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SFR Returns and HPA - A cross-section study across the United States

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Contents

1 Executive Summary

1. **Conclusions across MSA Total Returns**: Lower price tier MSAs have higher rental yields and lower HPA[1]. By contrast, higher price tier MSAs have lower rental yields and higher HPA (Figure 1) (1).[2]

[1] Please see the Appendix for definitions for MSA selection, net yields, and total returns

[2] This concurs with prior research that because leasing has a higher debt capacity, constrained firms are willing to pay a higher yield to relax their borrowing constraint. The authors 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 influencing rents housing markets as in they appear in the market

2. **Conclusions after analysis within MSAs**, 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. Zip code-level HPA appears to be tightly linked to city-level outcomes, whereas rent may be driven more by neighborhood-level incomes.

3. **Conclusions local to homes in Raleigh:** HPA over the past ten years is higher in lower-price tiers that predominately compose SFR subsidiary portfolios. This aligns with the previous conclusion 2. Please see Figure 2 (4). Based on adjusted price-to-rent ratios - the inverse of SFR yields - one can observe that rent prices have steadily increased over this period.

4. Based on constructing rental yields for 30 MSAs from 1986-2014 for renter-occupied properties, I find that on average across MSAs, total return is 8.9%; rental yield is 4.5% and HPA is 4.3%. The share of rental yield is 51% on average.

5. **Income Growth is key to HPA** (Malpezzi [1999])[3]

2 Objectives

1. Locally to Wake County:

   (a) **If one were to focus on Raleigh, ignore the addition of net rental yield, and only compare HPA between two different property selection strategies how would they compare?** I previously showed that almost all SFR purchases were below 400, 000 USD - a contrast that is markedly different from Acre's approved homes' price tiers (Ahluwalia [2022]). Given this fact, *what are the average price movements (HPA) of all single-family residences that are aligned with the SFR portfolio selection - particularly for Raleigh from 2012 - 2022? How does this HPA compare to Acre's selection criterion in Raleigh - particularly our buy-box with home prices that span 400, 000 and 1.95 million USD? How can we make sense of the disparity in HPA?*

   (b) Recent portfolios have begun to tailor their marketing to a highly educated populace with higher income potential. In general, we have characterized Raleigh as a city that has the potential to become a "high-amenity city" - like other metropolitan areas because it is composed of recession-proof industries. Therefore, it is natural to ask: *Across MSAs, how does income growth relate to HPA and home price tiers?*.

for corporate assets (See (Eisfeldt and Rampini [2008]))

[3] I used CoreLogic's Rental trends dataset used in Andrea Eisfeldt & Andrew Demers, 2014. "The Returns to Single Family Rental Strategies," 2014 Meeting Papers 737, Society for Economic Dynamics.

(c) Finally, our central thesis also implies that, first, because we eliminate or minimize the burden of transaction and operating costs we also reduce risk. Second, under very stringent assumptions about portfolio size and mean home price, we in essence take the results of the prior statement and reconstitute these operational and capital expenditures back into customers' pockets (the value creation aspect of Acre). While I cannot assess this statement, based on the current state of our portfolio and the tenure of our residents, I can interrogate the net yields of SFRs under appropriate assumptions - couched in prior research - at both the MSA and zip code levels. This allows us to 1) provide more empirical and data-driven assessments to investors that anchor our value-proposition and 2) with the recognition of such facts focus arguments that address the unique nature of Raleigh and Durham metros - such as land share.

2. To better contextualize (1c) I investigate:

   (a) The relationship between net rental yields and HPA in both lower-tier price and higher-tier price cities (also known as the "superstars" (Gyourko et al. [2013]).

   (b) Income growth and HPA growth as a proportion of the total populace.

3 Across MSA Analysis Details

The negative relationship between net rental yields and HPA across MSAs implies that:

1. The cross-sectional dispersion over the long-run averages of total returns is fairly low (approximately 1%). This could be explained in part by a similar conclusion from Himmelberg et al Himmelberg et al. [2005]. In this study, a user-cost model is presented that implies that rents will be lower in locations with higher expected capital gains. If there is a forecast of low supply elasticity, high amenity cities would have higher HPA. Thus buying would be a hedge against future price increases in rent.

2. An alternative explanation is that lower-price tier cities have credit-constrained consumers. The negative relationship between price levels and rental yields would then naturally arise from differences in the convenience yields rents provide by increasing renter vs. owner borrowing capacity as in Eisfeldt and Rampini [2008].

