreciation, with 90% of loadings in a univariate "industry CAPM"-style regression using data from 1985 to 2014, including an intercept, falling between 0.8 and 1.2.[29] Similarly, we also note that if one regresses ZIP-code-level house price appreciation over the period 1986–2014 on city fixed effects only, the R^2 is 71%. Adding 1990 and 2013 income (which enter negatively and positively, respectively), the R^2 increases only marginally, to 72%. Finally, adding a 1985 price quintile dummy, and the distance from city hall, the R^2 becomes 75% with both variables entering negatively. Clearly, ZIP-code-level house price appreciation is tightly linked to city-level outcomes.[30] Each year from 1986 to 2014, we compute the standard deviation of house price appreciation across ZIP codes, and find that the average standard deviation is 5.6%. By contrast, the time series average of the cross-section standard deviation of ZIP code house price appreciation in excess of the city-level means is only 3.4%. Thus, the differences between the across and within city dispersion estimates are larger for house price appreciation. That is, rental yields display a similar amount of dispersion within cities versus across cities, whereas house price appreciation varies more across cities than within cities. This fact seems interesting for models of housing demand. It suggests that there is a strong city-level factor driving house price appreciation, whereas rents may be driven more by neighborhood-level incomes.

4.3 | ZIP code-level total returns

To summarize the findings for how total returns comprised by net rental yields and house price appreciation vary by price tier within cities across ZIP codes, the bottom left panel of Figure 6 plots the ratio of the average total returns from 2013 to 2017 in the lowest two price quintiles in each city, relative to the city-level average. Almost all of these ratios are at or above 1.

There may be several reasons why low-price tier ZIP codes might generate higher total returns. With respect to rental yields, it is possible that Core Logic underestimates credit and vacancy costs in the lowest tiers, biasing net rental yields up; however, we find the same pattern of declining yields in the house-level data underlying recent securitizations of SFR properties. Net rents

[29] We do note, however, that Core Logic may shrink their noisy ZIP-level estimates toward the city-level mean when cleaning their data.

[30] See Glaeser et al. (2014) for a model of house price dynamics consistent with a strong city-level factor.

in these price tiers may be more volatile over the housing cycle, and therefore, more risky. ZIP-code-level house price appreciation certainly appears to have more city-level risk in lower price tiers.[31] The average loadings of ZIP-code-level house price appreciation on city-level house price appreciation are declining with price tier. These loadings are 1.04, 1.05, 1.00, 0.95, and 0.93, from the lowest to highest price quintiles, respectively. Thus, lower tier ZIP codes do appear to be riskier. Lower tier ZIP codes may also have benefited from gentrification or innovations in lending practices.[32]

Summarizing how much portfolio optimization across ZIP codes might improve SFR returns, the bottom right panel of Figure 6 displays the distribution of average total returns across all ZIP codes for the period 2013–2017. To construct average total returns by ZIP code for the purposes of this illustrative figure, we add the average house price appreciation from 1986 to 2014 to average net yields from June of each year 2013–2017. We present results using only the overlapping sample in Section 5 below. Although using averages over different time periods is imperfect, we use the longer house price appreciation sample to estimate representative average total returns because house price appreciation from 2013 to 2017 was much higher than average; however, our ZIP-code-level yield data only go back to 2013. As documented in the city-level analysis, rental yields appear to be much more stable than house price appreciation is over time. Thus, we argue that we can approximately capture much of the relevant cross-sectional heterogeneity in net yields using the shorter sample; however, we acknowledge that our choice is driven by data availability. Indeed, to our knowledge, ZIP-code-level rents are unavailable to researchers from any electronic source outside of the recent time period, and, as noted, ours is the first academic study to use the recent Core Logic data on net rents.

ZIP-code-level stylized facts

1. Net rental yields decline with house prices within cities.
2. House price appreciation does not increase with house prices within cities.
3. As a result, total returns decline with house prices within cities.
4. There is more measured dispersion in house price appreciation across cities than within cities across ZIP codes. ZIP-code-level house price appreciation appears to be tightly linked to city-level outcomes.
5. By contrast, the dispersion in yields is of similar magnitude at the ZIP code and city levels.

