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# TOTAL RETURNS TO SINGLE FAMILY RENTALS

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**ABSTRACT**

The market value of US Single Family Rental assets totals more than $2.3 trillion. We believe that we provide the first systematic analysis of total returns to Single Family Rentals over a long time period, in a broad and granular cross section. We find that total nominal returns are approximately equalized across US cities, at about 8.5%, the same order of magnitude as equity returns. On average, net rental yields and house price appreciation have each contributed around half of the 8.5% total return. However, these two components are negatively correlated in the cross section. High price tier cities accrued more capital gains, while low price tier cities had higher net rental yields. Within cities, we show that lower-price-tier zip codes have higher total returns as a result of both higher yields and higher house price appreciation.

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A data appendix is available at http://www.nber.org/data-appendix/w21804

# 1 Introduction

Single family rentals represent 35% of all rented housing units in the US, and have a market value of approximately \$2.3 trillion.[1] Analogous to the dividend yields and capital gains that constitute total equity returns, total returns to single family rental assets have two components: rental yields and house price appreciation. There are many important studies of either housing returns from house price appreciation, or of rent-to-price ratios in the literature, however we believe we are the first to consider total returns to single family houses accounting for both rental yields net of expenses, and house price appreciation, in a broad and granular cross-section, and a long time series.[2] We construct a dataset containing rental yields and house price appreciation data for Single Family Rental (SFR) assets, and study the total returns to this large and understudied asset class over a long time period from 1986 to 2014, and in a broad and granular cross section across US cities and zip codes.

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

There is considerable interest in single family rentals as an asset class. We show that

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

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

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

Understanding the drivers of the returns to Single Family Rentals is important for housing economics more broadly. Since the Great Financial Crisis, homeownership rates have steadily declined. The current low homeownership rate of 63.6% is a level not seen in the US since the 1960s.[6] Institutional ownership of single family rental properties may reduce the cost of capital through diversification and lower operating costs through economies of scale. However, whether institutional involvement in single family rentals is sustainable depends on the characteristics of the returns to single family rentals, and whether the returns are compatible in the long run with institutional investors' objectives and constraints. Our study describes how the returns to single family rentals vary in the time series and cross section. The facts we present inform investors in real single family rental assets, as well as in single family rental asset backed securities, about historical asset performance, and about variation in returns in the cross section of cities and zip codes. A historical perspective can

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

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

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

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

also help to put into context how this asset class might be expected to perform, and to understand what challenges investors might face. Our study also aims to inform policy makers, who are concerned about the effect of institutional investment and securitization on housing markets by lending insight into how investors might analyze potential portfolios of homes. Finally, the stylized facts we develop about rental yields and house price appreciation in the cross section are also independently useful for informing theories of housing valuations across cities, zip codes, and price tiers. One caveat to interpreting our study is that we construct city and zip-code level total return indices which abstract from any special characteristics of rental homes such as lower maintenance and selection into rental status.

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

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

Our city-level results for 1986-2014 uncover some striking stylized facts. First, we show that rental yields tend to be highest in the lowest-price-tier cities, and monotonically decline

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

with price tier.[8] If rents were constant across price tiers, this would be a tautology, but high quality houses should, all else equal, have both higher rents and higher purchase prices. Empirically, however, rental yields are substantially higher in lower-price-tier cities. On average, yields were 6.1% in the lowest price quintile across cities, and 2.4% in the highest price quintile over the period 1986-2014, a difference of nearly 4%. By contrast, higher-price-tier cities have experienced more house price appreciation over the period we study.[9] Indeed, we find that city-level house price appreciation monotonically increases with price tier. From 1986 to 2014, house price appreciation in the lowest tier cities averaged 3.1%, while it averaged 5.5% in the highest tier. As a result, total returns are more equated in the cross section of cities than either individual component is.[10] Indeed, cities with higher rental yields have tended to have lower house price appreciation. The lowest-price-tier cities do display slightly higher total returns of 9.2%, as compared to 7.9% for the highest price tier. This is because there is more dispersion across price tiers in net rental yields than in house price appreciation, and this benefits the lower tiers. Note that including rental yields completely overturns the popular wisdom that investing in coastal cities, which tend to have high prices and high house price appreciation, dominates investing in interior, so-called "fly-over" cities. Also striking is the fact that the pooled time series cross-section averages of annual city-level net yields and house price appreciation are almost exactly equal, at 4.2% and 4.3%, respectively. House price appreciation appears to display higher time series volatility than rental yields do in our data, however. Thus, lower-price-tier cities, with a larger contribution to returns from rents, seem to have higher Sharpe ratios, with slightly higher average returns to the rest of the country, and lower return volatility.

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

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

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

[10]We show in the Appendix that Internal Rates of Return (IRR's) on single family rental investments are approximately linear in net yields and house price appreciation, with each element contributing approximately equally.

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

code-level house price appreciation analysis, we utilize Core Logic's monthly zip code-level house price index data.

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

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

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

# 2 Related Literature

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

The most closely related study to ours is the contemporaneous paper by Jorda, Knoll, Kuvshinov, Schularick, and Taylor (2017), which documents the total returns to housing internationally, at the *country* level, for developed nations over a very long sample, back to 1870. The distinct contribution of our paper is to study variation in total returns within the US, across cities and zip codes, rather than at the country level. Their finding that at the national level both rental yields and house price appreciation are key inputs to total returns is consistent with our measurement and results. To our knowledge, the only other academic study of Single Family Rentals is the recent paper by Malloy, Mills, and Zarutskie (2017).[12] That paper also focuses on Single Family Rentals as an asset class. However, an important distinction is that they do not study rental yields, but instead focus only on the capital gains component of returns from house price appreciation. Including rental yields is a major benefit of our study, because, for about half of the cities in the US, house price appreciation represents significantly less than half of the total return. The sample of focus in Malloy, Mills, and Zarutskie (2017) is also distinct from ours. Rather than constructing returns over a long time period or broad cross section as we do, that paper instead focuses on the post-crisis period only, with a cross section emphasis on locations with concentrated institutional investment. Thus, our study is distinct from, and complementary to theirs. Their paper

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

presents convincing evidence that although institutional investor purchases of single family homes were concentrated in geography and time, that their behavior was distinctly different from that of other housing investors. In particular, they show that single family rental investors had longer holding periods. Our findings support their conclusion that the single family rental business may not simply be a trade based on depressed housing prices following the financial crisis, but rather a sustainable asset class for institutional investors. This view is also supported by the performance of the Real Estate Investment Trusts based on SFR strategies that have gone public after the housing recovery.

