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THE RETURNS TO SINGLE FAMILY RENTALS

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ABSTRACT

Single family rentals have a market value of $2.3 trillion. We believe our study is the first to consider the total returns to this large, unique asset class over a long time period and in a broad and granular cross section, down to the house level. Single-family rental investments pay dividends of rental payments and capital gains from house price appreciation (HPA). We show that a portfolio of US homes benefitted equally from dividends and capital gains. Nominal annual HPA and net rental yields both averaged about 4.4% since 1986. Across MSAs, rental yields decline with prices, while HPA increases with prices. As a result, "total returns" are approximately equated across MSA's. By contrast, across zip codes within cities, both rental yields and HPA decline with prices. Thus, total returns appear to be highest, within MSA's, in the lowest price tiers.

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- data appendix

1 Introduction

Single family rentals represent 35% of all rented housing units in the US, with a market value of approximately $2.3 trillion.[1] We consider the returns to this large and unique asset class over a long time period and in a broad and granular cross section, down to the house level. Understanding the drivers of the returns to single family rentals (SFR) is critical for forming porfolios of SFR assets. Portfolio formation is an increasingly important part of SFR investment. Up until very recently, almost all of the approximately 12 million single family rentals were owned by individuals or small investors. However, following the financial and housing crisis of 2008, investment by large investors increased substantially. The largest seven institutional investors alone now own over 100,000 homes, worth over $17.5 billion.[2] Moreover, there is currently about $14 billion of SFR backed bonds outstanding, from 27 issuances averaging about $500 million each. Most of these issuances have been backed by a single institutional borrower's portfolio. However, four multi-borrower deals from three lenders have also been brought to market in the past year. These multi-borrower deals have significant potential for future growth. The vast majority of SFR properties owners do not have access to capital markets except through bank loans.

Our study of how the returns to SFR vary in the time series and cross section, and how portfolios might be formed, informs investors in real SFR assets, as well as in SFR asset backed securities. It also helps to forecast how this asset class might be expected to perform, and 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. 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.

The returns to SFR are comprised by dividends from net rents, and capital gains from house price appreciation (HPA). We construct and analyze time series for rental yields net of operating expenses and HPA at the city and zip code levels, and use recent data from SFR asset backed bonds to study house level returns. At the city level, we construct mean variance efficient portfolios, and discuss their properties. We discuss practical issues such

[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 US home is worth approximately $200,000, and our calculations indicate that the average rental home is worth 25% less.

[2] See "The single-family rental business: securitization and stresses arrive," Deutsche Bank, August 21, 2014.

as the impact of leverage and operating costs on portfolio formation in the context of house level returns. Although there are many studies of housing returns from HPA in the literature, we believe we are the first to consider total returns to single family houses accounting for both net rental yields and house price appreciation in a broad and granular cross-section, and a long time series.[3] Including both components is crucial, because, as we show, the cross-sectional correlation between the two components is strongly negative at the MSA level.

We construct a time series describing MSA level returns for the largest 30 MSA's 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 our long time series for gross rental yields at the MSA level, we 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, we use a hedonic model, along with a nonparametric adjustment for the different sample representation between owned and rented housing units to construct our gross rental yield time series. To construct net yields from gross yields, we use a formula which accounts for all renovation and operating costs as the appropriate fraction of either home value, size or rent. We use time and MSA specific data for real estate taxes and vacancies. We show that, on average, net yields are about 60% of gross yields, and this is consistent with house level data from SFR bond annexes. We then combine our resulting time series for net rental yields with a corresponding time series for annual HPA we construct from Core Logic's monthly house price index data. We analyze what industry participants call "Total Returns," namely the sum of net rental yields and annual capital gains.[4] 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 in the SFR space, and are analogous to stock returns from dividends and capital gains. Moreover, as we will show, Internal Rates of Return (IRR's) on SFR investments are approximately linear in net yields and HPA, with each element contributing approximately equally. Finally, Total Returns, unlike IRR's, do not depend on the holding period considered. We will, however, report some results on IRR's for comparison.

Our MSA level results for 1986-2014 uncover some striking stylized facts. First, we show

[3]We will make our code and constructed gross and net yield data for 30 MSA's from 1985-2013 publicly available at `https://sites.google.com/site/andrealeisfeldt/`. Our yield data can be combined with publicly available or proprietary data on HPA to form MSA level total returns.

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

that rental yields tend to be highest in the lowest price tier cities, and vice versa. If rents were constant, this would be a tautology, but high quality houses should, all else equal, have both higher rents and higher purchase prices. Rental yields were on average 6.8% in the lowest price quintile, and 3.5% in the highest price quintile over the period 1986-2014. By contrast, higher price tier cities have experienced more HPA over the period we study.[5] Over the same period, HPA in the lowest tier averaged 3.3%, while it averaged 6% in the highest tier. As a result, Total Returns are more equated in the MSA cross-section than either individual component is. Indeed, cities with higher rental yields have tended to have lower HPA. The lowest price tier cities display very slightly higher total returns of 10% vs. 9.5% for the highest price tier. Note that including rental yields completely overturns the popular wisdom that investing in coastal MSA's, which tends to have high prices and high HPA, dominates investing in the fly-over cities, for example. Also striking is the fact that the pooled time series cross-section averages of annual MSA level net yields and HPA are almost exactly equal, at 4.5% and 4.3%, respectively. It is important to note, however, that HPA displays much higher volatility than rental yields. Mean reversion in HPA is a key to this equality result holding at lower frequencies. By contrast, at higher frequencies, such as over the last few years, HPA has contributed significantly more to total returns.

We construct mean variance efficient (MVE) portfolios based on total returns, HPA, and Net Yields at the MSA level. We consider each component of total returns separately because of the heterogeneity in SFR investor types. It seems plausible that the resulting variation in preferences over leverage and exposure to the constraints and covenants of bond ratings leads to heterogeneous portfolio objectives and constraints, resulting in clientele effects in the SFR space. Our IRR analysis shows how leverage and interest coverage considerations imply different portfolio constraints for individual, small institutional, and large institutional investors. As is typical, unconstrained portfolios have extreme weights and imply that a significant fraction of cities should be shorted. Imposing no short sales leads to a five city portfolio comprised mainly by (perhaps surprisingly) Pittsburgh. This result reflects the fact that higher HPA cities' also display high HPA volatility. We also show that the weights in an MVE portfolio based on total returns are very highly correlated with the weights of an MVE portfolio based on HPA alone, while they are actually negatively correlated with the weights constructed from net yields. This is likely due to the fact that HPA is much more volatile in the time series, and displays more cross-sectional heterogeneity, than rental yields do. The

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

close relationship between the portfolio weights implied by total returns and those implied by a sole focus on HPA is striking because of the SFR and commercial real estate industry focus on net yields, also known as “cap rates,” short for ”capitalization rates”. However, we find that a rule-of-thumb focus on maximizing cap rates would lead to a portfolio not as different from the total return MVE portfolio as one might expect, because the low volatility HPA cities have low average HPA and high net yields.

We construct zip code level total returns at the monthly frequency from 2012-Present, the period for which we have zip code level net yield data. We utilize a a detailed new dataset from Core Logic, Rental Trends, which was developed in 2012 by Core Logic to support institutional investment in SFR strategies.[6] Rental Trends reports median net rental yields, or “cap rates” by zip code, property type, and number of bedrooms, constructed using proprietary data from MLS records, tax records, actual vacancies, tenant credit events, and Core Logic’s home price index model and reports. For our zip code level HPA analysis, we utilize Core Logic’s monthly zip code level house price index data.

We find that, similar to our results at the MSA level, net rental yields decline with price level. However, by contrast with the MSA level data, we find that HPA also tends to decline with price level. This is consistent with theories of gentrification, as well as theories of the effects of subprime finance. As a result of both net yields and HPA declining with house prices, total returns clearly decline with house price level and it appears that investors may find higher returns from properties in the lower price tiers within cities. We note that HPA in the lower tier zip codes do tend to display higher betas on city level HPA, so these higher returns may be compensation for higher risk. Vacancy and credit risk are likely to make rental yields similarly more risky in lower price tiers. We also note that most zip codes load heavily on their MSA level HPA factor, with 90% of loadings falling between 0.76 and 1.23 using monthly data from 1985 to the present. Consistent with these high loadings of zip level HPA on MSA level HPA, we find that there is more dispersion in HPA across MSA’s than within MSA’s. The standard deviation of HPA across cities is 5.1%, whereas it is 3.8% within cities on average over the period 1985-2013, and 5.2% vs. 4.6% for 2012-1013. On the other hand, the dispersion in yields is similar across these two levels of aggregation, with average standard deviations of 1.3% across MSA’s vs. 1.7% within MSA’s over the period 2012-2014 for which we have zip code level net yield data.

Finally, we discuss returns at the house level, using data from existing securitizations of SFR portfolios. We show that one reason why yields decline with price levels at the zip code

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

and MSA level is that there is a positive yield on a zero value house, or a positive intercept in a regression of rent on prices. This makes sense because the kitchen and bathrooms are the most expensive rooms in any home, and the increase in value from additional rooms declines after accounting for those two crucial housing inputs. In other words, houses, below a minimum value, certainly appear to be indivisible goods. We also show that there is considerable variation in the collateral across SFR issuers. Collateral purchased earlier appears to have performed better, possibly due to better pricing when the housing market was more distressed. We also find variation across issuers in terms of operating efficiency, with large issuers having lower operating costs and thus smaller differences between gross and net yields. We attribute this to economies of scale. Leverage also plays an important role in institutional SFR strategies. Because institutions tend to face benchmark return thresholds, they typically aim for maximum allowable leverage. Leverage in SFR deals is constrained mainly by debt service coverage ratios (DSCR), rather than loan to value (LTV) ratios due to constraints from bond ratings agencies. In other words, the DSCR constraint tends to bind first as leverage increases, leading investors to prefer high yield (vs. high HPA properties).

2 Literature Review

Our contribution is to document the stylized facts about MSA and zip code level returns to SFR investments. We study total returns, or the sum of net yields and HPA, as well as each component, and expenses. We also discuss portfolio formation, as well as institutional and operational constraints. In contemporaneous work, Malloy and Zarutskie (2013) develop facts about institutional investor purchases of single family homes, in particular noting their concentration in geography and time.

In the 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.[7] Himmelberg et al. (2005) provides a clear description and assessment of the P/R ratio implied by inverse user costs. They use a user cost model to impute an annual rental cost to owned properties and to ask whether the early part of the millenium represented a bubble in house prices. The six inputs to

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

their user cost model are: the risk-free rate, property taxes, mortgage interest deductions, depreciation, capital gains, and the housing risk premium.

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, while rents are more stable. Following Campbell's (1991) decomposition of stock returns, Campbell et al. (2009) conduct a variance decomposition of the rent-price ratio using a dynamic Gordon growth model. They find that there is an important 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, 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 influencing rents housing markets as in they appear to in the market for corporate assets.

In the time series, HPA by city is typically modeled with an error-correction model (ECM) as in Malpezzi (1999) and Capozza et al. (2004). The ECM imposes cointegration in the long run between income and house prices. Thus, in the first stage, fundamental housing values are estimated as fractions of income. Then, momentum and error correction terms are estimated in the second stage. Recent work has attempted to model house prices, and less often rents, in general equilibrium macroeconomic models. Davis and Nieuwerburgh (2014) review some of these recent advances.

Across-city dispersion in HPA in the cross-section is shown to be correlated with variation in supply constraints in Saiz (2010), and with regulatory constraints in Gyourko et al. (2008). Gyourko et al. (2013) document a positive correlation between HPA and variation in amenities and productivity, and coined the term "superstar cities" to describe the growing inequality between cities. Van Nieuwerburgh and Weill (2010) develop an intriguing 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 HPA, and lead to superstar cities.

Finally, HPA 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. 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. Guerrieri et al. (2013) build on these ideas, but emphasize the role of geographical spillovers in a spatial equilibrium model. They provide empirical evidence supporting the presence of such spillovers. Using data from the 2000-2005 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.

3 SFR IRR example

Although we mainly focus on Total Returns comprised by net rental yields and house price appreciation, we present an internal rate of return calculation for a representative SFR investment in order to illustrate the typical composition, timing and magnitudes of cash inflows and outflows. Figure 1 presents our spreadsheet model and the associated assumptions for the purchase and sale of a typical BTR home over a five year horizon.

The key assumptions for our spreadsheet model are the home's square footage, price per square foot, and gross rental yield. We use parsimonious but representative values of 2,000 square feet at $100 per square foot, and a gross yield of 9%. Upon purchase, the home must be renovated, cleaned, and leased. Thus, expenses in the first year are higher than in subsequent years. We assume that the home is purchased and renovated in year zero, and leased at the beginning of year one. At that time, leasing fees and vacancy costs are paid, and for simplicity we do not account for turnover within the five year investment period. This omission is offset by our assumption that renovation takes one year, which is substantially longer than is typical. Credit losses, property management fees, taxes, HOA, insurance, repairs, and capital expenditures are paid annually.

The bottom panel of Figure 1 highlights that some expense assumptions are a fraction of rent (vacancy and credit losses, property management and leasing fees), while others are more suitably assumed to be a fraction of the capital investment, or subsequent home value (property taxes, HOA fees, insurance, repairs and maintenance).[8] Looking at the rows describing the expenses in the top panel of Figure 1, one can see that expenses linked to home value are on average over four times the magnitude of those linked to rents. Most of

[8]Our assumptions closely follow those in Tirupattur (2013), however we note that these are similar to other sources, such as Bernanke (2012), and Core Logic Rental Trends. See the Appendix for a description of Rental Trends.

the variation in rental yields is driven by variation in house prices, as carefully documented in Campbell et al. (2009). Because rents are smoother than house prices, when house prices increase substantially, such as in 2006, net yields decline considerably as a fraction of gross yields. This is because costs which vary as a fraction of house prices act somewhat like fixed costs when applied to gross rents.