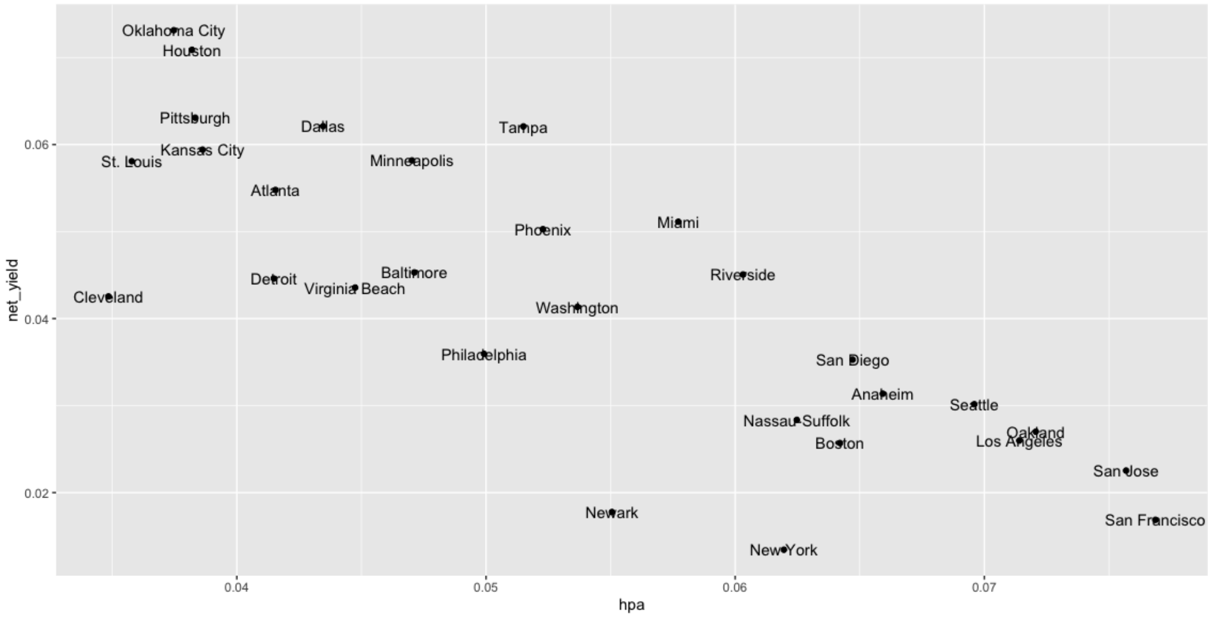

Figure 1: Annualized average MSA level HPA vs. net rental yields 1986-2014

4 Within-MSA variation details

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 slightly higher within cities[4].

This contrast to the city-level data is couched in 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 Guerrieri et al. [2010] (Kolko [2007]). As a result of both net yields declining, and house price appreciation being flat or decreasing with house prices, total returns decline with the house price tier at the zip code level. Thus, my results suggest that investors may find higher average returns from properties in the lower price tiers within cities.

[4] Average dispersion in city-level yields in the data constructed using AHS data is 2.2% for the shorter 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 2013-2017 was 1.3% on average, equal to the average within city dispersion estimate

4.1 How do we begin to analyze within-MSA variation in total returns?

To study variation in total returns to SFRs within cities, across ZIP codes, I 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.

This data contains property-level net yields (also known as "capitalization" or "cap" rates) for 11 million units or about 75%of SFR homes. I also 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, I 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, and across ZIP codes.

5 Building Total Returns at the MSA level

The following is based on a proposed methodology employed in Eisfeldt and Demers [2014].

I first construct a time series describing MSA level returns for the largest 30 MSAs from 1986 to 2014 using data from the American Housing Survey (AHS) conducted annually by the Census Bureau, combined with Core Logic's House Price Index data, which is available monthly. To construct the longitudinal time series for gross rental yields at the MSA level, I use the AHS data. The survey is conducted at the house level but contains an MSA identifier. Because of the relatively low representation of single-family detached rentals in the AHS data, I use a hedonic model, along with a non-parametric adjustment for the different sample representations between owned and rented housing units to construct the gross rental yield time series.