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

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

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

from Sydney and London respectively, largely corroborate our findings in the AHS for the US from 1986-2014.

The second methodology treats housing analogously to more liquid financial assets, and argues that lower discount rates imply higher valuations, and that momentum traders can amplify house price movements in the short run, while rents are more stable. Following Campbell's (1991) decomposition of stock returns, Campbell, Davis, Gallin, and Martin (2009) conduct a variance decomposition of the rent-to-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 due to stronger repossession rights, constrained firms are willing to pay a higher yield in order to relax their borrowing constraint. We document higher rental yields at lower price points both in the time series and in the cross-section, which is consistent with a similar role for financial constraints driving rents higher in lower price tiers.

House price appreciation has been studied extensively in the forecasting literature. While we do not forecast house price appreciation for the purposes of this paper, we follow the literature in conceptually considering city-level house price processes as best described by a two-stage error correction model in which house prices grow with income, but exhibit momentum and mean reversion. Malpezzi (1999) and Capozza, Hendershott, and Mack (2004) are classic references.[14] Realized house price appreciation has been shown to be highly correlated with the degree of physical constraints such as water and mountains ( Saiz (2010)), as well as regulatory constraints such as zoning restrictions (Gyourko, Saiz, and Summers (2008)). Gyourko, Mayer, and Sinai (2013) documents a positive correlation between house price appreciation and variation in amenities and productivity, and coined the term "superstar cities" to describe the growing inequality between cities.[15] Due to this and other variation in city characteristics, the first stage of house price appreciation forecasting models often include either city fixed effects, or interactions of population or income with supply elasticity.[16] Second stage momentum and mean reversion coefficients

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

[15] See also Davidoff (2014).

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

also vary significantly across cities. This is consistent with the idea that because housing pays a dividend in the form of a non-tradable service, markets are local, as emphasized in the assignment model literature Määttänen and Terviö (2014) and Landvoigt, Piazzesi, and Schneider (2012) and in the sorting literature, such as Van Nieuwerburgh and Weill (2010). Van Nieuwerburgh and Weill (2010) develop an assignment model of income and housing to show how sorting of higher income consumers into higher productivity cities might explain recent cross-sectional patterns in city-level house price appreciation, and lead to superstar cities. Although city-specific effects are important, we note that recent work by Cotter, Gabriel, and Roll (2014) shows that, empirically, house price appreciation has become more correlated across cities in recent years.[17]

Finally, recent work has attempted to model house prices, and less often rents, in general equilibrium macroeconomic models. Davis and Nieuwerburgh (2014) and Piazzesi and Schneider (2016) review some of these recent advances. In particular, house price appreciation within cities has been studied in the context of different patterns of development and gentrification, as well as in the context of financial innovations such as subprime lending. Guerrieri, Hartley, and Hurst (2013) emphasize the role of geographical spillovers in a spatial equilibrium model of gentrification, and provide empirical evidence supporting the presence of such spillovers.[18] Using data from the 2000-2005 boom in San Diego house prices, along with an assignment model which incorporates financial constraints, Landvoigt, Piazzesi, and Schneider (2012) provide evidence of the effects of subprime lending on house prices at the lower end. To our knowledge, a theory of both rental yields and house price appreciation patterns in the cross section remains a gap in the literature.

# 3 City-Level Total Returns

We focus on total returns from net rental yields and house price appreciation. These total returns are analogous to total stock returns from dividends and capital gains. We also note that total returns, unlike internal rates of return, are insensitive to the holding period, and total returns summarize returns that would be reported annually by institutional investors.[19] We begin by documenting gross and net rental yields, and house price appreciation, at the city level from 1986 to 2014 for the top 30 cities by number of AHS observations in 1985. We

[17]See also Giglio, Maggiori, and Stroebel (2015) and Giglio, Maggiori, and Stroebel (Forthcoming) for studies of very long run housing discount rates using data freeholds vs. leaseholds.

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

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

describe this data, our variable names, and empirical procedures in detail in the Appendix. In the Internet Appendix, we describe results for 1986 to 2019 for which data for a smaller set of fifteen MSA's is available in the AHS.

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

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

We implement this calculation for Total Returns to single family rentals in city $j$ at time $t = 2008$, for example, using our two data sources as follows:

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

The AHS is conducted bi-annually, in odd-numbered years, between May and September. To match this timing, we compute annual house price appreciation each year from June to June using Core Logic's monthly House Price Index (HPI) data. We use the rent reported in the beginning of period AHS survey, since this rent represents the dividend over the holding period. This measurement timing has the added benefit of using rent and price data from the same AHS survey, which avoids loss of data due to the sample varying over time.[20] 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.

## 3.1 City-Level Net Rental Yields

We begin with a detailed description of our measurement of the second term, representing net rental yields bi-annually by city. Our first step is to compute gross rental yields on single family homes by city using the AHS data. Although there are about twelve million single family rental homes in the US, these homes constitute only a small fraction of the AHS sample. Thus, to construct a city-level rental yield for single family homes (as opposed to

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

multi-family dwellings), we begin by estimating rental yields for *owned* single family homes, which constitute the vast majority of the single family sample, in the AHS using a hedonic model.[21] We index time by $t$, city by $j$, and house observation by $i$. First, we estimate a hedonic regression using all rented housing units in the AHS for the largest 30 cities to come up with rental prices for key housing characteristics as follows:

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

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

A key consideration in constructing representative total returns for single family rental assets is the higher prevalence of rental units in lower price tiers.[24] Therefore, to construct our city-level gross rental yields, we weight each house-level observation according to the empirical price distribution of rented units using the following method. First we apply the hedonic model to each house to predict its rent. We then order observations in increasing order of their predicted rent. We bin all homes (owned and rented) into deciles. This gives us an empirical density for each of rented and owned homes. The density for rented homes is decreasing in predicted rent, while the density for owned homes is increasing. The

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

[22]The regression results appear in the Appendix.

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

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

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

Figure 2 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 the pre and post housing price peaks. It was popularly stated that in 2011, home prices were back to 2003 levels and, consistent with this, our estimates show that the distribution of P/R in 2011 closely resembles that from 2003.