In our example, net yields and house price appreciation contribute approximately equally to annual total returns. Total returns are, on average, also close to the annualized internal rate of return implied by setting the net present value of the annual cash flows equal to zero. However, this clearly depends on assumptions, including the investment horizon. We systematically compare IRR's to total returns under reasonable assumptions in Figure 2. We use three sets of assumptions, detailed in Table 1. In particular, we use an all equity investment, an example small investor investment from a multiborrower backed SFR bond, and an example large investment from a single borrower backed SFR bond, defined by their leverage ratios and borrowing constraints as detailed in the caption to Figure 2. Importantly, note that all IRR's are approximately (and undetectably different from) linear in the two inputs into total returns, namely net yields and HPA, and that each element contributes about equally to the total IRR.

We also note that the fact that our example net yields are approximately sixty percent of gross yields is consistent with the ratio of net to gross yields on securitized SFR homes.[9] In sum, our example closely represents the actual collateral owned by institutional investors, and the either assumed or incurred expenses associated with them. We will use similar assumptions when computing net yields in our MSA level analysis.

4 City Level Total Returns

We focus on total returns because they are insensitive to the holding period, summarize returns that would be reported annually in a private equity structure, and are analogous to stock returns from capital gains and dividends. We demonstrated the relationship between total returns and IRR's in Section 3, in which we showed that IRR's are linear in net yields and HPA. We begin by documenting gross and net rental yields and house price appreciation at the MSA level from 1985 to 2013 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

[9] See, for example Shen and Mele (2014). To have their bonds rated, issuers must detail these cost assumptions.

Appendix.

At the MSA level, we construct total returns annually by summing net rental yields constructed using the AHS data, and annual realized HPA constructed using Core Logics monthly HPI data. We report yields and HPA 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 typica annual return calculation for a stock j at $t = 2008$ is:

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

We approximate this calculation for Total Returns to SFR in MSA j at time $t = 2008$, for example, using our two data sources as follows:

$$SFR\ Total\ Return_{j,2008} = \frac{HPI_{\text{j, CL June 2008}}}{HPI_{\text{j, CL June 2007}}} + \frac{Rent_{\text{j, AHS 2007}}}{Price_{\text{j, AHS 2007}}}.$$

The AHS is conducted annually between May and September. To match this timing, we compute annual HPA from June to June using Core Logic's monthly HPI data. It is important to note that we must use the contemporaneous rent and price data from the same AHS survey, since there are no home identifiers and the sample varies over time. However, 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. We also argue that this is better than the alternative of using the 2008 yield data in 2008 returns, since our chosen method implies that the timing of the measurement of the denominator of each return component matches. Our resulting total return series thus covers 1986-2014, using Core Logic's HPI data from June 1985-June 2014, and data on prices and rents from the 1985-2013 AHS surveys.

We begin with the second term, representing net rental yields annually by MSA. Our first step is to compute gross rental yields on single family homes by city using the AHS data. Although there are about twelve million single family rental homes in the US, these homes constitute only a small fraction of the AHS sample. Thus, to construct an MSA level rental yield for single family homes, we begin by estimating rental yields for owned single family homes in the AHS as follows. We index time by t, MSA by j, and house observation by i. First, we estimate a hedonic regression using the rented housing units in the AHS for the largest 30 MSA's to come up with rental prices for key housing characteristics as follows:

$$\ln(\text{MonthlyRent}_i) = \beta_{0,j} + \beta_{0,t} + \beta_1\text{ROOMS}_i + \beta_2\text{BEDS}_i + \beta_3\text{BATHS}_i + \\ \beta_4\text{AIRSYS}_i + \beta_5\text{UnitType}_i + \beta_6\text{Age}_i + \epsilon_i$$

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 MSA's, 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 a dummy variable for housing type (attached or detached homes), and Age is a categorical variable corresponding to the decade of construction. 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. This gives us both a price and and an estimated rent for each owner-occupied unit in the AHS.[10]

Figure 3 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, while 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 pre and post housing price peak. 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 construct our MSA level gross rental yields, we weight each house level observation according to the empirical price distribution of rented units. This is necessary because within all cities, there tends to be more rental units in the lower price tiers, in which, as we show, rental yields are higher. For each city, in each year, we re-weight the owner-occupied houses as follows. First, we order observations in increasing order of their predicted rent. We then use 100 percentile bins to construct the empirical density of renter-occupied homes in the predicted rent space. Finally, we compute the median rent-to-price ratio among owner-occupied units, using the density of renter-occupied units to take a weighted median. Note that relative to an unweighted median, this nonparametric procedure reduces the weight on

[10] 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 house price indexes and will provide reliable estimates of the prices of house and neighborhood characteristics."

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. Without re-weighting rental yields, estimated MSA level yields are lower than those from Zillow or Core Logic for years for which we have overlapping data. However, our re-weighted yields match these other data fairly well. Figure 4 displays a pooled city, time series average of the weight of rented units in the predicted rent space. Figure 5 plots our estimated gross yields against those from Zillow for 2013, and Figure 6 plots our estimated net yields against Core Logic's cap rates in 2013.

Figure 7 plots the average gross and net rental yields, as well as the contribution of net yields and expenses to gross yields over time at a national level, weighting our MSA level estimates by population. The Data Appendix (Demers and Eisfeldt (2015)) contains additional details on the construction of net yields, which require data, for example, on how both tax rates and vacancy rates have varied over time and across cities. Gross yields averaged 7.4% over the sample, reached their highest level of 8.5% in 1999, and bottomed out at 6% in 2007. Using our population weighed national average yields, it appears that the boom in house prices relative to rents began around the year 2000. However, the larger boom in prices from 2003 to 2007 led to a substantially larger fluctuation in gross yields than had been observed previously, at least back to 1985. Figure 7 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 41%, and this is broadly consistent with data from bond annexes for SFR collateralized securities. As noted in the example in Section 3, expenses which are likely to vary with home prices rather than gross rents are over four times as large in magnitude as expenses which are likely to be computed off 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 51% of gross yields in 2007, and reached a low of 36% of gross yields in 1999-2000. Finally, population weighted national average net yields averaged 4.3% over our sample, peaking at 5.4% in 1999 and reaching a low of 3% in 2007.

Having carefully described the drivers of gross and net rental yields, we now turn to annualized HPA. We briefly review the empirical time series framework typically used to model MSA level HPA.[11] House prices are typically thought to be cointegrated with income in the long run, that is, in the long run income and house prices should grow at the same rate.

[11] See, for example, Malpezzi (1999).

This cointegrating relationship then implies that, in the long run, consumers spend a constant fraction of their income on housing. We informally assess the cointegration relationship between income and house prices by plotting the share of income spent on housing in 1991 vs. 2011 by income quintile in Figure 8 using data from the Consumer Expenditure Survey from the Bureau of Labor Statistics. As one can see, this share is approximately constant for most income quintiles.[12] Thus, we follow the literature in considering MSA 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.[13]

While we do not forecast HPA for the purposes of this paper, we note that, as shown by Saiz (2010), realized HPA has been highly correlated with the degree of physical constraints such as water and mountains, as well as regulatory constraints such as zoning restrictions. In our sample, the cities with the five highest average annualized HPA realizations were San Francisco, San Jose, Los Angeles, Seattle, and San Diego, respectively. As argued by Saiz (2010) and Davidoff (2014), this may be because cities with more constrained supply tend to have greater natural amenities, and these facts appear consistent with the model in Van Nieuwerburgh and Weill (2010). In practice, due to this and other variation in MSA characteristics, the first stage of HPA forecasting models often include either MSA fixed effects, or interactions of population or income with supply elasticity.[14] Second stage momentum and mean reversion coefficients vary significantly across cities. This is consistent with the idea that because housing pays a dividend in the form of a non-tradeable service, markets are local, as emphasized in the assignment model literature Määttänen and Terviö (2014) and Landvoigt et al. (2012) and in the sorting literature, such as Van Nieuwerburgh and Weill (2010).

We compute annualized realized HPA at the MSA level using Core Logic's HPI data, which is available at a monthly frequency from 1976 to the present. To approximately match the timing of the AHS survey, which is computed between May and September, we

[12]Piazzesi, Schneider and Tuzel (2007) find that the aggregate expenditure share of housing is stable over 1950-2000. The BLS data show that it has increased slightly for lower quintiles and by contrast has decreased slightly for the upper quintiles. As a result of the increased inequality in the share of income spent on housing, the average has also increased slightly due to the effect of this mean-preserving spread through Jensen's inequality.

[13]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 HPA 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 one-year intervals and longer horizons display reversion.

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

compute HPA from June to June each year, and report, for example, 2008 HPA as the realized HPA from June 2007 to June 2008. Figure 9 plots national realized HPA along with net rental yields, weighting the top 30 MSA's by population as above. The larger variation in HPA is clear from the graph. While the average HPA of 4.4% is very close to the average net yield of 4.3% over the period 1985-2013, the time series standard deviation of HPA is 6.7%, as compared to 0.6% (an order of magnitude lower) for net rental yields.

Next, we examine HPA and net rental yields together across MSA's. Figure 10 plots MSA level average annualized HPA vs. average net rental yields for our sample from 1985 to 2013. Clearly, there is a strong negative relationship. We show that this relationship is driven partly by different behavior across price tiers. Lower price tier cities tend to have higher rental yields, and lower HPA. By contrast, higher price tier cities tend to have lower rental yields and higher HPA. To see this, each year, we sort cities into quintiles according to their HPI. We then compute HPA and rental yields in the following year for each quintile, and average across years. Figure 11 plots average annualized HPA and average net rental yields, along with implied total returns, from 1986-2014 by price quintile, from lowest to highest, and clearly illustrates that rental yields decline in price while HPA increases with price.[15] 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. Thus, there appear to be different valuations for owning and renting the same quality of house.

Figure 12 shows that a similar pattern holds without aggregating by price tier, by plotting average net rental yields and HPA from 1986-2014 by city. Cities are sorted from left to right in order of highest to lowest average net rental yields. Although the pattern is not monotonic, the (typically more expensive) cities on the right side of the figure have the lowest net rental yields, but tended to experience higher annual HPA. The correlation between average net yields and HPA across MSA's is -0.69. We noted above that, on average over this long time series, net rental yields and HPA contributed roughly equally to total returns. Although HPA varied in the time series by a much larger amount, in the cross-section HPA and net rental yields display about the same amount of variation. The standard deviation of the time series averages of MSA level net rental yields and HPA are both 1.3%. This is consistent with MSA level error-correction models of HPA in which trend growth rates display less variation across cities than the momentum and error correction terms do. Finally, the correlations

[15]Due to momentum in HPA, it is somewhat mechanical that higher HPI cities will have higher HPA. However, mean reversion attenuates this. Moreover, we estimated the diagonals of the empirical transition matrix across price tiers to be 0.92, 0.83, 0.89, 0.91, and 0.94, from the lowest to highest tier, respectively.

between average total returns and average net yields and HPA are 0.36 and 0.39 respectively. Table 3 presents the MSA level data, sorted in decreasing order by average total returns from 1986-2014.

The negative relationship between net yields and HPA across MSA's implies that the the cross-sectional dispersion in long run averages of total returns is relatively low (1%). The approximate equality of total returns across cities in the long run can possibly be understood in the context of the user cost model described in Himmelberg et al. (2005). That paper presents a user cost model which 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 HPA, then buying may have been perceived as an important hedge against future price increases. However, this explanation seems to suggest that rents should eventually catch up to price growth. Giglio et al. (2015) and Giglio et al. (Forthcoming) study very long run housing discount rates using data freeholds vs. leaseholds and provide evidence against housing bubbles. In facct, 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 vs. owner borrowing capacity as in Eisfeldt and Rampini (2009).

The average experience over our long sample is in contrast to the recent period from 2012-2014, the returns period for purchases after 2011, during which most of the SFR purchases took place. Malloy and Zarutskie (2013) emphasize that purchases by large investors, defined as having purchased more than 200 homes since 2000, increased significantly during these years. Averaging across cities during these three years, mean net rental yields were 4.4%, and mean HPA was 7.2%. Figure 13 plots MSA average net yields and HPA over the three years 2012-2014, again in the order of declining net yields. Two things are apparent. First, there is no clear negative relationship between net rental yields and HPA over this period. The measured cross-sectional correlation between average net yields and HPA over this shorter period is 0.03. Investors in Atlanta, Detroit, Houston, Miami, Tampa and Phoenix, for example, achieved both net rental yields and HPA above the cross-sectional average from 2012 to 2014. Second, the dispersion in HPA was much greater than the dispersion in rental yields. The cross-sectional standard deviation of average HPA was 4.4% vs. 2.1% for net yields. As a result, HPA accounts for more of the variation in total returns during this time period. The lack of negative correlation between net yields in the recent sample vs. the longer time series is also reflected in the difference in the cross-sectional standard deviation of average total returns across these two time periods, and in the fact that the cross-sectional standard deviation for total returns exceeds that for either net yields or HPA in the recent sample (4.9%), whereas it is lower than both in the longer time series (1.0%). Finally, it is also reflected in the higher correlation between total returns and either of its components. The correlations between average total returns and average net yields and average HPA over the recent sample are 0.46 and 0.90 respectively.