5 | COMBINING CITY AND ZIP-CODE-LEVEL RESULTS

Figure 7 presents a visual summary of our results for total returns across and within U.S. cities. Each panel presents data for cities by price tier along the x-axis, and ZIP codes by price tier along the y-axis. Red cells indicate higher returns, and blue cells denote lower returns. Starting with net rental yields, the top left panel clearly shows that rental yields decrease with price tier both across cities, and within cities across ZIP codes. The highest average net rental yields for the period for which we have ZIP -code-level net yield data are found in the lowest-price-tier ZIP codes of the lowest-price-tier cities in the bottom left corner.

[31] Hartman-Glaser and Mann (2016) find that house price appreciation is more volatile in lower income ZIP codes.

[32] See Kolko (2007) and Guerrieri et al. (2013) for evidence of gentrification effects, and Landvoigt et al. (2012) for evidence of the impact of subprime lending.

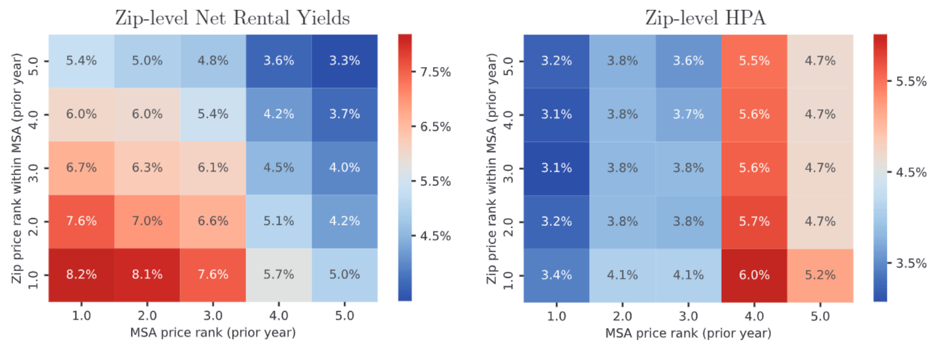

FIGURE 7 Heat maps of rental yields and house price appreciation across city and ZIP code-level price tiers. Left panel plots net yields from 2013 to 2017 by ZIP and MSA price rank (1 = Low, 5 = High). Right panel plots house price appreciation at the ZIP code level by ZIP code and MSA price rank (1 = Low, 5 = High) [Color figure can be viewed at wileyonlinelibrary.com]

The top right panel of Figure 7 shows that, although the across city pattern tends to consistently display higher house price appreciation in higher-tier cities, the cross-ZIP-code pattern in house price appreciation is fairly flat. The cells are more red moving across city-level price tiers from left to right, whereas the color is constant along the vertical dimension depicting ZIP-code-level price tiers.

Despite relatively flat house price appreciation across ZIP codes, due to the declining pattern of net yields within cities, total returns are highest in the lower tier ZIP codes. That is, although total returns are approximately equated across cities, lower-price-tier ZIP codes have higher total returns (cells are more red at the top, and blue at the bottom). Thus, we conclude that the highest total returns to single-family rentals appear to be in the lower priced ZIP codes. In higher-price-tier cities, these higher total returns are driven by high house price appreciation. This is consistent with the strong city-level house price appreciation factor documented in Section 4.2, as well as with the sorting model in Van Nieuwerburgh and Weill (2010). We reiterate, however, that we are not aware of a model that allows for renting and that can simultaneously explain both the house price appreciation and rental yields patterns we document. By contrast, in lower-price-tier cities, the higher total returns in lower-price-tier ZIP codes are driven by higher rental yields. This fact seems consistent with the model of financial constraints in Eisfeldt and Rampini (2009), but again that paper does not attempt to explain both rental yields and capital gains together.

The variation in the composition of total returns implies that which city-level price tier an investor chooses to invest in might be driven by the capital structure of the investment, along with violations of Miller and Modigliani (1958) capital structure irrelevance. Investing in lower-price-tier cities, with higher rental yields, will alleviate leverage constraints from debt service coverage ratios, which tend to bind in higher price environments. On the other hand, investing in higher-price-tier cities leads to higher capital gains, which can be important for returns in private equity structures with shorter holding periods.