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

Figure 3 plots the average gross and net rental yields using the baseline expense assumptions and data, as well as the contribution of net yields and expenses to gross yields over time at a national level, by weighting our city-level estimates by population. Gross yields averaged 7.5% over the sample, reached their highest level of 8.7% in 1998, and bottomed out at 5.7% in 2008. Figure 3 also plots the contribution of net yields, and the contribution of expenses, to gross yields. On average, the contribution of expenses to gross yields is 40%, and this is broadly consistent with data from bond annexes for single family rental collateralized securities. 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 as percentages of gross rents. The largest two expenses, real estate taxes and repairs and maintenance, both vary with home prices. These costs, which are essentially fixed costs from the perspective of moving from gross to net yields, rose in importance as prices increased relative to rents. As a result, expenses peaked at 52% of gross yields in 2008, and reached a low of 36% of gross yields in 1997. Finally, national average net yields averaged 4.5% over our sample, peaking at 5.6% in 1999 and reaching a low of 2.7% in 2008.

## 3.2 City-Level House Price Appreciation

Having carefully described the drivers of gross and net rental yields, we now turn to the results for house price appreciation. We compute annualized realized house price appreciation at the city level using Core Logic's House Price Index (HPI) data, which is available at a monthly frequency from 1976 to the present. To account for the higher representation of rental homes in lower price tiers within cities, we use Core Logic's tier 2 price index, which covers homes with price levels between 75% and 100% of the city-level median house price. However, our results are very similar using Core Logic's tier 11 index, which covers all price levels, as we show in the Internet Appendix. This is because, as we will show in Section 4, while net rental yields vary substantially across price tiers, the relation between house price appreciation and price tier is fairly weak. To approximately match the timing of the AHS survey, which is computed between May and September, we compute house price appreciation from June to June each year, and report, for example, 2008 house price appreciation as the realized house price appreciation from June 2007 to June 2008. Figure 3 plots the time series of national realized house price appreciation along with net rental yields. The much larger variation in house price appreciation is clear from the graph. While the average house price appreciation of 4.4% is very close to the average net yield of 4.5% over the period 1986-2014, the time series standard deviation of house price appreciation is 7.2%, as compared to 0.7% (an order of magnitude lower) for net rental yields.

## 3.3 City-Level Total Returns

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

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

Figure 4 shows that a similar pattern holds without aggregating by price tier. This Figure presents a scatter plot of the time series averages of city-level annualized house price appreciation vs. the time series average of city-level net rental yields from 1986 to 2014. Clearly, there is a strong, negative relationship. The (typically more expensive) cities in the bottom right quadrant of the figure have the lowest net rental yields, but tended to experience higher annual house price appreciation. Accordingly, the correlation between average net yields and house price appreciation across cities is -0.65. We noted above that on average over this long time series net rental yields and house price appreciation contributed roughly equally to total returns. Although house price appreciation varied in the time series by a much larger amount, in the cross-section house price appreciation and net rental yields display about the same amount of variation. The cross section standard deviation of the time series averages of city-level net rental yields and house price appreciation are 1.6% and

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

1.4%, respectively.

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

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

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

Next, we examine a simple portfolio objective which might be appealing to investors, namely an objective which selects cities with higher total returns. Table 2 displays cities' house price appreciation in column 2. Finally, we consider that institutional investors may also seek portfolios which enable high leverage. Under current conditions of high and rising price levels, leverage is most constrained by the minimum debt service coverage ratio on net rental yields relative to interest payments. The debt service coverage ratio required to receive a bond rating is about 1.2. According to bond annex data from single family rental securitizations, most loan to value ratios range between 60% and 70%. At a 60% loan to value ratio, and at a 6% rate of interest, which falls between individual borrower rates and single borrower securitization rates, a yield of 4.35% is required in order to satisfy a typical DSCR of 1.2. In the current environment, investors may prefer higher yield assets. These assets are more prevalent in lower-price-tier cities.

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

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

# 4 Zip Code-Level Total Returns

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

## 4.1 Zip Code-Level Net Rental Yields

To get an idea of how much optimization of locations within a city might improve single family rental asset performance, we first discuss the relative amount of cross-sectional variation in net yields within cities, across zip codes, vs. across cities. On average from 2013-2017, the cross-sectional standard deviation in net yields across zip codes, within cities was 1.3%, which is slightly lower than the 1.6% dispersion across cities in the city-level data we construct using the AHS data from 1986 to 2014.[28]

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

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

## 4.2 Zip Code-Level House Price Appreciation

We find that while net rental yields decline with price tier within cities, as they do across cities, house price appreciation appears to also decline with price tier within cities. This is in stark contrast to the pattern of increasing house price appreciation across city-level price tiers. Since rental yields and house price appreciation both decline with price tiers

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

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

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

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

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

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

[30] See Glaeser, Gyourko, Morales, and Nathanson (2014) for a model of house price dynamics consistent with a strong city-level factor.

### 4.3 Zip Code-Level Total Returns

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

There may be several reasons why low price tier zip codes might generate higher total returns. With respect to rental yields, it is possible that Core Logic underestimates credit and vacancy costs in the lowest tiers, biasing net rental yields up, however we find the same pattern of declining yields in the house-level data underlying recent securitizations of single family rental properties. Net rents in these price tiers may be more volatile over the housing cycle, and therefore more risky. Zip code-level house price appreciation certainly appears to have more city-level risk in lower price tiers.[31] The average loadings of zip code-level house price appreciation on city-level house price appreciation are declining with price tier. These loadings are 1.04, 1.05, 1.00, 0.95 and 0.93, from the lowest to highest price quintiles, respectively. Thus, lower-tier zip codes do appear to be riskier. Lower-tier zip codes may also have benefited from gentrification or innovations in lending practices.[32]

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

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

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

recent Core Logic data on net rents.

**Zip Code-Level Stylized Facts:**

1. Net rental yields decline with house prices within cities.

2. House price appreciation does not increase with house prices within cities.

3. As a result, total returns decline with house prices within cities.

4. There is more measured dispersion in house price appreciation across cities than within cities across zip codes. Zip code-level house price appreciation appears to be tightly linked to city-level outcomes.