The correlation between total returns in the recent sample 2012 to 2014 and the overall sample is 49%. This correlation is fairly high but is depressed by the relatively unique experience during the housing recovery, during which HPA contributed more significantly to total returns, in particular in distressed areas such as Phoenix and Atlanta. To get an idea of the stability one might have in a portfolio selected on total returns above a certain threshold, the average AR(1) coefficient across cities from regressing total returns on its own lag, including a city fixed effect is 0.65, and the average R^2 from these regressions is 44%.

The comparison between long run and recent total MSA level returns can be understood in the context of the literature on variation in rent to price ratios, and the time series process which describes MSA level HPA. Campbell et al. (2009) shows that most of the variation in rent to price ratios is driven by variation in HPA, similar to the Campbell (1991) result for stock price dividend ratios. Thus, rents tend to be more stable than prices. Moreover, as described by the error correction model used to describe HPA in the time series, MSA (and aggregate) house prices display mean reversion. Putting these two results together allows for the following interpretation of MSA level total returns: Although HPA may vary substantially in the cross-section over short horizons, mean reversion tends to reduce this dispersion in the long run. Because dispersion in rental yields tends to be driven by variation in house prices, the same is true for net yields, as well as total returns.

Finally, we discuss the implications of these results for portfolio formation. We first examine a simple portfolio objective which might be appealing to investors, namely an objective which selects MSA's with higher total returns. Table 4 ranks MSA's in decreasing order, and displays the cities' corresponding ranks for average net yields and HPA. Most institutional investors desire a leveraged portfolio, and, under current conditions, leverage is most constrained by the minimum debt service coverage ratio (DSCR), typically about 1.2, required to get the bond rated. According to bond annex data from SFR securitizations, most loan to value ratios (LTV's) range between 60% and 70%. At a 60% LTV, and at a 6% rate of interest (in between individual rates and single borrower securitizations), a yield of

4.35% is required in order to satisfy a typical DSCR of 1.2. We highlight cities which have net yields above 4.35% in bold.

Table 5 presents the portfolio weights implied by mean variance efficiency allowing for short sales, and (more realistically) restricting city shares to be positive. We drop the Newark and Nassau-Suffolk MSA's to avoid singularity. We report portfolio weights for total returns, and for each component separately, along with the return and standard deviation on the minimum variance portfolio. We also report results with shares constrained to be greater than zero but less than 20%. It is more difficult to securitize portfolios that are too concentrated geographically. On the other hand, it is more difficult to operate and manage portfolios that are too geographically diversified. However, mean variance efficiency does not lead to a very geographically diversified portfolio, as can be seen.[16]

As is typical, unconstrained portfolios have extreme weights and imply that a significant fraction of cities should be shorted. Imposing no short sales leads to a five city portfolio comprised mainly by (perhaps surprisingly) Pittsburgh. This result reflects the fact that higher HPA cities' also display high HPA volatility. We plot the efficient frontier for total returns restricted to have positive, but less than 20% allocations in Figure 14. Note that this puts the portfolio comprised 100% by Pittsburgh outside the efficient frontier!

The weights in an MVE portfolio based on total returns are very highly correlated with the weights of an MVE portfolio based on HPA alone, while they are actually negatively correlated with the weights constructed from net yields. This is likely due to the fact that HPA is much more volatile in the time series, and displays more cross-sectional heterogeneity, than rental yields do. The close relationship between the portfolio weights implied by total returns and those implied by a sole focus on HPA is striking because of the SFR and commercial real estate industry focus on net yields, also known as "cap rates," short for "capitalization rates". However, we find that a rule-of-thumb focus on maximizing cap rates would lead to a portfolio not as different from the total return MVE portfolio as one might expect, because the low volatility HPA cities have low average HPA and high net yields.

MSA level Stylized Facts: To summarize, the MSA level stylized facts describing total returns and their components in US data from 1986 to 2014 are as follows:

[16]See Cotter et al. (2014) for a detailed study of the time varying potential for diversification of HPA risk in the cross-section of MSA's. Our study includes both HPA and net rental yields. Accounting for both inputs is important, since we show the negative cross-sectional correlation between these two return components.

1. Gross and net rental yields tend to decline with price.
2. Conversely, realized HPA 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. The cross-sectional standard deviations of average net rental yields and HPA are about equal, but HPA is much more volatile in the time series.
5. The period with heavy institutional investment, 2011-2013, was anomalous in that:
   (a) Rental yields and HPA were not negatively correlated.
   (b) HPA was a more important driver of total returns than rental yields were.

5 Zip Code Level Total Returns

We use Core Logic's Rental Trends dataset to examine net rental yields at the zip code level at the monthly frequency from 2012 to 2014. This data contains property-level net yields (also known as "cap rates") from over 35,000 single-family rental homes. We use Core Logic's HPI data at a monthly frequency to compute zip code level HPA annually from June to June, to match the timing of the MSA level analysis using AHS data. Similarly, we use the June snapshot of net yields from Rental Trends. Our zip code level sample includes 2,357 zip codes across the 30 largest MSA's.

To get an idea of how much optimization of locations within a city might improve SFR return profiles, we first discuss the relative amount of cross-sectional variation in net yields and HPA within cities, across zip codes, vs. across MSA's. Figure 16 displays the distribution of total returns across all zip codes for the time period from 2012-2014. To construct total returns by zip code, we add the average HPA from 1986-2014 to average net yields from June of each year 2012-2014. We use the longer HPA sample to study representative total returns because HPA from 2012-2014 was much higher than average, whereas our zip level yield data only goes back to 2012. Yields, as we have seen, are much more stable than HPA is over time. Thus, we argue we can approximately capture much of the relevant cross-sectional heterogeneity in net yields using the shorter sample, but, in the end, we are constrained by data availability. On average, the standard deviation in net yields across MSA's in Core Logic's net yield data from 2012-2014 was 1.3%, very close to the average of the dispersion in our estimated MSA level net yields using AHS data from 1985-2013. The advantage of the Core Logic data is the ability to compare yields within cities, across zip codes. On average from 2012-2014, the cross-sectional standard deviation in net yields across zip codes, within MSA's was 1.7%, or slightly higher than the dispersion across cities. cross-sectional variation in HPA displays the opposite pattern, with larger differences. The dispersion in HPA within cities, across zip codes is lower on average (3.8%) than it is across cities (5.1%) over the sample from 1985 to 2013. On average in 2012 and 2013, the same pattern holds, but with smaller differences (5.2% across, 4.6% within). We noted above that zip code level HPA loads heavily on city level appreciation, with 90% of loadings in a univariate "industry CAPM" style regression using data from 1985-2014, including an intercept, falling between 0.76 and 1.23. We do note, however, that Core Logic likely shrinks their noisy zip level estimates towards the city level mean when cleaning their data. Finally, we also note that if one regresses zip code level HPA over the period 1985-2013 on MSA 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 HPA is tightly linked to city level outcomes.

We find that while net rental yields decline with price tier within cities, as they do across MSA's, HPA also appears to decline with price tier, which is in stark contrast to the pattern across MSA's. Since rental yields and HPA are actually positively correlated across price tiers within cities, there appear to be opportunities for substantially larger total returns in the lower price tiers. This is in contrast to the MSA level data, in which the negative correlation between rental yields and HPA implied a more flat total return distribution across MSA's.[17] Figure 17 plots average excess yields and HPA over their respective MSA level average, by house price quintile, for the period from 2012 to 2014 over which we have overlapping Core Logic data on both. Clearly, the lower price quintiles performed better along both dimensions. Figure 18 plots average excess HPA over the MSA level average by house quintile for the longer period from 1986-2014. Again, we see that there is much less dispersion in HPA over longer horizons, however the declining pattern across price tiers is still present. To summarize these findings, Figure 19 plots the ratio of the average total returns from 2012-2014 in the lowest two price quintiles in each MSA, relative to the MSA level average. Almost all of these ratios are above 1. The exceptions are New York and

[17] For the zip code level price quintile analysis, we drop Dallas, Houston and Kansas City, for which we do not have adequate data on zip code level prices from Zillow.

Detroit, in which the lower tiers did not have higher HPA than the higher tiers over this period.

There may be several reasons why low price tier MSA's 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 in these price tiers may be more volatile over the housing cycle, and therefore more risky. Zipcode level HPA certainly appears to have more city level risk in lower price tiers. The average loadings of zip code level HPA on MSA level HPA are declining with price levels. 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 zips may also have benefited from gentrification or innovations in lending practices.[18]

Zip Code Level Stylized Facts:

1. Net rental yields decline with house prices within MSA's.
2. HPA declines with house prices within MSA's.
3. As a result, total returns decline with house prices within MSA's.
4. There is more measured dispersion in HPA across MSA's than within MSA's across zip codes. Zip code level HPA 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 MSA levels.

6 House Level Total Returns

The fourteen single-borrower SFR bond issuances between November 2013 (the first such issuance) and January 2015 provide us with rich data on 53,806 single-family rental properties backing \$7.8 million in notional bond value.[19] In particular, we observe underwritten gross

[18] 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.

[19] As described in the data appendix, each bond issuance comes with and Annex A providing property-level detail on the collateral.

rents, net income, and broker-price opinions (BPOs) on each property.[20] We treat the BPOs as an unbiased estimate of the market value. The fourteen issuances come from seven different institutional SFR operators.

To provide a rough comparison to the AHS and Core Logic net yields, we first sum all securitized net income and divide by the total securitized property value to arrive at 5.0% as a weighted measure of net income from these SFR properties.[21] This compares to 4.3% from the 2013 AHS data and the 6.0% from 2013 CoreLogic RentalTrends (using our panel of 30 cities). Recall that we compare yields from these two sources in Figure 6.

We study the determinants of the income earned by each property. Because of the low time-series volatility of yields, and because all property characteristics were measured within an 18 month time span, we abstract from the time dimension. We index each house observation by i, zip by j, and each issuance by $m \in \{1, 2, ...14\}$. We estimate the following regression using the rented housing units in the bond annexes:

$$\text{Annual Income}_i = \beta_{0,j} + \beta_{0,m} + \beta_1 \text{BPO VALUE}_i + \epsilon_i$$

Zip code fixed effects and issuer fixed effects are captured by $\beta_{0,j}$ and $\beta_{0,m}$. BPO VALUE is the property value as determined by a third-party broker at the time the property is rented. This broker also provides the monthly rent for underwriting purposes. We annualize the underwritten rent amount to form the variable Annual Income. We report the values of $\beta_{0,m}$ in Table 6 and we view the similarity across separate issuances from the same SFR operators as evidence of the reliability of the estimates.

We estimate β_1 to be 2.5%, implying that net income increases \$2,500 if property value increases from \$100,000 to \$200,000. Note that this is considerably lower than the 5.0% average net income of these properties. This is because there is a positive intercept, meaning that a worthless house seemingly rents for a positive amount. The regression $\text{Annual Income}_i = \beta_0 + \beta_1 \text{BPO VALUE}_i$ yields an estimate for β_0 of \$4,472.[22] Figures 20 and 21 provide illustrative scatter plots of the bond annex data. Figures 20 clearly displays

[20] Underwritten net income accounts for vacancy and bad debts, i.e., subtracts off some cash to allot to said categories, though all the properties in the sample are leased.

[21] At an issuance level, this varies from 4.3% for IH 2014-SFR2, which has the highest average BPO values, to 6.2% for AH4R 2014-SFR2.

[22] There is certainly some nonlinearity as the value of a house approaches zero. If we estimate on only properties with a value under \$120,000, the estimate of β_0 drops to \$3,676 and the estimate of β_1 climbs to 3.1%.

the positive intercept. Figure 21 shows the resulting downward-sloping net income ratio.[23]

As suggested by the heterogeneity in issuer profitability, there is considerable dispersion in house-level expense ratios, defined as the ratio of rent minus net income to rent. The mean expense ratio is 42%. We demonstrate the heterogenity in Figure 22, which plots the distribution of expense ratios. Consistent with our findings in the time series, we find that (possibly because costs which scale with house prices act like fixed costs relative to rents) the expense ratio is increasing with property value. After controlling for zip code and operator fixed effects, an increase in property value from $100,000 to $200,000 increases the expense ratio by 1.5% (for example, from 30 to 31.5%).

The popular press has claimed that SFR operators have focused on distressed properties that hit the market following the subprime boom and bust. If true, this would make sense for at least three reasons. First, from a capital structure perspective, it makes sense to turn credit constrained owners into renters, since, as discussed, leasing has a higher debt capacity. Second, the returns to SFR strategies depend on the dividends from net rents, and the capital gains from house price appreciation. Purchasing distressed homes at a discount can thus improve returns. Finally, and relatedly, foreclosure auctions allowed institutional purchasers to buy homes in bulk, thereby substantially reducing the typically large search and brokerage costs associated with acquisitions. To assess this popular claim empirically, we examine the geography and HPA performance of the portfolios of homes collateralizing SFR backed bonds. Figure 24 plots peak to trough vs. trough to current house prices for the cities with the largest market share of SFR collateral, along with the other largest MSA's. The CBSAs with the five largest shares of SFR properties in securitized products are Phoenix (13.9%), Atlanta (12.1%), Tampa (7.3%), Houston (5.2%), and Las Vegas (4.7%). Figure 24 shows that cities with larger peak to trough losses have tended to experience larger trough to present gains in home values. On the other hand, at least in the securitized SFR's, there does not seem to be a high correlation between house price dynamics in the boom and bust period, and property selection. If that were the case, we would expect more of the high share cities to appear in the upper left quadrant representing large peak to trough losses and trough to present gains.