To construct net yields from gross yields, I use a formula that accounts for all renovation and operating costs as the appropriate fraction of either home value, size, or rent.

name	net_yield	hpa	total return
Tampa	6.200000	5.100000	11.300000
Oklahoma City	7.300000	3.700000	11.000000
Houston	7.100000	3.800000	10.900000
Miami	5.100000	5.800000	10.900000
Dallas	6.200000	4.300000	10.500000
Minneapolis	5.800000	4.700000	10.500000
Riverside	4.500000	6.000000	10.500000
Phoenix	5.000000	5.200000	10.200000
Pittsburgh	6.300000	3.800000	10.100000
Seattle	3.000000	7.000000	10.000000
San Diego	3.500000	6.500000	10.000000
Oakland	2.700000	7.200000	9.900000
San Jose	2.300000	7.600000	9.900000
Kansas City	5.900000	3.900000	9.800000
Atlanta	5.500000	4.200000	9.700000
Los Angeles	2.600000	7.100000	9.700000
Anaheim	3.100000	6.600000	9.700000
Washington	4.100000	5.400000	9.500000
San Francisco	1.700000	7.700000	9.400000
St. Louis	5.800000	3.600000	9.400000
Baltimore	4.500000	4.700000	9.200000
Nassau-Suffolk	2.800000	6.200000	9.000000
Boston	2.600000	6.400000	9.000000
Virginia Beach	4.400000	4.500000	8.900000
Philadelphia	3.600000	5.000000	8.600000
Detroit	4.500000	4.100000	8.600000
Cleveland	4.300000	3.500000	7.800000
New York	1.300000	6.200000	7.500000
Newark	1.800000	5.500000	7.300000

Figure 2: Rankings of Top 30 Cities from 1985 - 2014: Blue highlights the maximum in that column

Please see the Appendix for more details on modeling for imputation, weighting scheme, and assumptions for constructing gross and net yields.

6 A specific focus on Raleigh

Before we discuss HPA, we should estimate the house level distribution of price to gross rent ratios (P/R) for each AHS year from 1985 to 2019. I 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, while rents grew at a fairly steady rate. One can see the rightward shift in the P/R distribution in 2005 and 2007 relative to both pre-and post- housing price peaks.

Because the P/R represents the inverse of gross SFR yields it is important to note this observation for understanding the HPA analysis for SFR versus Acre's portfolio.

Specific to Raleigh, the homes selected in the SFR portfolio - deemed as lower-price tiers - also display significantly higher HPA than those homes in Acre's buy-box. Notice that within the Raleigh zip-code, the higher-priced tier homes also reflect the broader within-MSA zip-code results for the 30 most populated cities: average HPA declines with price increases. Moreover, for Acre homes it is apparent that there is a long-run mean reversion for the time interval: 0.8% reflecting a result that concurs with earlier results across MSAs[5]. Th the unconditional standard deviation in the annualized change for the SFR index is higher(9.2%) versus Acre's higher-priced tiers' index (8.5%), indicating that there is greater volatility in lower-priced tiers from quarter to quarter. Finally, the choice for the repeat sales model was used with the understanding of the following:

1. For each sampled house, the repeat-sales approach assumes that the quality attributes and their coefficients are constant. Attributes are subject to change from a mix of improvements and deterioration due to age, and their coefficients reflect, in part, consumer preferences that change over time. For example, the presence of pools has marginally decreased the values of homes in Cary, North Carolina in the past 10 years.

2. Repeat-sales indexes also omit a large number of transactions since they are confined to houses for which at least two sales are available in public records. Previous work has argued that this constraint implies significant revisions.

[5] Due to momentum in HPA, it is somewhat mechanical that higher HPI cities will have higher HPA. However, mean reversion attenuates this.