5. By contrast, the dispersion in yields is of similar magnitude at the zip code and city levels.

# 5 Combining City and Zip Code-Level Results

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

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

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

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

# 6 Conclusion

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

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

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

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

It is also possible that the propensity of households to rent vs. buy may grow, or remain elevated, increasing the importance of single family rentals (currently about 35% of all rental households). According to the American Community Survey, the homeownership rate peaked in 2007 at about 67%, and fell to 63% by 2014. This represents a change in housing status from owned to rented for over 1.5 million households and about $228 billion in housing value. Several structural (or at least persistent) factors may have contributed to the recent decline in homeownership. Standards for mortgage lending, which got stricter during the housing downturn, have continued to tighten. Reports by the Urban Institute document that the median borrower FICO score at origination climbed from 700 in 2001 to 710 by 2007, and has since gone up to 750.[33] At the same time, student debt has increased dramatically, growing 166% from 2005 to 2012, potentially reducing borrowers' mortgage capacity.[34] Notably, there has not been an offsetting decline, but instead an increase, in auto or credit card debt.[35] Moreover, employment for the relatively large millennial generation was impacted heavily by the great recession, and renting has been a popular option for the age group at which household formation previously peaked. The age at which a majority of individuals are homeowners has increased from 32 in 1990 to 38 in 2012,[36], and the August 2014 Fannie Mae National Housing Survey finds 32% of respondents would rent if they were going to

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

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

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

[36] ACS data analyzed in Kolko (2014).

move.[37] For these reasons, we argue that understanding the single family rental asset class is important, and our paper aims to fill the existing gap in the literature on the total returns to single family homes as investible financial assets.

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[37] `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:** Plot of average ratio of rental to owned densities of housing units by rent tier within cities. We non-parametrically re-weight homes within cities to adjust weighted median net rental yields. The re-weighted distribution more accurately represents the actual distribution of rented homes across the distribution of rent levels.

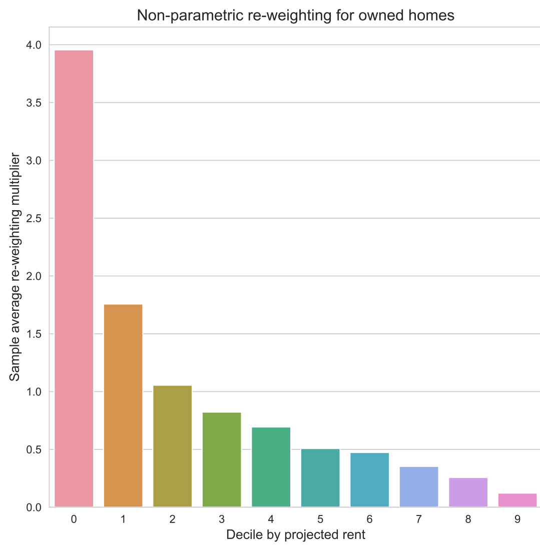



**Figure 2:** Price-to-Rent Ratios, Owned Homes: AHS data and Hedonic Model 1985-2013.

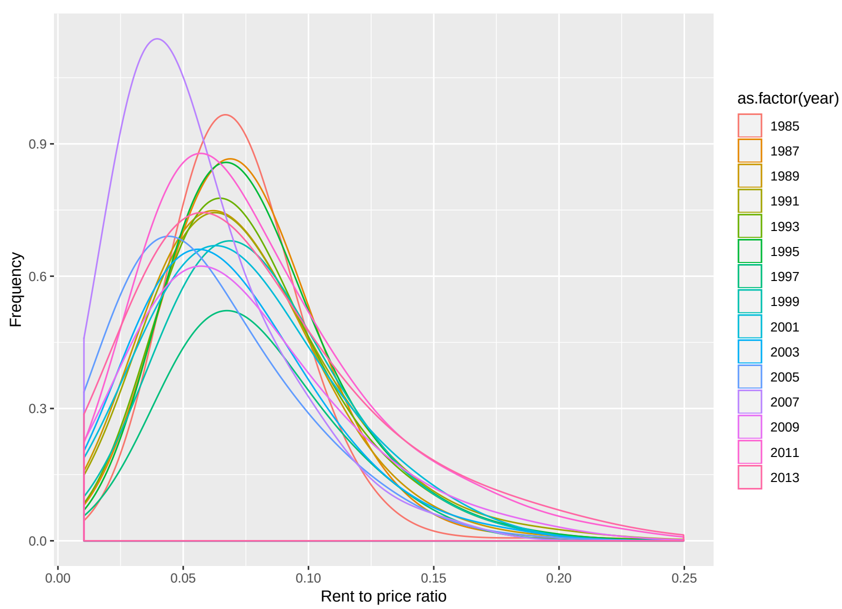


**Figure 3:** Gross yields, net yields, and expense rates vs. House Price Appreciation, national averages 1986-2014. National net rental yields are computed as by taking a city population weighted average of the city-level weighted medians of gross yields, net yields, and expense rates from 1986-2014. House price appreciation is June$_{t+1}$ on June$_t$, recorded at June$_{t+1}$. See Equation (2) for timing details.