Finally, we use the bond annex data to investigate the relation between SFR investment post-crisis and subprime lending pre-crisis. We pair the bond annex data with Core Logic's LoanPerformace data on nonagency subprime originations by zip code as follows: We bin

[23]This picture reinforces the need for differentiating between the rent-to-price ratios of renter-occupied and owner-occupied homes, as discussed in the previous section.

the 53,806 properties in our dataset into zip codes and count the number of properties by zip.[24] We then compute the average monthly subprime originations (by value) between 2003 and 2008 in each zip code in the LoanPerformance data. We find some limited support for subprime borrowers being turned into SFR renters. The correlation between the two variables is 0.37. The two variables are plotted in Figure 23, and here it is clear that the zip codes with the highest property counts tend to have higher past subprime originations.

7 Conclusion

In this paper, we study the returns to single family rental strategies over a long time series, from 1986 to the present, in order to understand the drivers of SFR returns, to consider portfolio formation and capital structure, 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. We utilize detailed cross-sectional data, down to the house level in the recent time period, and incorporate the effects of operating costs, taxes, and vacancies. Single family rentals are an important asset class, constituting about $2.2 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 SFR backed bonds are outstanding. Thus, we argue that SFR is an interesting, large, asset class, which is new to large institutional, and securitized, investment. The securitized SFR market also has considerable growth potential, in particular with the recent ratings and issuances of multi-borrower backed bonds.

It is also possible that the propensity of households to rent vs. buy may grow, or remain elevated, as well, increasing the importance of single family rentals (currently about 35% of all rental households). According to the ACS, the homeownership rate peaked in 2007 at about 67%, 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.[25] At the same time, student debt has increased dramatically, growing

[24] The most frequent zip code is 85037 in Phoenix, with 334 properties.

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

166% from 2005 to 2012, potentially reducing borrowers' mortgage capacity.[26] Notably, there has not been an offsetting decline, but instead an increase, in auto or credit card debt.[27] Moreover, employment for the relatively large millenial generation was impacted heavily by the recent recession, and renting has been 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,[28], and the August 2014 Fannie Mae National Housing Survey finds 32% of respondents would rent if they were going to move.[29] For these reasons, we argue that understanding the SFR asset class is important, and our paper aims to fill the existing gap in the literature on the total returns to single family homes.

[26] `http://www.newyorkfed.org/studentloandebt/index.html`.
[27] See `http://www.newyorkfed.org/microeconomics/hhdc.html#/2014/q3`.
[28] ACS data analyzed in Kolko (2014).
[29] `http://www.fanniemae.com/portal/about-us/media/corporate-news/2014/6166.html`

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Figures and Tables: Please view in color

Figure 1: Pro Forma Example: All Equity SFR Investment.

Years out	0	1	2	3	4	5
Capital Invested	$ 215,700					
Revenue						
Gross Rent		$ 19,413	$ 19,995	$ 20,595	$ 21,213	$ 21,850
Gross yield (=R/(P+capex) ratio)		*9.0%*	*9.3%*	*9.5%*	*9.8%*	*10.1%*
Expenses						
Expenses linked to gross rent		(2,142)	(1,326)	(1,366)	(1,407)	(1,449)
Expenses linked to home value		(5,608)	(6,355)	(6,704)	(6,999)	(6,899)
Total Expenses		$ (7,750)	$ (7,681)	$ (8,071)	$ (8,407)	$ (8,348)
Operating Free Cash Flow		$11,663	$12,314	$12,525	$12,806	$13,501
Net Yield = Operating ROA		*5.4%*	*5.7%*	*5.8%*	*5.9%*	*6.3%*
Home Value	$ 215,700	$ 227,132	$ 239,624	$ 252,804	$ 263,927	$ 260,136
House Price Appreciation (HPA)		*5.3%*	*5.5%*	*5.5%*	*4.4%*	*4.3%*
Total Return: Net Rental Yield + HPA		*10.7%*	*11.2%*	*11.3%*	*10.3%*	*10.6%*
Total Free Cash Flow	$ (215,700)	$ 11,663	$ 12,314	$ 12,525	$ 12,806	$ 273,637
Unlevered IRR:	9.2%					

	Assumptions highlighted	Assumptions or Implied Percentages	
House Characteristics			
Bedrooms	3		
Bathrooms	2		
Square Feet	2,000		For calculations per square foot.
Price per square foot	$100.00		Key purchase price input.
Year 1 Assumptions:			
Capital Investment			
Purchase Price	$ 200,000.00		Implied by square feet and price/sq. ft.
Renovation			
Paint	$ 2,400.00	$1.20	Cost per square foot
Floor	$ 2,800.00	$1.40	Cost per square foot
Appliances	$ 4,000.00		Assume directly
Landscaping	$ 2,000.00		Assume directly
Cleaning	$ 500.00	$0.25	Cost per square foot
General Repairs	$ 4,000.00	$2.00	Cost per square foot
Total Renovation	$ 15,700.00	7.9%	Implied % renovation cost/purchase price
Total Invested Capital	$ 215,700.00		
Baseline First Year Income and Expesnses			
Revenue			
Gross Rent	$ 19,413.00	9.00%	Gross yield from the data
Vacancy	$ (485.33)	2.5%	% of gross rent (Vacancy rate of 10% once every 4 years)
Credit Loss	$ (142.49)	0.7340%	% of gross rent
Effective Gross Rent	$ 18,785.18	96.77%	Implied % effective gross rent
Expenses			
Property Management	$ 1,145.37	5.900%	% of gross rent
Leasing Fees	$ 368.85	1.900%	% of gross rent
Property Taxes	$ 2,696.25	1.250%	% of capital investment
HOA Fees	$ 808.88	0.375%	% of capital investment
Insurance	$ 808.88	0.375%	% of capital investment
Repairs and Maintenance	$ 1,294.20	0.600%	% of capital investment
Total Expenses	$ 7,122.41	3.302%	Implied % total expenses/capital investment
Annual Assumptions:			
Gross rent growth rate		3.00%	annually
Credit loss		0.73%	% of gross rent
Property Management		5.90%	% of gross rent
Property taxes+HOA+insurance+repairs		2.00%	% of home value
Cap Ex		1.15%	% of home value
HPA			Core Logic Jan./Jan. forecast for the years 2015-2020 as of 03/19/2015
Closing costs in year 5		5.50%	% of home value

Figure 2: Internal Rates of Return are Approximately Linear in Yields and HPA.

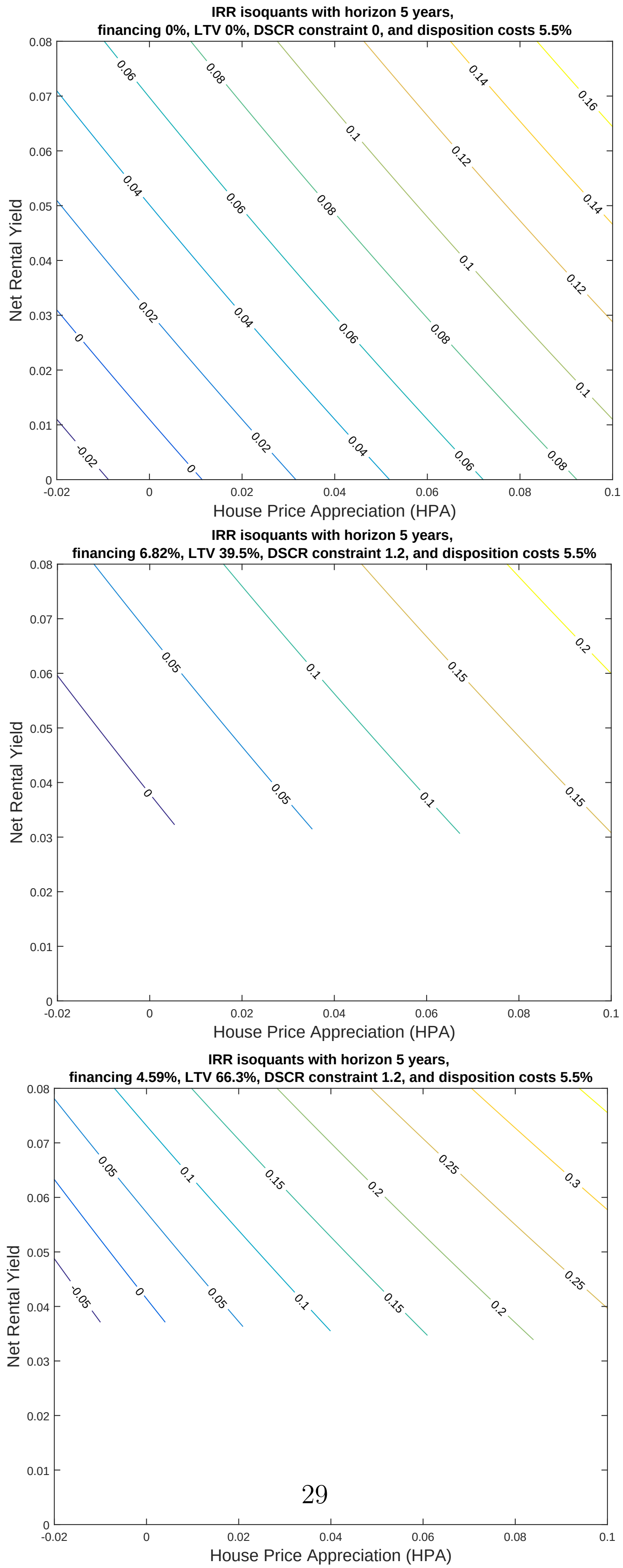

Figure 3: Price to Rent Ratios, Owned Homes: AHS data and Hedonic Model 1985-2013.

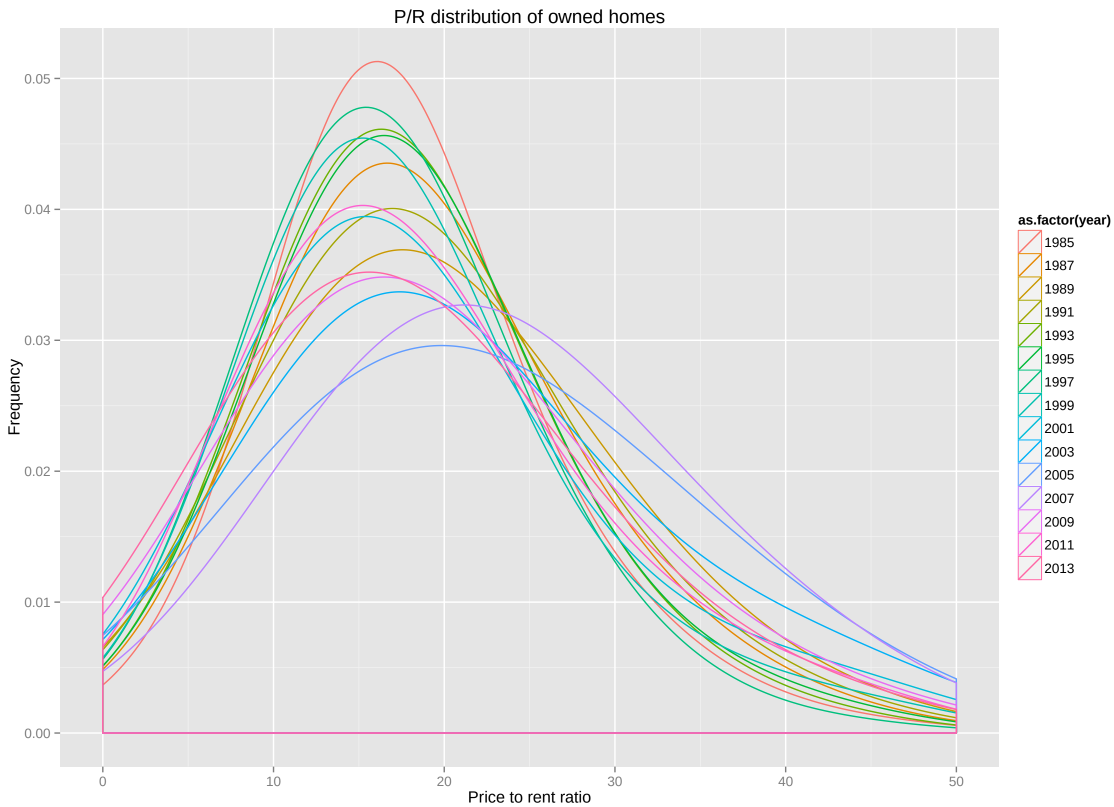

Figure 4: Non-parametric weights, pooled average over cities and years: Fraction of rented homes across percentiles of predicted weights from the AHS.

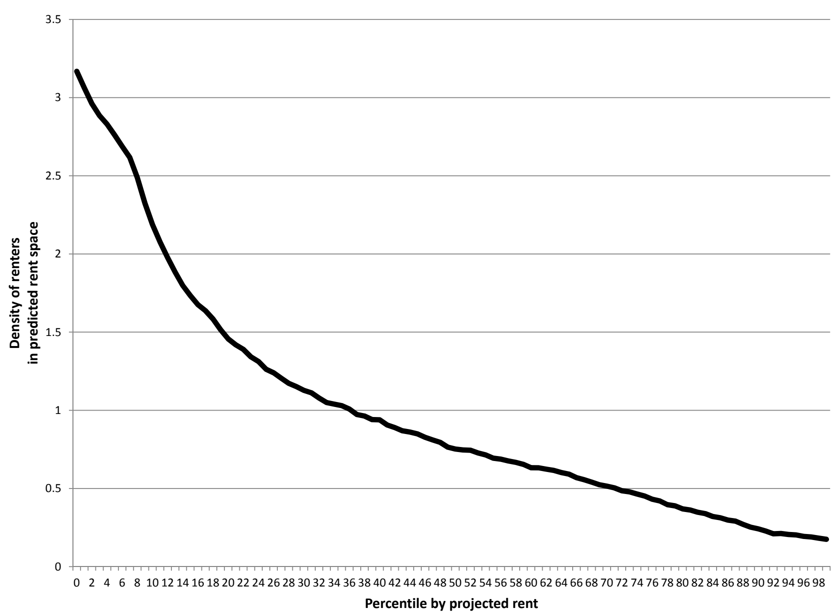

Figure 5: Gross yields estimated from AHS vs. Zillow gross yields 2013.