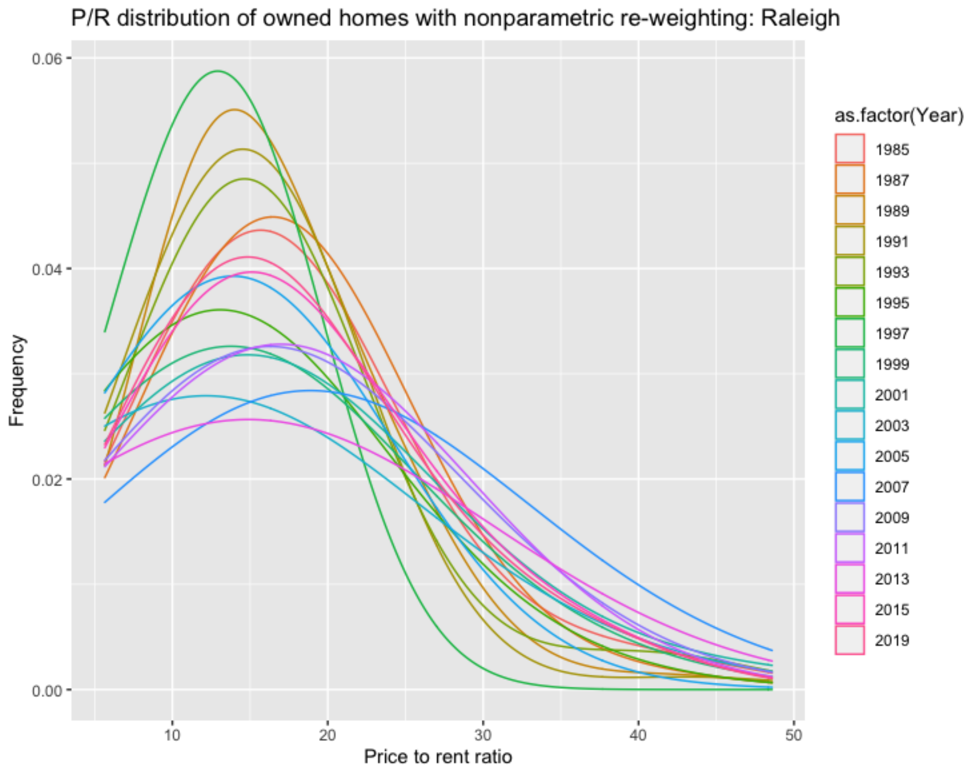

Figure 3: P/R Ratio for Raleigh Owned Homes - Odd Years (1985 - 2019)

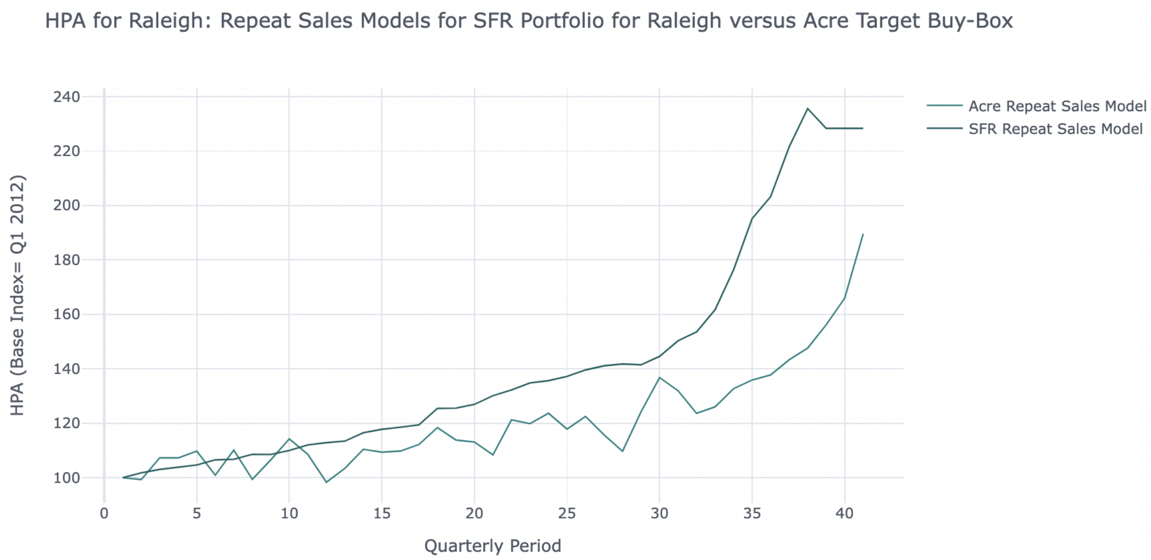

Figure 4: HPA: SFR - selected homes versus Acre - selected homes in Raleigh (Source: MLS listings)

7 Income Growth and HPA

Capozza et al. found that a 1% rise in a metro area's real income leads to almost a 0.5% increase in real median house prices. The authors interpret the coefficient as an income elasticity, then consumers are buying about 5% more housing when incomes are 10% higher. This is consistent with, but at the lower end of, other estimates of income elasticities Capozza et al. [2004]. **TODO** - add more details for Raleigh here.

8 Appendix

8.1 Definitions

1. The formula for Total Returns is Net Rental Yield + Home Price Appreciation (HPA). Total Returns are a useful measure for considering institutional participation in SFR, because they represent the return reported to participants in the typical private equity structure that has been used by institutional investors of SFR portfolios, and are analogous to stock returns from dividends and capital gains. Total Returns, unlike internal rate of return, do not depend on the holding period considered Eisfeldt and Demers [2014].