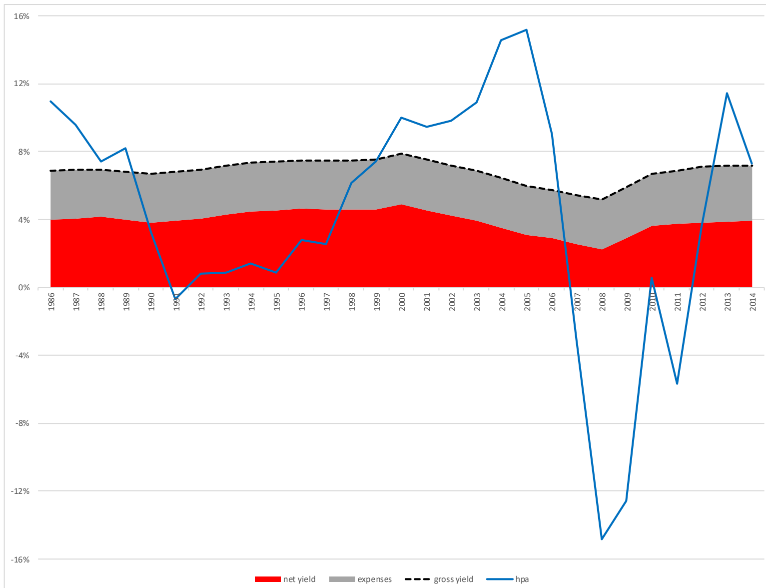



**Figure 4:** Annualized average city-level house price appreciation vs. net rental yields 1986-2014.

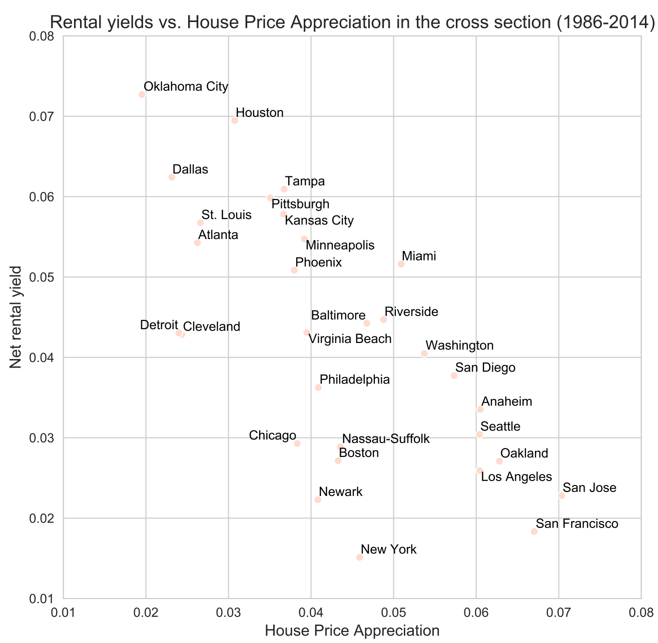


**Figure 5:** Annualized average city-level house price appreciation, net rental yields, and total returns 1986-2014 by house price quintile, lowest (1) to highest (5).

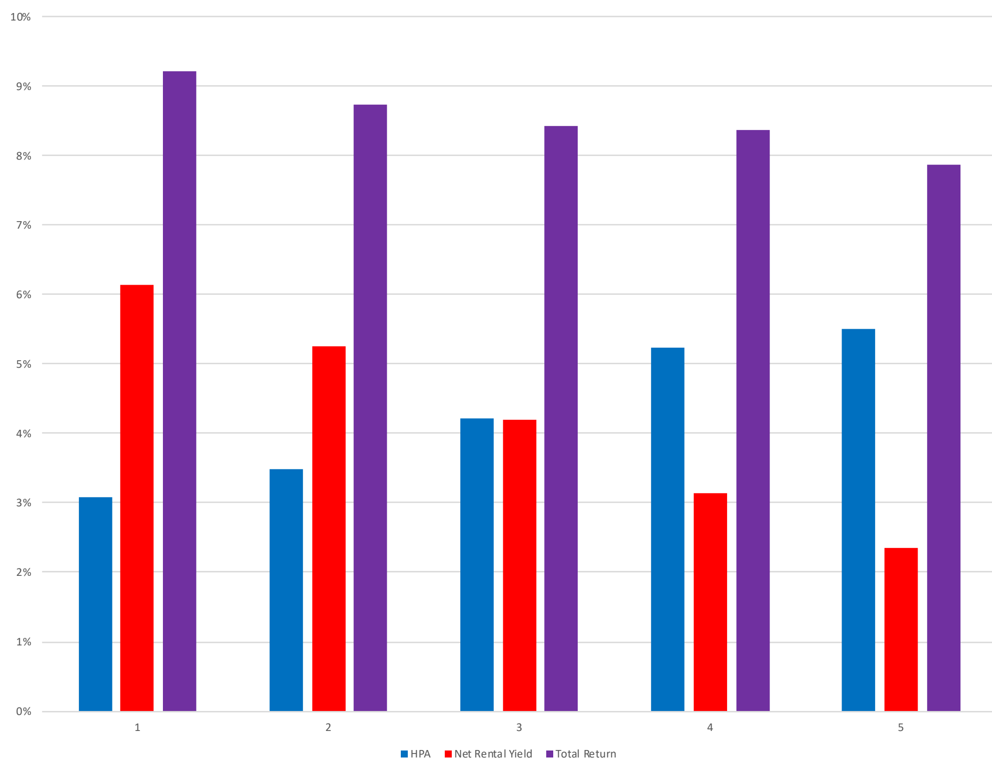


**Figure 6:** Zip code-level rental yields and HPA. Top Left: Zip code-level net yields and house price appreciation relative to city-level averages, from 2013-2017, by house price quintile. Top Right: Zip code-level house price appreciation relative to city-level average, from 1986-2016, by house price quintile. Bottom Left: Zip code-level distribution of total returns from 2013 to 2017. Bottom Right: Average of lowest two price quintile total returns to overall city-level average 2013-2017.