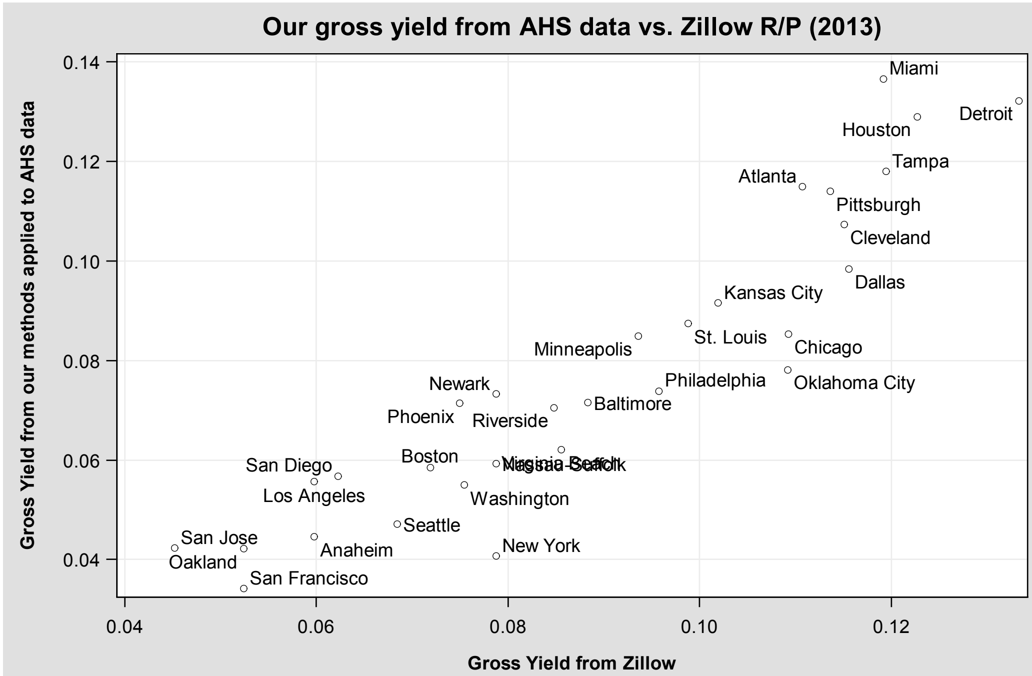

Figure 6: Net yields estimated from AHS vs. Core Logic cap rates (net yields) 2013.

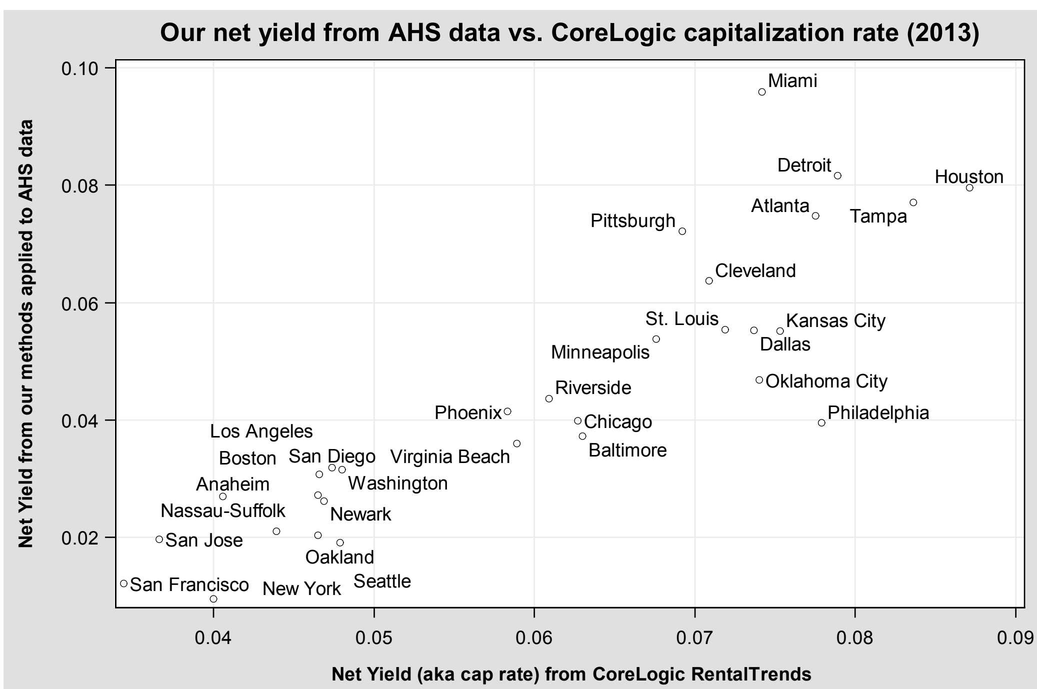

Figure 7: Gross yields, net yields, and expense rates. Population weighted averages 1985-2013.

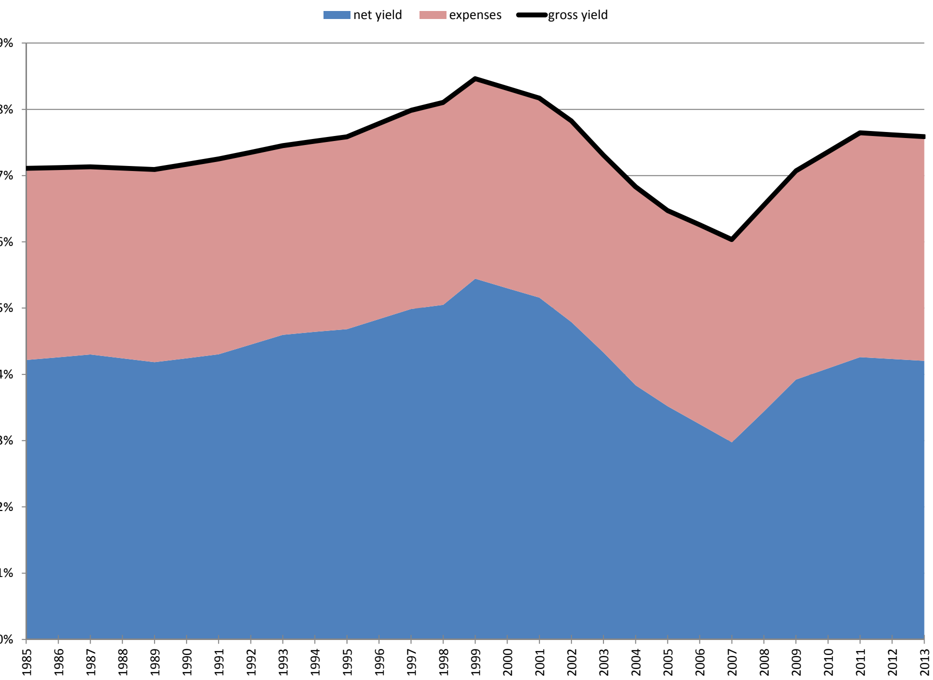

Figure 8: Percentage of income spent on housing by income quintile. Data Source: Consumer Expenditure Survey.

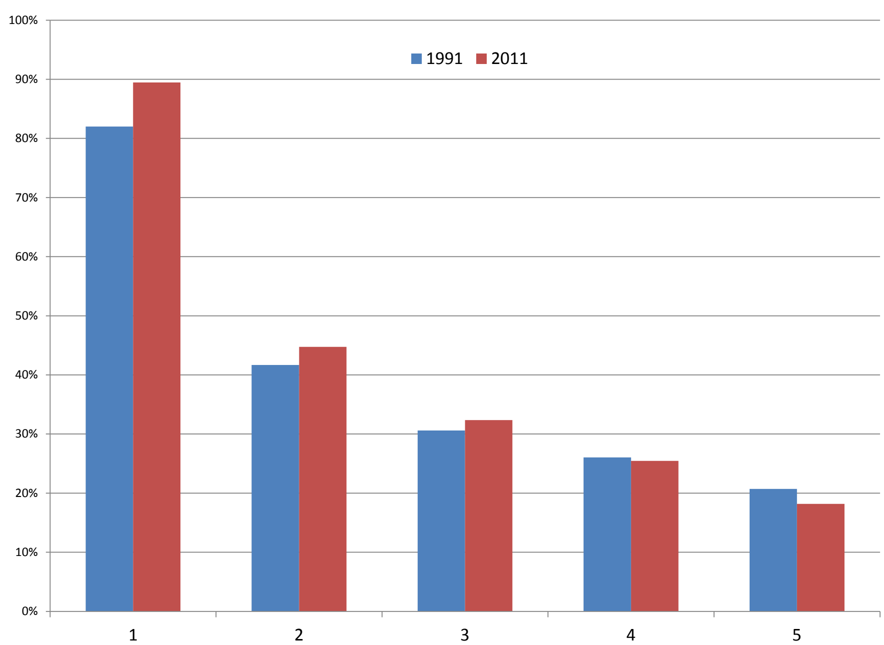

Figure 9: Net Rental Yields and HPA. Population weighted averages 1985-2013. HPA is June$_{t+1}$ on June$_t$, recorded at June$_t$.

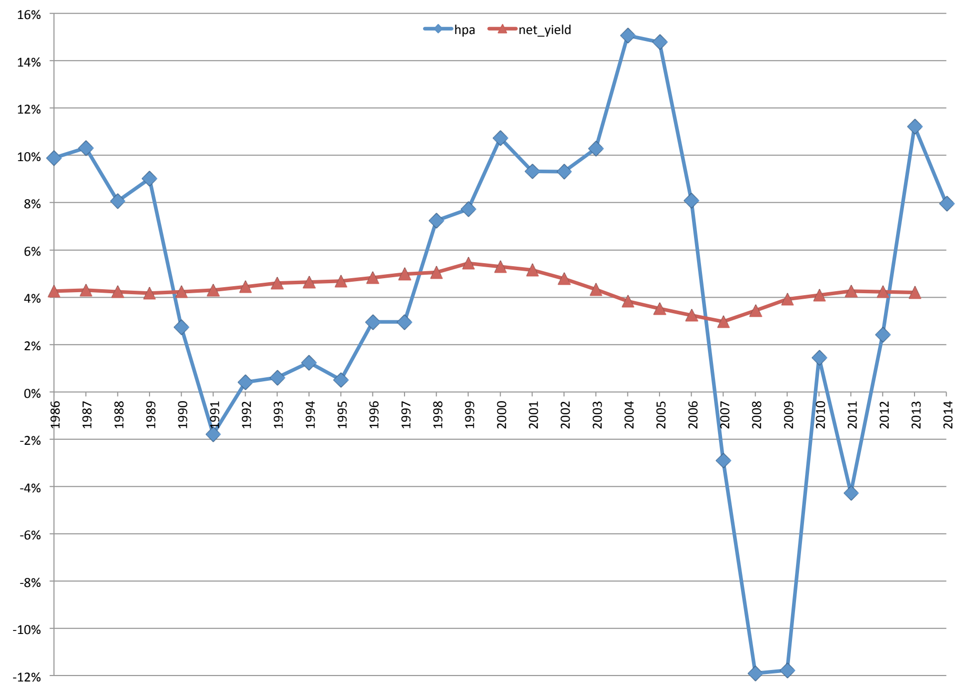

Figure 10: Annualized average MSA level HPA vs. net rental yields 1986-2014.

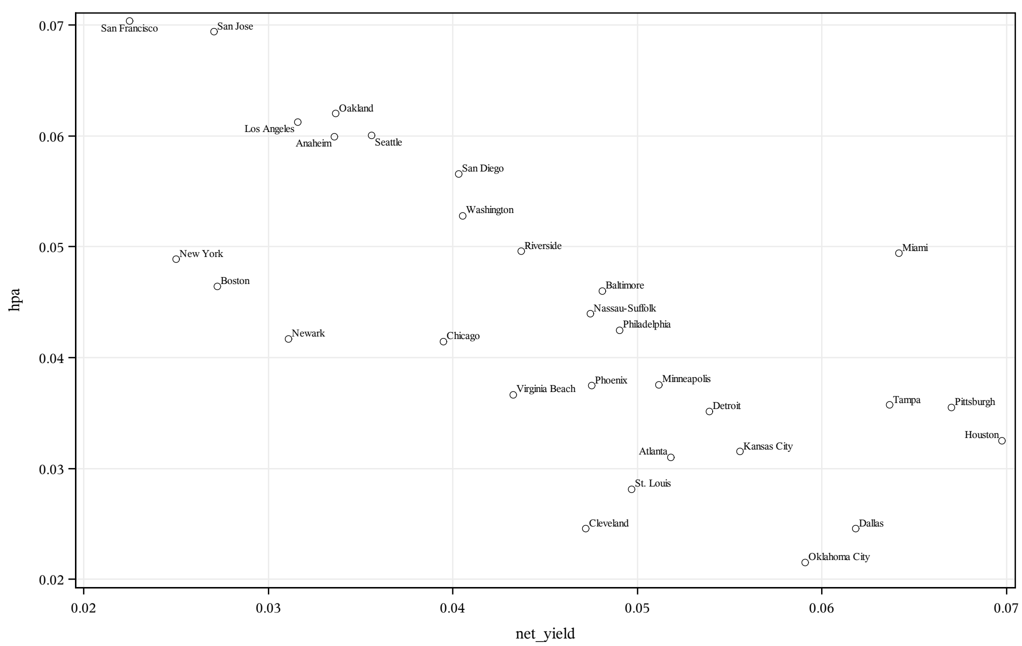

Figure 11: Annualized average MSA level HPA, net rental yields, and total returns 1985-2013 by house price quintile, lowest (1) to highest (5).