2. Larges Cities are determined based on 1) total investment by 14 institutional investors' bond purchase opinions and 2) the total population of the city.

8.2 Aggregating Rental to Price ratios with non-parametric weights

An issue was posed when one attempts to find the median rent-to-price of rental homes, but the dataset has rent-to-price ratios computed on owned homes. To account for sample selection in our dataset of rent-to-price ratios, I weight the owned homes in a city to the distribution of rental homes. (I do not use the alternate methodology – to estimate the hedonic coefficients on owned homes, and then compute rent-to-price ratios on rental homes directly – because there are not enough rental homes for a meaningful sample in some city-year bins. Indeed, the less populated and very same cities are the ones with a low ratio of rental homes.) This procedure is similar to the non-parametric approach used in Barsky et al. [2002].

Sample selection is an issue because rent-to-price ratios are decreasing in house prices (and in-house rents).

For each city each year, I re-weight the owner-occupied houses as follows. First, line up all the houses by predicted rent. Then bin by percentile of predicted rent.

Next, determine the density of renter-occupied in the predicted rent space. Finally, compute the median rent-to-price ratio among owner-occupied, using the density of renter-occupied to take a weighted median.

Note that relative to an unweighted median, this non-parametric procedure reduces the weight on expensive homes, which 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 smaller homes).

8.3 Imputing rents with a hedonic model

I employ a hedonic model (as in Malpezzi 2002) to project the log rent of a home upon

1. Metropolitan statistical area (MSA) fixed effect
2. Year fixed effect
3. Unit type fixed effect (i.e., detached, attached, condo, or apartment)
4. Number of rooms
5. Number of bathrooms
6. Dummy for central air
7. Year unit built categories (by decade to 1970, then every 5 years)

I do this to unit age because it is a categorical variable before 1995. I do not use square feet because of the large number of missing observations.

The hedonic model is estimated upon renter-occupied homes. It enables me to compute the rent for each owner-occupied home using its characteristics.

8.4 Net Yields Assumptions

Starting from gross yields, I compute net yields using the following costs, some of which are expressed as a percentage of rent and some of which are a percentage of home value. I use expense ratios from Morgan Stanley, "The New Age of Buy-To-Rent," July 31, 2013. Similar, but less comprehensive, assumptions appear in Bernanke (2012) "The US Housing Market: Current conditions and policy considerations." The assumptions underlying Core Logic's Rental Trends, discussed below, are also broadly consistent with this work. However, some of their cost estimates rely on direct proprietary data rather than ratios of rent or house price.

1. Insurance: 0.375% of price
2. Repairs: 0.6% of price
3. Capex: 1.15% of price
4. Property manager: 5.9% of price
5. Tax: On price[6]

[6] Sources are Emrath (2002) for 1990 and 2000 tax rates from Census data, and the National Association of Home Builders (NAHB) for 2005 to 2012 tax rates from ACS data. The tax rate data are available by state.

6. Vacancy: On Rent

This now allows me to create a panel dataset of net yields for 30 cities for 29 years.

8.5 SFR Home Selection for Repeat Sales Model

Using the MLS listings (from January 1, 2012 - August 27, 2022), the SFR portfolio of homes was derived based on (Ahluwalia [2022]).

1. Price: 253,000 to 399,999 USD
2. At most 1.75 acres
3. A garage may or may not be present
4. There is no constraint on bedrooms and bathrooms
5. Vintage year of 1900 - 2022

8.6 Acre Home Selection for Repeat Sales Model

The source of the date is exactly from the same timeline and source.

1. Price: Above 400,000 USD
2. At most 1-acre lot
3. 3-5 bedrooms
4. Detached Properties only
5. 2 or more bathrooms
6. Detached Garage
7. Vintage year of 1995 and above

8.7 Hedonic Model Details for HPA index creation

I employ the method detailed in Janssen et al. [2001].

8.8 Sanity Checks

I employed alternate sources for several data points to check the quality of my input data.

1. Gross yields: I have Zillow rent-to-price ratios from their hedonic model applied to both rented and owned homes in their database. These data start in 2011.

2. Vacancy rates: I have national vacancy rates for rental homes from the Census Bureau, which use the Current Population Survey (CPS) and Housing Vacancy Survey (HVS). I also have vacancy rates from CoreLogic, which uses the USPS.

3. Net yields: I have CoreLogic cap rates (defined in the main text) starting in 2012.

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