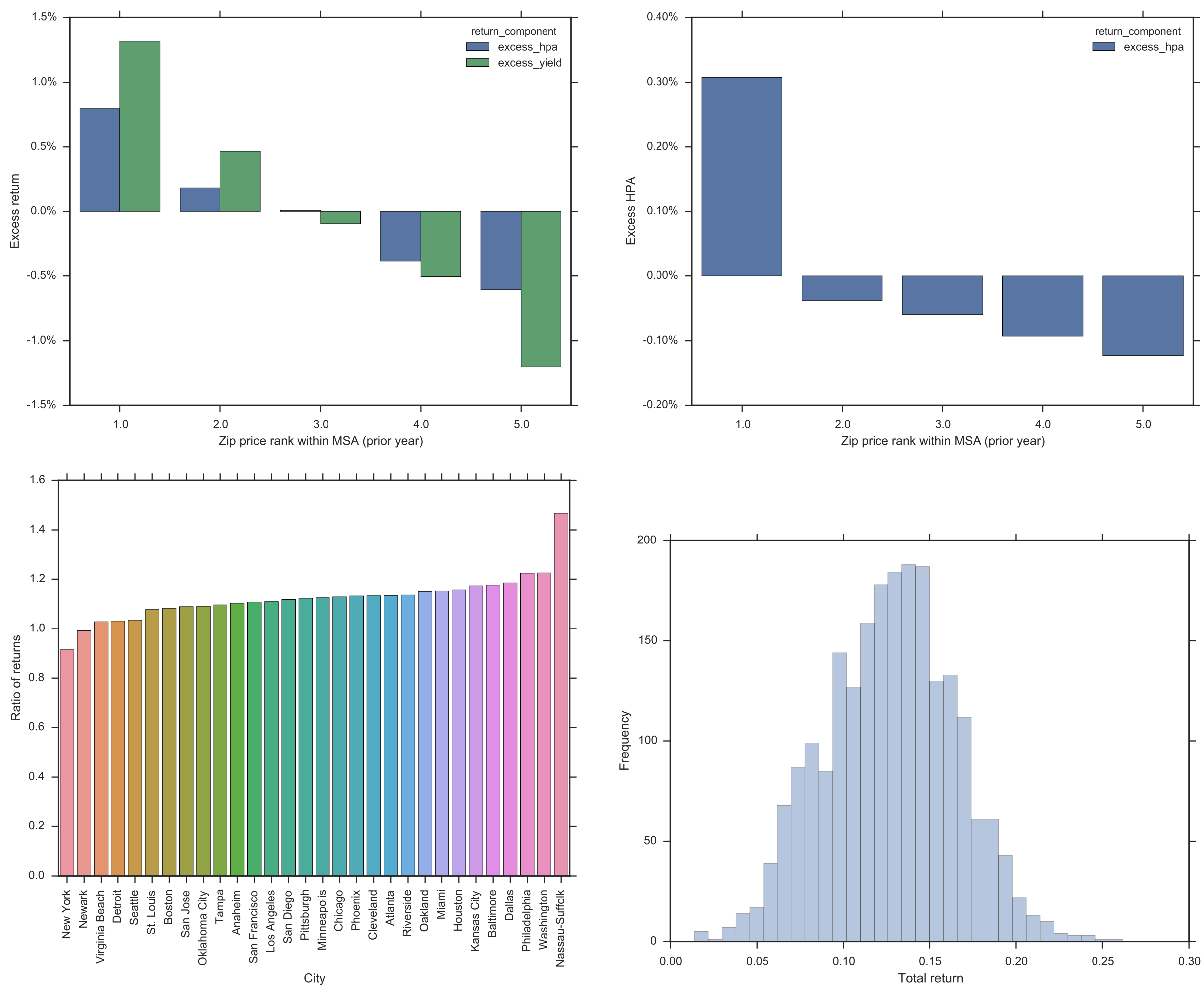


**Figure 7:** Heat maps of rental yields and house price appreciation across city and zip code-level price tiers. Left panel plots net yields from 2013-2017 by zip and MSA price rank (1=Low, 5=High). Right panel plots house price appreciation at the zip code level by zip code and MSA price rank (1=Low, 5=High).

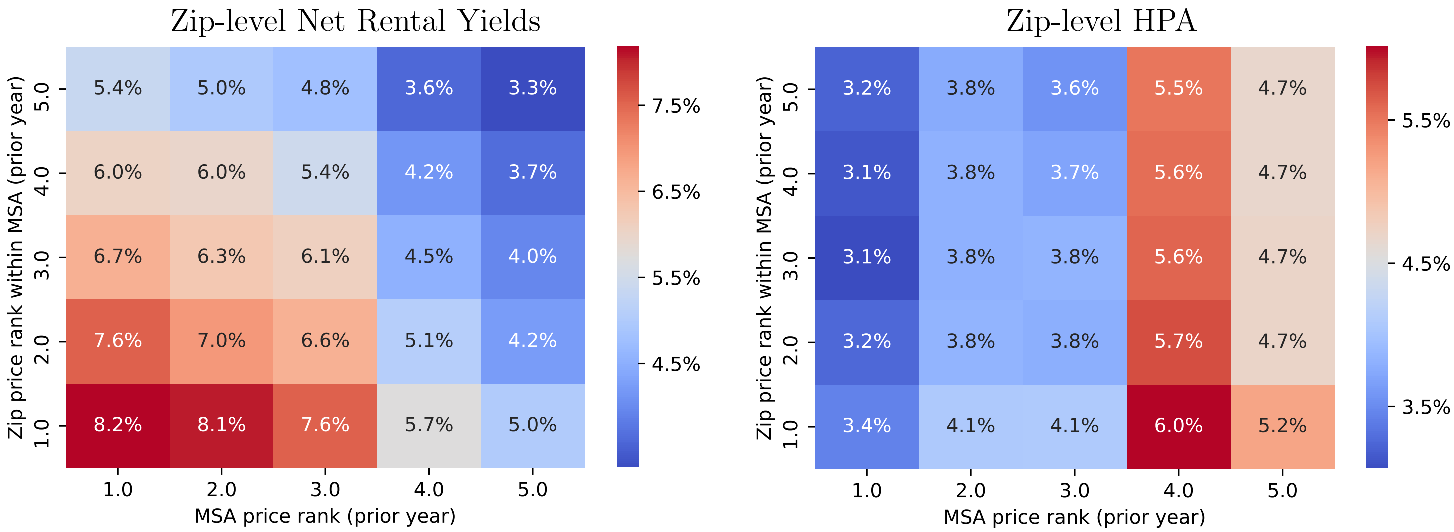


**Table 1:** Average Net Rental Yields, house price appreciation, and Total Returns by pooled time series, cross-section annual city Price Quintile from 1986-2014.

| Price Quintile | Net Rental Yield | House Price Appreciation | Total Return |
|---|---|---|---|
| 1 | 6.1% | 3.1% | 9.2% |
| 2 | 5.3% | 3.5% | 8.7% |
| 3 | 4.2% | 4.2% | 8.4% |
| 4 | 3.1% | 5.2% | 8.4% |
| 5 | 2.4% | 5.5% | 7.9% |

**Table 2:** Average Net Rental Yields, House Price Appreciation, and Total Returns by city from 1986-2014, sorted in declining order by observed biannual Sharpe Ratio.