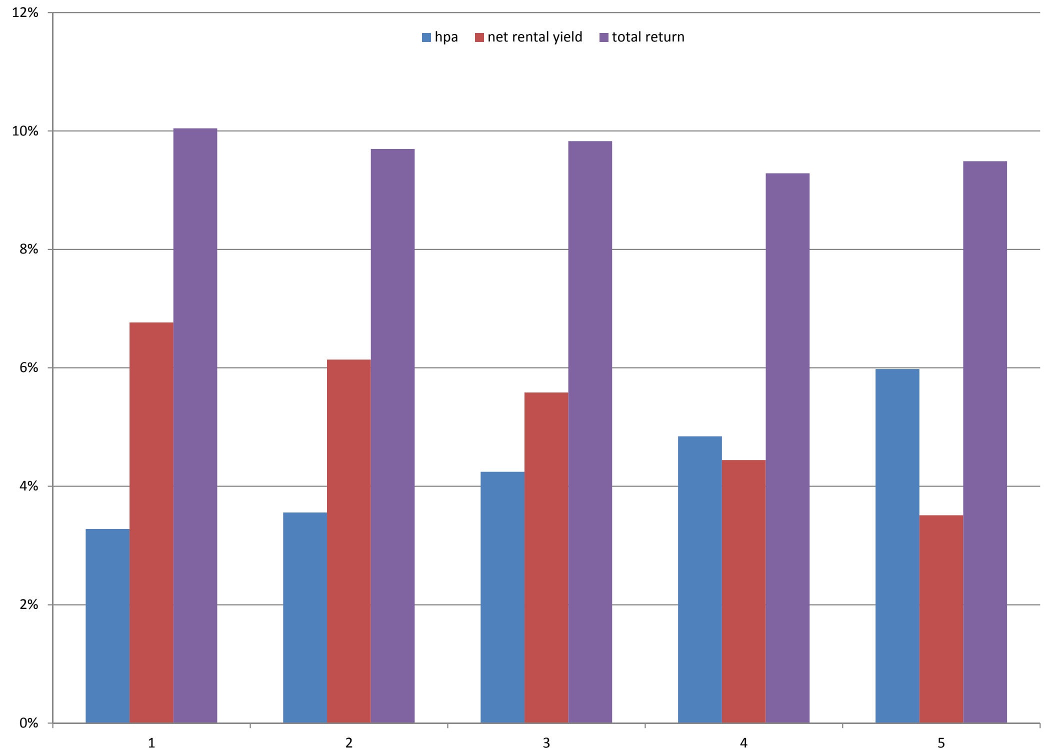

Figure 12: Annualized average HPA and net rental yields 1985-2013, top 30 cities.

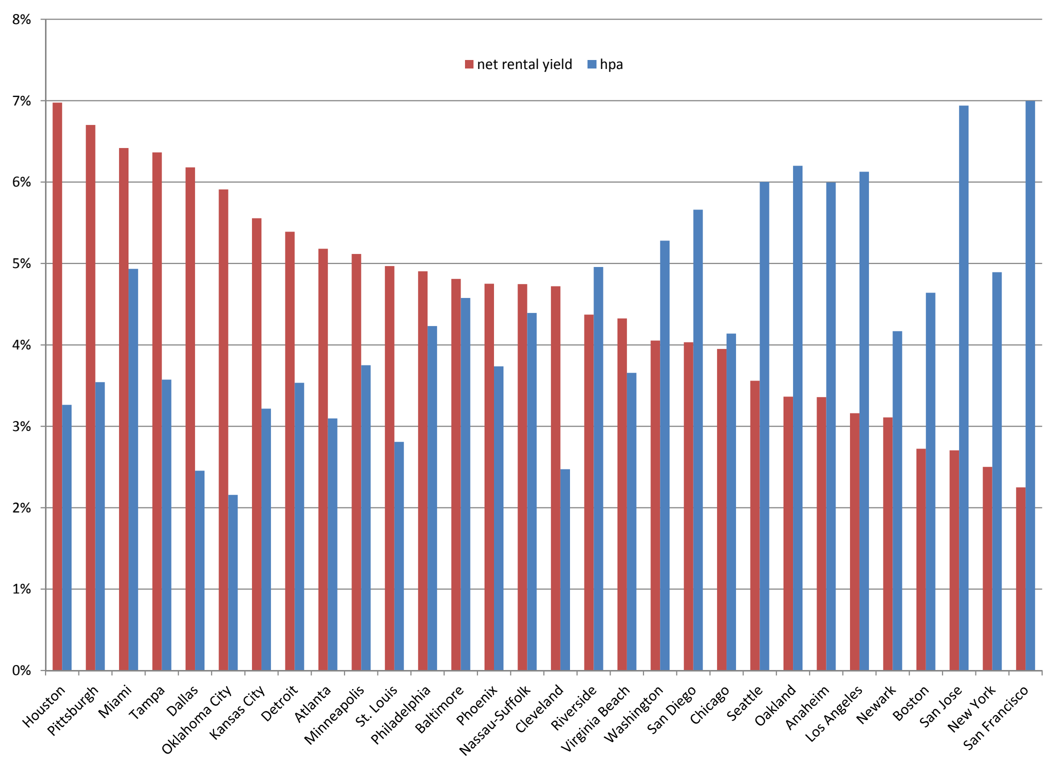

Figure 13: Annualized average HPA and net rental yields 2011-2013, top 30 cities.

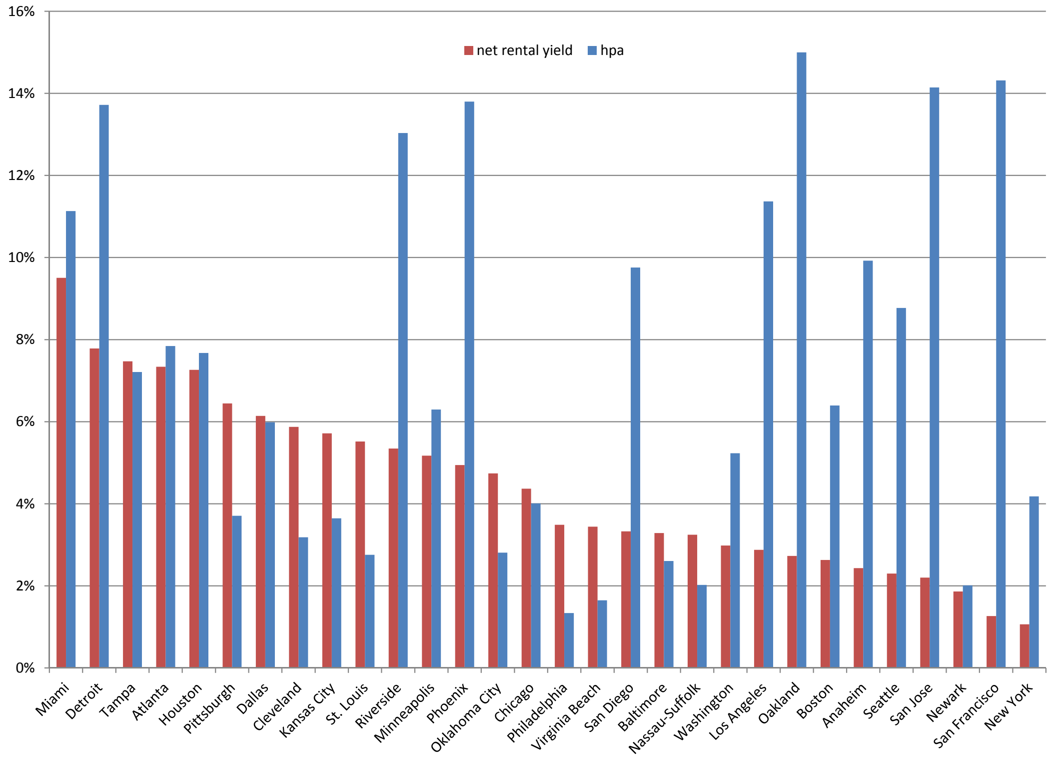

Figure 14: Mean-variance optimization of total returns (1985-2013) without short sales and a maximum allocation of 20% to each city. Cities receiving highest weights are labeled by name.

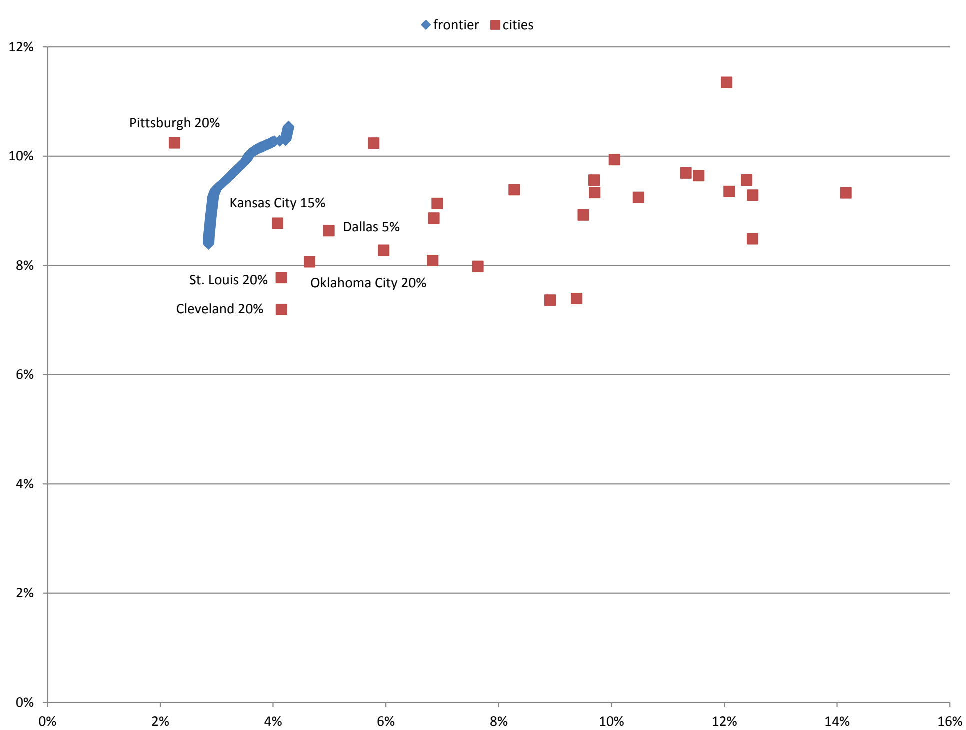

Figure 15: Zip code level variation in HPA and net yields.

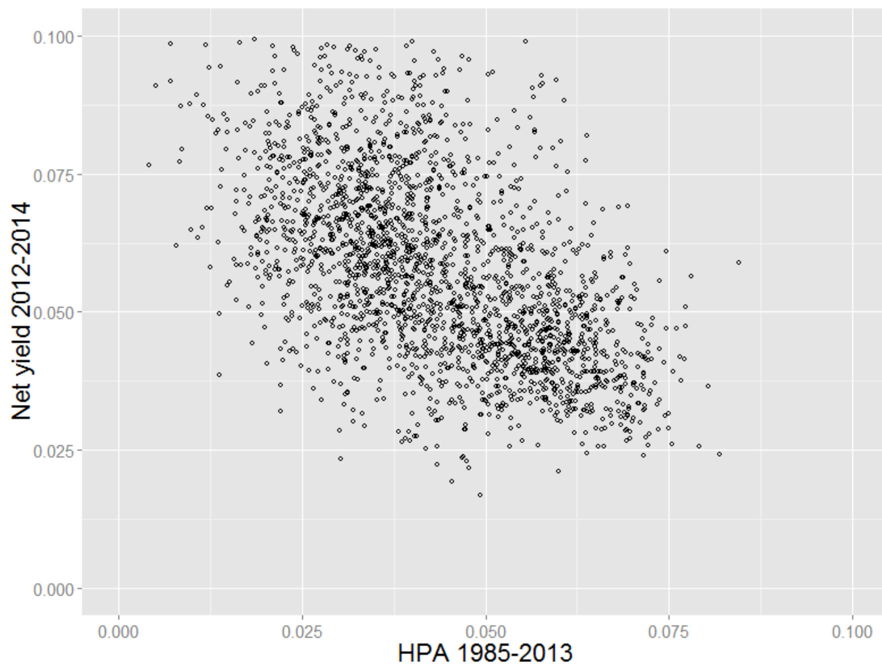

Figure 16: Zip code level distribution of total returns.