6 | CONCLUSION

In this paper, we study the returns to single-family rental strategies over a long time series, from 1986 to 2014, in order to understand the drivers of single-family rental returns, and to evaluate the sustainability of institutional investor participation. We also aim to provide a useful set of stylized facts for models of housing markets. Importantly, we emphasize the contribution to total returns from both net rental yields and house price appreciation. Prior studies typically focus on only one component of these.

At the city level, we find that net rental yields decline with price tier, whereas house price appreciation increases with price tier. As a result, looking at either component in isolation leads to the opposite ranking of cities in the cross section. At the city level, total returns are approximately equated, despite the varying composition of returns. However, due to the fact that net rental yields appear to be substantially less volatile than house price appreciation is, measured Sharpe ratios are higher for lower-price-tier cities with a larger contribution to total returns from rental yields. Miller Modigliani violations may also guide portfolio formation, because leverage constraints are affected differently by dividend yields, which can relax debt service coverage ratios, and capital gains, which can relax loan to value ratios. Clienteles that prefer income generating assets may prefer homes in lower price tiers with higher dividends in the form of rental yields. Private equity investors seeking shorter- or medium-term capital gains may, on the other hand, prefer higher-price-tier cities.

Within cities, both net rental yields and house price appreciation decline with price tier, although house price appreciation displays fairly low variation within cities. Thus, higher total returns are generated by the lower price tiers within cities. Indeed, there is more dispersion in house price appreciation across cities than across ZIP codes within cities, indicating a strong city-level factor in house price appreciation. Yields, on the other hand, display a similar amount of variation across and within cities, though variation is actually slightly higher within cities.

Single-family rentals are an important asset class, constituting about $2.3 trillion in market value. Although most all of these assets are currently owned by individual or small investors, there has been a marked increase in institutional participation in recent years. At present, more than $14 billion in single-family rental backed bonds are outstanding. Thus, we argue that single-family rental is an interesting, large, asset class, which is new to large institutional, and securitized, investment. The securitized single-family rental market also has considerable growth potential, in particular with the recent ratings and issuances of multiborrower backed bonds, and Fannie Mae's decision to guarantee a single-family rental backed loan.

It is also possible that the propensity of households to rent versus buy may grow, or remain elevated, increasing the importance of single-family rentals (currently about 35% of all rental households). According to the American Community Survey, the homeownership rate peaked in 2007 at about 67% and fell to 63% by 2014. This represents a change in housing status from owned to rented for over 1.5 million households and about $228 billion in housing value. Several structural (or at least persistent) factors may have contributed to the recent decline in homeownership. Standards for mortgage lending, which got stricter during the housing downturn, have continued to tighten. Reports by the Urban Institute document that the median borrower FICO score at origination climbed from 700 in 2001 to 710 by 2007, and has since gone up to 750.[33] At the same time, student debt has increased dramatically, growing 166% from 2005 to 2012, potentially reducing borrowers' mortgage capacity.[34] Notably, there has not been an offsetting decline, but instead an increase, in auto or credit card debt.[35] Moreover, employment for the relatively large millennial generation was impacted heavily by the great recession, and renting has been

[33] http://www.urban.org/research/publication/housing-finance-glance-may-2015l

[34] http://www.newyorkfed.org/studentloandebt/index.html.

[35] See http://www.newyorkfed.org/microeconomics/hhdc.html#/2014/q3.

a popular option for the age group at which household formation previously peaked. The age at which a majority of individuals are homeowners has increased from 32 in 1990 to 38 in 2012,[36] and the August 2014 Fannie Mae National Housing Survey finds that 32% of respondents would rent if they were going to move.[37] For these reasons, we argue that understanding the single-family rental asset class is important, and our paper aims to fill the existing gap in the literature on the total returns to single-family homes as investible financial assets.

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ORCID

Andrea L. Eisfeldt https://orcid.org/0000-0001-7819-1837

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Additional supporting information may be found online in the Supporting Information section at the end of the article.

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