| City Name | Net Yield | House Price Appreciation | Total Return | % of Total Return from Net Yield | Standard Deviation | Sharpe Ratio |
|---|---|---|---|---|---|---|
| Pittsburgh | 6.0% | 3.5% | 9.5% | 63.1% | 2.2% | 4.29 |
| St. Louis | 5.7% | 2.7% | 8.3% | 68.1% | 4.1% | 2.02 |
| Dallas | 6.2% | 2.3% | 8.6% | 73.0% | 4.5% | 1.88 |
| Houston | 6.9% | 3.1% | 10.0% | 69.3% | 5.8% | 1.72 |
| Oklahoma City | 7.3% | 2.0% | 9.2% | 78.8% | 5.6% | 1.64 |
| Kansas City | 5.8% | 3.7% | 9.4% | 61.2% | 6.7% | 1.42 |
| Cleveland | 4.3% | 2.4% | 6.7% | 63.8% | 4.8% | 1.4 |
| Minneapolis | 5.5% | 3.9% | 9.4% | 58.3% | 7.2% | 1.31 |
| Philadelphia | 3.6% | 4.1% | 7.7% | 47.0% | 6.4% | 1.2 |
| Atlanta | 5.4% | 2.6% | 8.1% | 67.4% | 6.8% | 1.19 |
| Baltimore | 4.4% | 4.7% | 9.1% | 48.6% | 7.7% | 1.18 |
| Virginia Beach | 4.3% | 3.9% | 8.3% | 52.2% | 7.2% | 1.15 |
| Seattle | 3.0% | 6.0% | 9.1% | 33.5% | 9.2% | 0.99 |
| Washington DC | 4.0% | 5.4% | 9.4% | 43.0% | 10.0% | 0.94 |
| Tampa | 6.1% | 3.7% | 9.8% | 62.4% | 10.5% | 0.93 |
| Chicago | 2.9% | 3.8% | 6.8% | 43.3% | 7.4% | 0.91 |
| Nassau-Suffolk | 2.9% | 4.4% | 7.2% | 39.9% | 8.4% | 0.86 |
| Boston | 2.7% | 4.3% | 7.0% | 38.6% | 8.4% | 0.84 |
| San Francisco | 1.8% | 6.7% | 8.5% | 21.5% | 10.5% | 0.82 |
| San Diego | 3.8% | 5.7% | 9.5% | 39.7% | 11.7% | 0.81 |
| Miami | 5.2% | 5.1% | 10.3% | 50.3% | 13.1% | 0.78 |
| Anaheim | 3.4% | 6.1% | 9.4% | 35.7% | 12.3% | 0.77 |
| San Jose | 2.3% | 7.0% | 9.3% | 24.5% | 12.5% | 0.74 |
| Phoenix | 5.1% | 3.8% | 8.9% | 57.2% | 13.4% | 0.66 |
| Detroit | 4.3% | 2.4% | 6.7% | 64.2% | 10.3% | 0.65 |
| Oakland | 2.7% | 6.3% | 9.0% | 30.1% | 13.8% | 0.65 |
| New York | 1.5% | 4.6% | 6.1% | 24.8% | 9.4% | 0.65 |
| Newark | 2.2% | 4.1% | 6.3% | 35.3% | 9.8% | 0.65 |
| Los Angeles | 2.6% | 6.0% | 8.6% | 30.0% | 13.4% | 0.64 |
| Riverside | 4.5% | 4.9% | 9.3% | 47.8% | 15.4% | 0.61 |
| Average | 4.2% | 4.3% | 8.5% | 49.1% | 8.9% | 1.14 |
| Stddev | 1.56% | 1.40% | 1.17% | 15.91% | 3.30% | 0.71 |

# A Appendix: Data Description

## A.1 Net Yield Panel Data Instructions

In this section, we describe how to produce the net yield panel from publicly-available data.[38]

**Data files** The Census conducts the American Housing Survey, which is sponsored by the Department of Housing and Urban Development (HUD). The data files can be downloaded from their website at `http://www.census.gov/programs-surveys/` The survey has been conducted in every odd-numbered year since 1973. The codebook for 1997-2013 can be found at `http://www.census.gov/programs-surveys/ahs/data/2013`. We use all of the odd-numbered years since 1985. Prior to 1985, the value of the home is a categorical variable, so we do not use those data. Beginning in 2015, the Census limited geocoding to the largest 15 metropolitan areas. Results for these cities are similar to our main results for the larger sample of 30 cities and appear in the Internet Appendix.

**Data selection** We remove observations without an MSA identifier, as we build our panel by city. We remove units in housing projects, those with bars on the windows, and those that are rent stabilized. We also remove observations missing data on tenure status, i.e., owner occupied or renter occupied.

We further clean the observations before the hedonic regression as follows:

- Delete if the ratio of household income to house value is greater than 2 (This identifies data errors in the house value field).
- Delete if the ratio of household income to annual rent is greater than 100 (This identifies data errors in the annual rent field).

Throughout the rest of the analysis, we restrict the sample to the top 30 cities by data points (after cleaning) in 1985, the first year in the sample. After cleaning, we still have over 5,000 houses in the sample for each year, as listed in Table A.1. The sample is larger in some years because the Census chose to sample certain cities more intensely. For example, the sample size of Minneapolis in 2007 is 1,662.

**Imputing rents with a hedonic model** We employ a hedonic model (as in Malpezzi 2002) to predict the log rent of a home using data on:

- Metropolitan statistical area (MSA) fixed effect
- Year fixed effect
- Unit type (condo, detached home, or other)

[38] We do not supply the CoreLogic data used to compute house price appreciation (and total returns) because of licensing agreements. Public-use house price appreciation data from FHFA for the 100 largest metros are available at `http://www.fhfa.gov/DataTools/Downloads/Documents/HPI`

**Table A.1:** AHS sample size after cleaning

| | N |
|---|---|
| 1985 | 6,362 |
| 1987 | 5,433 |
| 1989 | 6,606 |
| 1991 | 5,379 |
| 1993 | 6,796 |
| 1995 | 7,293 |
| 1997 | 4,325 |
| 1999 | 6,454 |
| 2001 | 5,094 |
| 2003 | 7,092 |
| 2005 | 5,289 |
| 2007 | 11,353 |
| 2009 | 5,849 |
| 2011 | 25,526 |
| 2013 | 7,608 |
| Total | 116,459 |

- Number of rooms
- Number of bathrooms
- Dummy for central air
- Year unit built categories (by decade to 1970, then every 5 years)[39]
- Log of square footage

The hedonic model is estimated upon renter-occupied units. It enables us to compute a rent for each owner-occupied home using its characteristics. We then have an estimate of a rent-to-price ratio for each owned home. The model estimates are presented in Table A.2.

**Aggregating rent-to-price ratios with nonparametric weights** We wish to find the median rent-to-price ratio for *rental* homes, but our dataset has rent-to-price ratios computed on *owned* homes. To account for sample selection in our dataset of rent-to-price ratios, we re-weight the owned homes in a city to match the distribution of rental homes using the method described in the main text. This procedure is similar to the nonparametric approach used in Barsky et al. (2002). In our main analysis, we 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 very same cities that are less populated are the ones

[39]We use categories for unit age because it is a categorical variable before 1995.