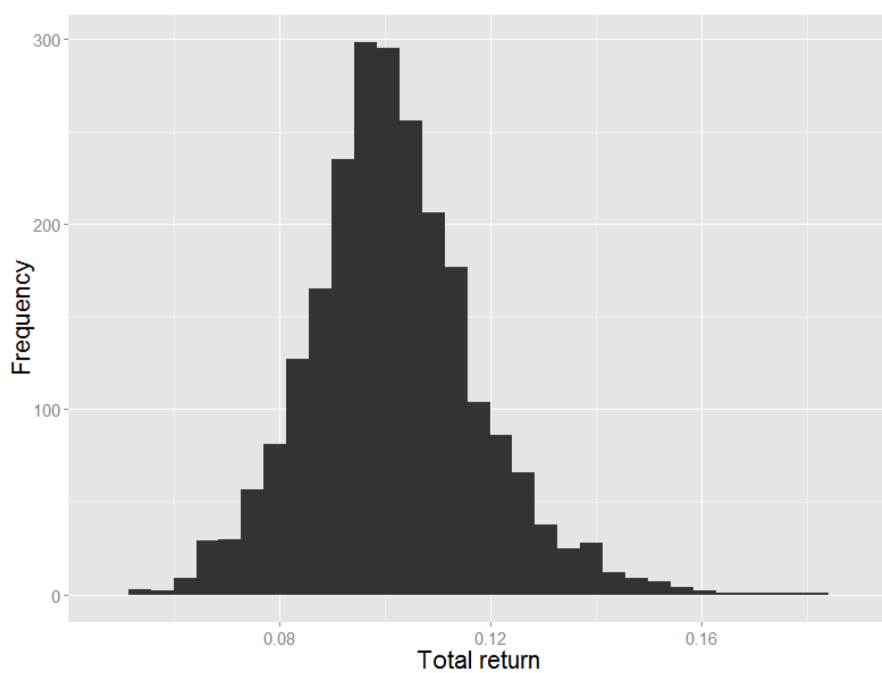

Figure 17: Zip code level net yields and HPA relative to MSA level averages, from 2012-2014, by house price quintile.

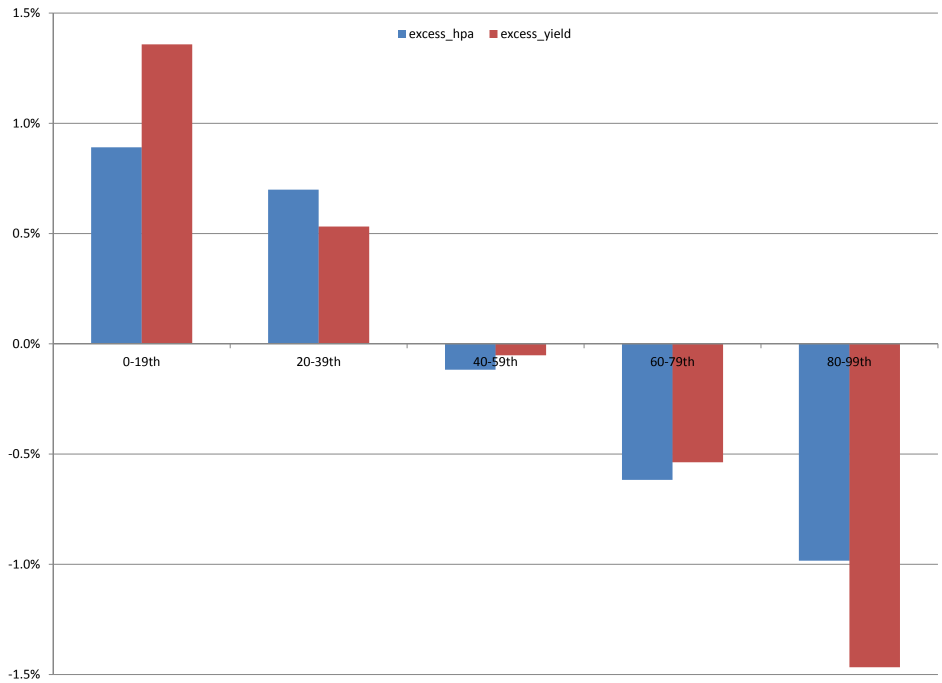

Figure 18: Zip code level HPA relative to MSA level average, from 1985-2013, by house price quintile.

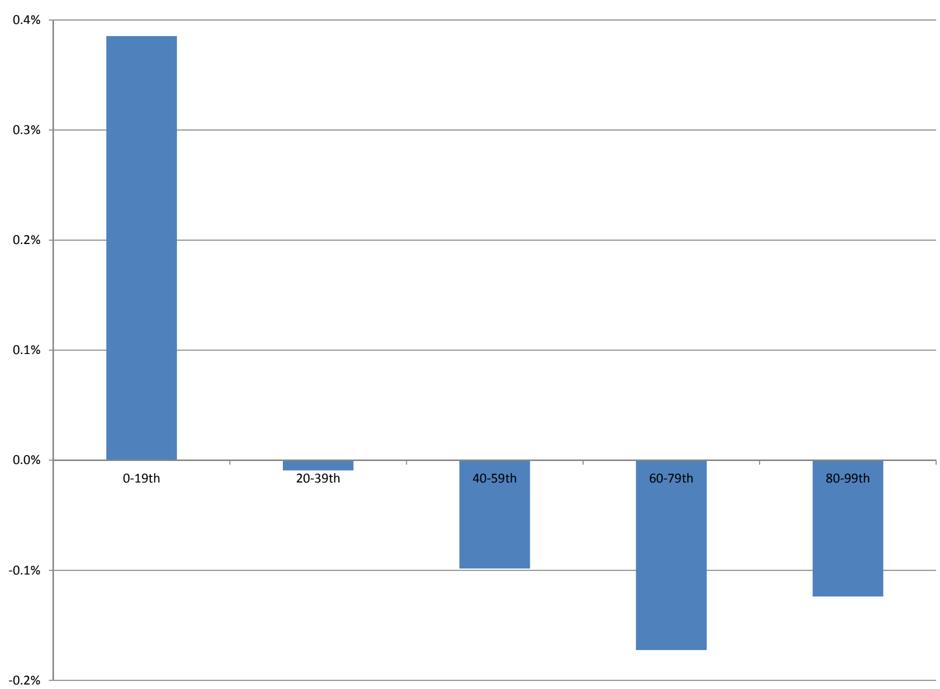

Figure 19: Average of lowest two price quintile total returns to overall MSA level average 2012-2014.

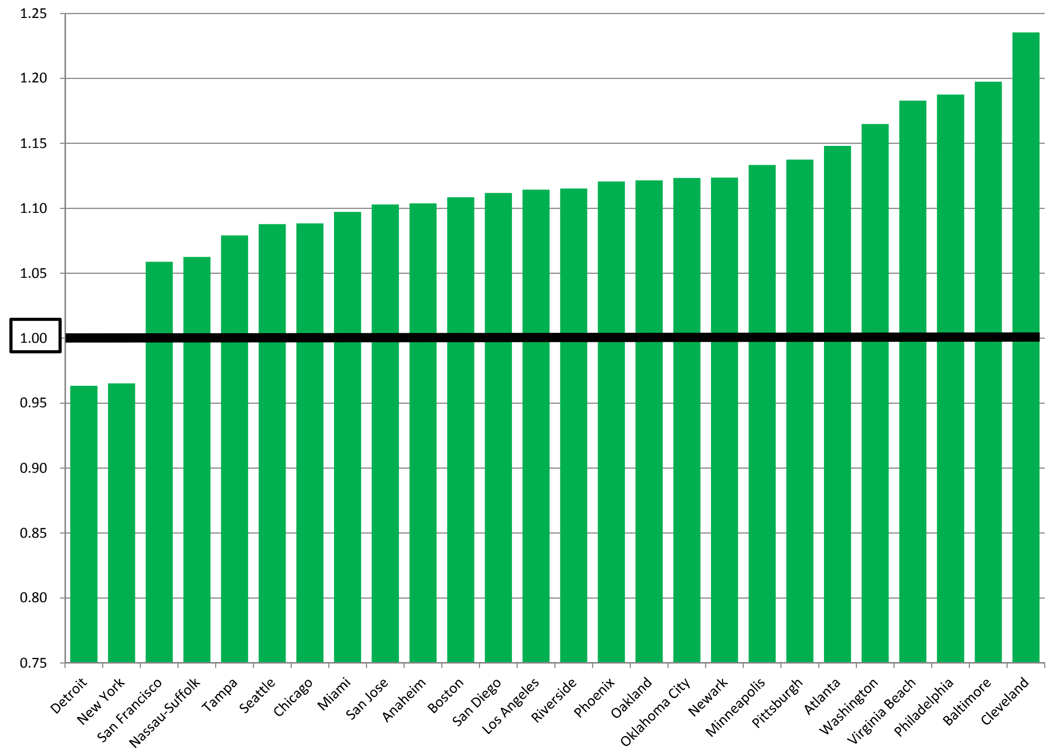

Figure 20: Underwritten net income is an increasing function of BPO value in SFR bond collateral.

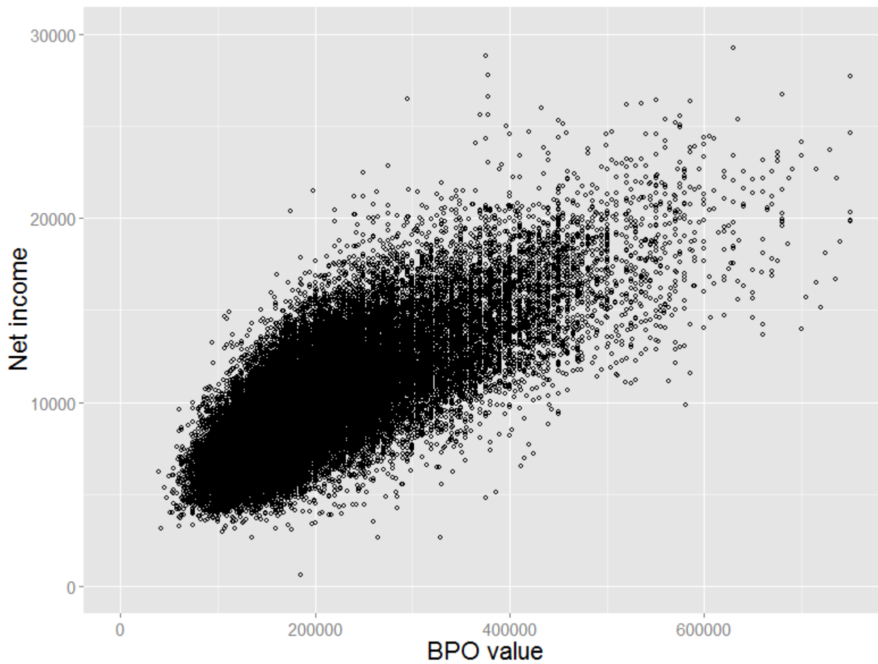

Figure 21: Underwritten net income ratio is a decreasing function of BPO value in SFR bond collateral.

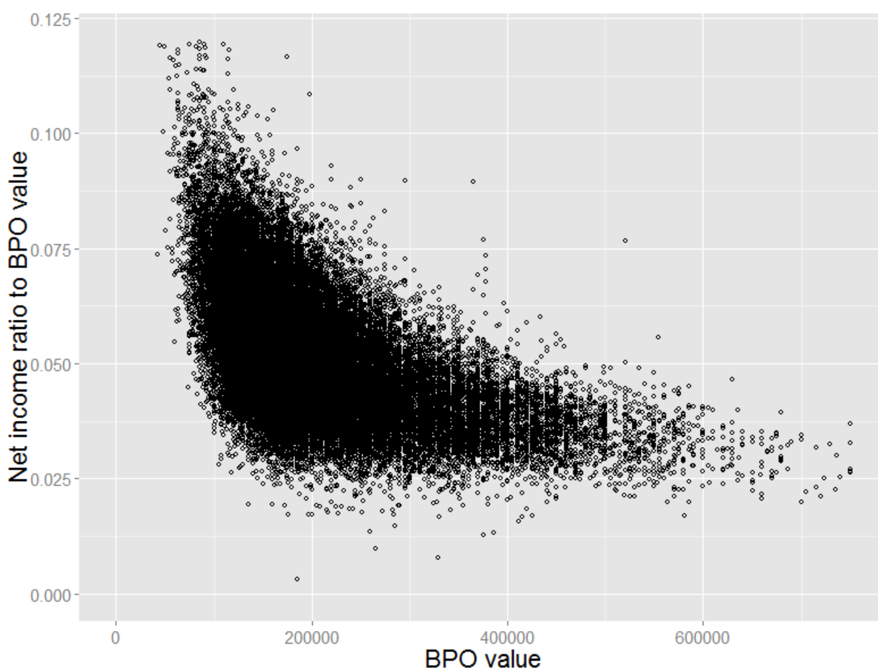

Figure 22: SFR securitized assets: house-level expense ratios demonstrate substantial heterogeneity.

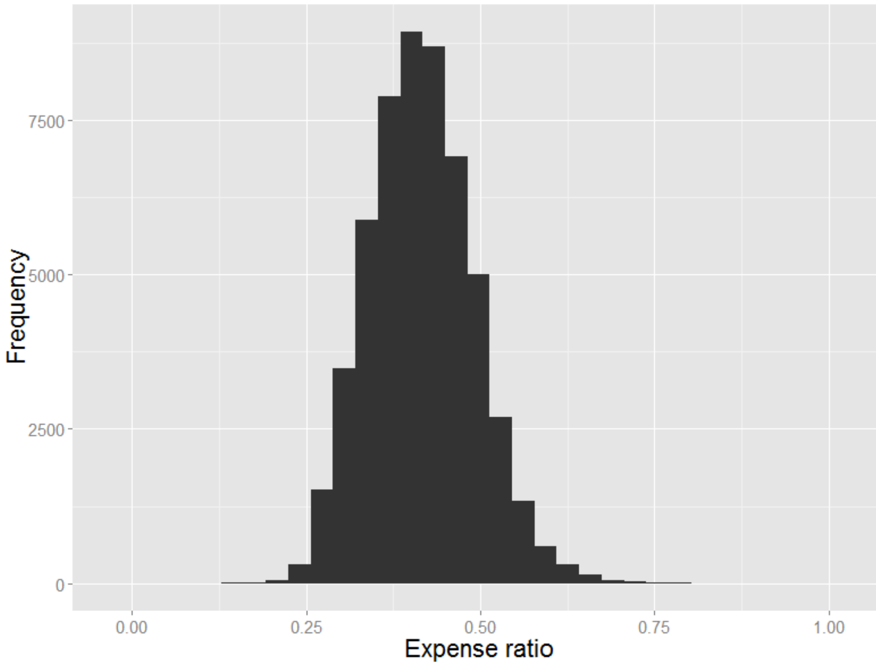

Figure 23: Subprime activity in 2003-2008 is positively related to SFR presence today.

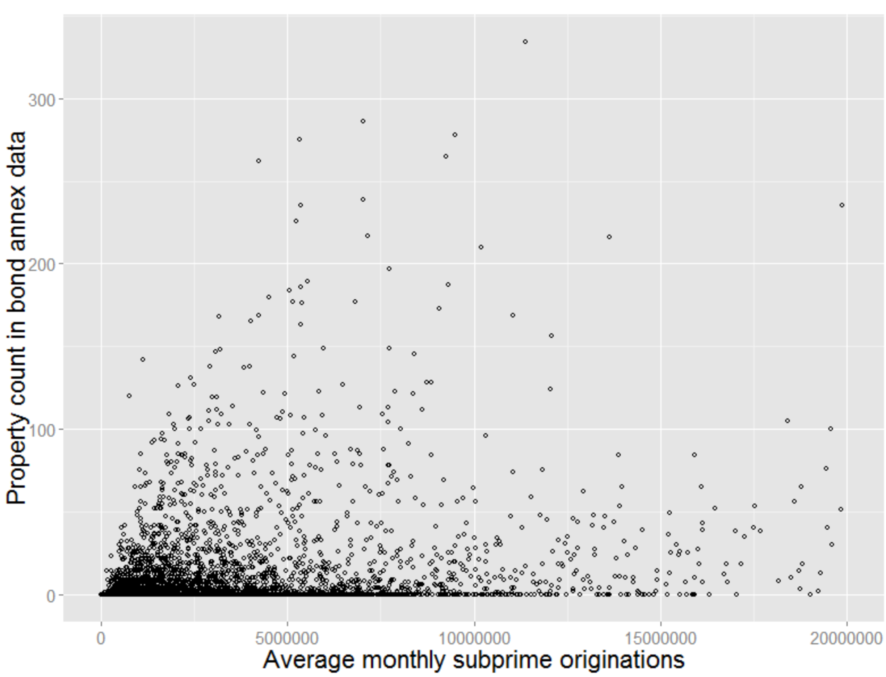

Figure 24: Peak to trough vs. Trough to current HPI. Blue cities have the largest share of properties in securitized products as of January 2015. Note that Miami lies underneath Phoenix.

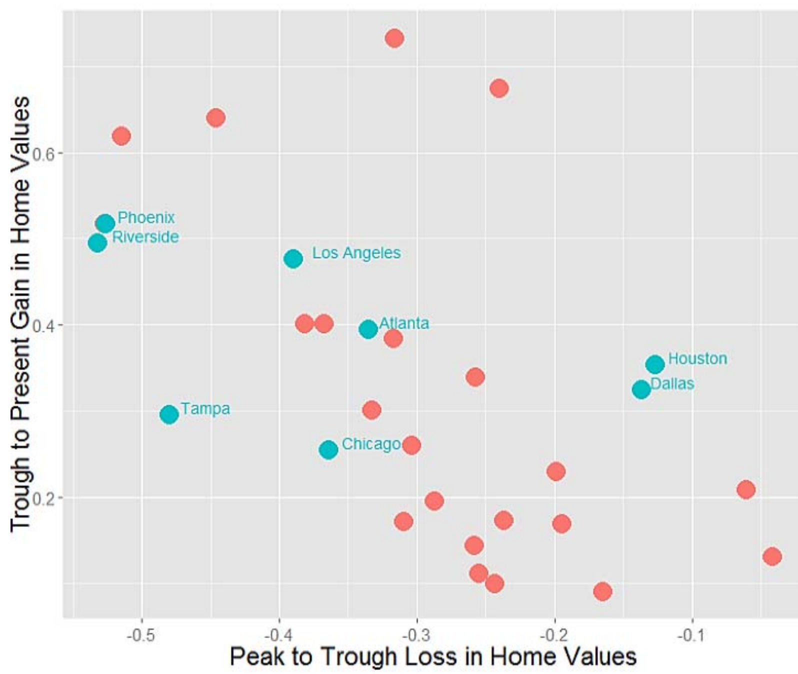

Table 1: Assumptions and Sources for IRR Examples.

	Unlevered	Small Investor	Large Investor
Length of investment	5	5	5
LTV	0.0%	39.5%	66.3%
Implied Leverage	1.00	1.65	2.97
Financing rate		6.82%	4.59%
Closing costs (% of sale)	5.50%	5.50%	5.50%
DSCR		1.2	1.2
Source		Loan ID 115 B2R Bond	AH4R 2014-SFR3

Table 2: Average Net Rental Yields, HPA, and Total Returns by pooled time series, cross-section annual MSA Price Quintile from 1985-2013.

Price Quintile	Net Rental Yield	HPA	Total Returnl
1	6.77%	3.28%	10.04%
2	6.14%	3.56%	9.69%
3	5.58%	4.24%	9.83%
4	4.44%	4.84%	9.29%
5	3.51%	5.98%	9.49%

Table 3: Average Net Rental Yields, HPA, and Total Returns by MSA from 1986-2014 and from 2012-2014, sorted in order of Total Returns from 1986-2014.

	1985-2013			2011-2013		
City Name	Net Yield	HPA	Total Return	Net Yield	HPA	Total Return
Miami	6.4%	4.9%	11.4%	9.5%	11.1%	20.6%
Pittsburgh	6.7%	3.5%	10.2%	6.4%	3.7%	10.2%
Houston	7.0%	3.3%	10.2%	7.3%	7.7%	14.9%
Tampa	6.4%	3.6%	9.9%	7.5%	7.2%	14.7%
San Diego	4.0%	5.7%	9.7%	3.3%	9.8%	13.1%
San Jose	2.7%	6.9%	9.6%	2.2%	14.1%	16.3%
Oakland	3.4%	6.2%	9.6%	2.7%	15.0%	17.7%
Seattle	3.6%	6.0%	9.6%	2.3%	8.8%	11.1%
Baltimore	4.8%	4.6%	9.4%	3.3%	2.6%	5.9%
Anaheim	3.4%	6.0%	9.4%	2.4%	9.9%	12.4%
Washington	4.1%	5.3%	9.3%	3.0%	5.2%	8.2%
Riverside	4.4%	5.0%	9.3%	5.3%	13.0%	18.4%
Los Angeles	3.2%	6.1%	9.3%	2.9%	11.4%	14.2%
San Francisco	2.2%	7.0%	9.2%	1.3%	14.3%	15.6%
Nassau-Suffolk	4.7%	4.4%	9.1%	3.2%	2.0%	5.3%
Philadelphia	4.9%	4.2%	9.1%	3.5%	1.3%	4.8%
Detroit	5.4%	3.5%	8.9%	7.8%	13.7%	21.5%
Minneapolis	5.1%	3.8%	8.9%	5.2%	6.3%	11.5%
Kansas City	5.6%	3.2%	8.8%	5.7%	3.6%	9.4%
Dallas	6.2%	2.5%	8.6%	6.1%	6.0%	12.1%
Phoenix	4.8%	3.7%	8.5%	4.9%	13.8%	18.7%
Atlanta	5.2%	3.1%	8.3%	7.3%	7.8%	15.2%
Chicago	4.0%	4.1%	8.1%	4.4%	4.0%	8.4%
Oklahoma City	5.9%	2.2%	8.1%	4.7%	2.8%	7.5%
Virginia Beach	4.3%	3.7%	8.0%	3.4%	1.6%	5.1%
St. Louis	5.0%	2.8%	7.8%	5.5%	2.8%	8.3%
New York	2.5%	4.9%	7.4%	1.1%	4.2%	5.2%
Boston	2.7%	4.6%	7.4%	2.6%	6.4%	9.0%
Newark	3.1%	4.2%	7.3%	1.9%	2.0%	3.9%
Cleveland	4.7%	2.5%	7.2%	5.9%	3.2%	9.1%
Average	4.5%	4.4%	8.9%	4.4%	7.2%	11.6%
Std Dev	1.3%	1.3%	1.0%	2.1%	4.4%	4.9%

Table 4: MSA's ranked in decreasing order by Total Return, along with their respective Net Yield and HPA Rank. Cities in bold have Net Yields greater than 4.35%, the yield which satisfies a Debt Service Coverage Ratio of 1.2 under baseline assumptions.

	Total Return	Net Yield Rank	HPA Rank
Miami	**11.4%**	3	10
Pittsburgh	**10.2%**	2	22
Houston	**10.2%**	1	24
Tampa	**9.9%**	4	21
San Diego	9.7%	20	7
San Jose	9.6%	28	2
Oakland	9.6%	23	3
Seattle	9.6%	22	5
Baltimore	**9.4%**	13	13
Anaheim	9.4%	24	6
Washington	9.3%	19	8
Riverside	**9.3%**	17	9
Los Angeles	9.3%	25	4
San Francisco	9.2%	30	1
Nassau-Suffolk	**9.1%**	15	14
Philadelphia	**9.1%**	12	15
Detroit	**8.9%**	8	23
Minneapolis	**8.9%**	10	18
Kansas City	**8.8%**	7	25
Dallas	**8.6%**	5	29
Phoenix	**8.5%**	14	19
Atlanta	**8.3%**	9	26
Chicago	8.1%	21	17
Oklahoma City	**8.1%**	6	30
Virginia Beach	8.0%	18	20
St. Louis	**7.8%**	11	27
New York	7.4%	29	11
Boston	7.4%	27	12
Newark	7.3%	26	16
Cleveland	**7.2%**	16	28

Table 5: Weights for Minimum Variance Portfolios, using Annual MSA Total Returns.

	Total Returns				HPA				Net Yield			
Anaheim		11%		-20%		29%		-20%		33%		20%
Atlanta		8%		13%		27%		15%	13%	88%	15%	20%
Baltimore		10%		20%		28%		20%		1%		-13%
Boston	2%	63%		-6%		48%		-12%		-91%		
Chicago		-5%		-20%		18%		-20%		25%		20%
Cleveland		0%	20%	20%		15%	20%	20%	6%	33%	8%	19%
Dallas	3%	-16%	4%	10%		-20%	18%	15%		-69%		20%
Detroit		-5%		5%		-2%		0%		-82%		13%
Houston		-23%		20%		-7%		20%		-25%		14%
Kansas City	2%	-29%	17%	20%		2%	11%	20%		43%		17%
Los Angeles		25%		19%		14%		16%		-100%		-20%
Miami		-38%		-20%		-15%		-20%		-15%		-14%
Minneapolis		39%		-20%		8%		-12%		68%		-16%
New York		-54%		20%		-41%		20%	21%	-4%	20%	20%
Oakland		-48%		-20%		-37%		-20%		-2%		2%
Oklahoma City	12%	100%	20%	20%	25%	88%	20%	20%		-62%		-12%
Philadelphia		84%		-2%		46%	8%	3%		-57%		13%
Phoenix		21%		11%		6%		8%		100%		-18%
Pittsburgh	80%	100%	20%	20%	75%	69%	20%	20%	23%	26%	20%	-4%
Riverside		61%		-4%		37%		-3%		-87%		-7%
San Diego		-84%		3%		-75%		4%		-38%		-3%
San Francisco		8%		-11%		-13%		-15%		26%	3%	20%
San Jose		38%		15%		40%		18%	16%	89%	13%	-20%
Seattle		-3%		5%		-12%		3%		-32%	1%	20%
St Louis		-83%	19%	20%		-99%	4%	7%	21%	100%	20%	20%
Tampa		-16%		-16%		-22%		-18%		-6%		-8%
Virginia Beach		-75%		-19%		-38%		-10%		39%		20%
Washington		9%		20%		7%		20%		100%		-20%
Shorts allowed	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Allocation constraint	None	None	20%	20%	None	None	20%	20%	None	None	20%	20%
Return	9.8%	9.5%	8.4%	8.2%	3.2%	3.2%	2.8%	2.6%	4.5%	3.8%	4.4%	4.2%
Standard Deviation	2.1%	0.5%	2.9%	1.1%	1.9%	0.2%	2.7%	1.0%	0.3%	0.0%	0.3%	0.0%

Table 6: SFR issuer net income dummies

issuance	$\beta_{0,m}$
AH4R 2014-SFR2	$2,644
AH4R 2014-SFR1	$2,577
AH4R 2014-SFR3	$2,193
IH 2013-SFR1	$1,958
SWAY 2014-1	$1,734
IH 2014-SFR1	$1,394
IH 2014-SFR3	$1,196
IH 2014-SFR2	$996
IH 2015-SFR1	$994
Progress 2014-SFR1	$720
ARP 2014-SFR1	$602
CAH 2014-1	$519
CAH 2014-2	$364
SBY 2014-1	0