**Table A.2:** Hedonic regression coefficients

| | coefficient | t value |
|---|---|---|
| condo | 0.03 | 1.86 |
| detached home | 0.02 | 2.76 |
| rooms | 0.04 | 10.04 |
| bedrooms | 0.03 | 4.94 |
| bathrooms | 0.17 | 25.11 |
| airsys | 0.12 | 12.55 |
| age | -0.29% | -17.17 |
| log sqft | 0.05 | 7.96 |
| | | |
| $n$ | 26,939 | |
| $R^2$ | 44.93% | |

with a low ratio of rental homes. However, we do present results using this method in the Internet Appendix, and the results are quite similar.

**Vacancy data** To compute net yields from gross yields, we need to know the percentage of rental homes that sit vacant. We can get this information from the AHS as well. We use the same dataset (including removing units in housing projects, those with bars on the windows, those that are rent stabilized, and those missing data). We label a home as a vacant rental if the survey identifies it as for rent only, for rent or for sale, or rented but not yet occupied. The vacancy rate is the ratio of this number to this number plus the number of renter-occupied homes. For cities with fewer than fifty observations in any given year, we regress vacancy rates for city $j$ and time $t$ for all city-year pairs for which there are more than 50 observations on city and time dummies, and use the predicted value from this regression.

**Tax rates** We also need a panel of tax rates to compute net yields. We use actual state-level tax rates from the following sources: For 1990 and 2000 we use the Census data tax rates reported by Emrath (2002), and for 2005 to 2012 we use the tax rates computed from ACS data and reported by the National Association of Home Builders (NAHB). We linearly interpolate missing state-year data.

**Interpolating missing years** As the survey is biannual and the tax rates are from Census, we linearly interpolate the rent-to-price ratios, vacancy rates, and tax rates to even-numbered years. We show that the effect of interpolation is minimal in the Internet Appendix.

**Net yields** Starting from gross yields, we 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. We 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 ours, however some of their cost estimates rely on direct proprietary data rather than ratios of rent or house price. We use actual tax and vacancy data.

- Insurance: 0.375% of price
- Repairs: 0.6% of price
- Property manager: 5.9% of rent
- Credit loss: 0.73% of rent
- Tax: state-level data, % of price
- Vacancy: MSA-level data, % of rent

The AHS data, our hedonic model, and these assumptions allow us to generate a panel dataset of net yields for N=30 cities for T=29 years. See the Internet Appendix for a sensitivity analysis to these cost assumptions.

**Data quality cross checks** We use the following alternate sources to check the quality of our data:

- **Gross yields:** Zillow reports rent-to-price ratios from their own hedonic model applied to both rented and owned homes in their database. These data start in 2011.
- **Vacancy rates:** Vacancy rates for rental homes are from Census, who use the Current Population Survey (CPS) and Housing Vacancy Survey (HVS). CoreLogic also reports vacancy rates using data from the U.S. Postal Service, and data from these sources are similar during the overlapping sample.
- **Net yields:** CoreLogic provides net rental yields (referred to as capitalization rates) starting in 2013.

## A.2 Other Data Sources

In addition to the net yield panel at the city level, we employ several other data sources at the MSA, zip code, and house level to describe net yields, capital gains, and leverage.

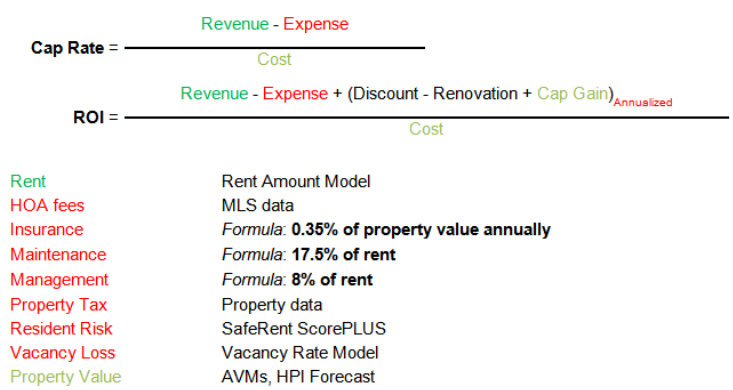
**House price appreciation from CoreLogic** To determine total returns at the city level, we pair the house price appreciation value for each city-year cell with its net yield. Monthly House Price Indices (HPI) by core-based statistical area (CBSA) are from CoreLogic for 1976-present. We use Tier 11 (all homes, including distressed) to determine city-level price tiers. To match the higher representation of rental homes in lower price tiers, and to be consistent with the weighting scheme for rental yields from the AHS data, we use CoreLogic's Tier 2 index for our main time series for city-level house price appreciation. CoreLogic's Tier 2 HPI focuses on homes with prices between 75% and 100% of the city-level median. Because the AHS is conducted each year between May and September, we set the HPI in each year to equal the HPI in June of that year. The house price appreciation is then the June-to-June percentage increase in HPI. We created a translation table from CBSA to MSA using data from the Missouri Census Data Center.

**House price tiers** To construct house price tiers, we first match the HPI from CoreLogic in June 2014 with the Zillow Home Value Index from June 2014.[40] We can then determine the price level in each year from 1985-2014 by appropriately deflating or inflating the price level using the corresponding house price index. The house price tiers assigned to each MSA and each zip code are dynamic, with transition matrix diagonals varying from 83% to 96%. The diagonals of the empirical transition matrix for cities across price tiers are 0.92, 0.83, 0.89, 0.91, and 0.94, from the lowest to highest tier, respectively. The highest tier-to-same-tier transition rate is found in the highest-priced tier at the zip code-level as well (94%).

**Gross Yields from Zillow** We use Zillow's characteristic-adjusted rent-to-price ratios to cross check our own calculations of gross yields in the Internet Appendix.

**Net Yields from CoreLogic** At the city level, we use CoreLogic's net yields to cross check our data for net yields in the Internet Appendix. At the zip code-level, we use CoreLogic's net yields as our primary data source. Their RentalTrends database tracks median rents of 1, 2, 3, and 4 bedroom homes back to 2011 in 10,146 zip codes. The database reports net yields, which are also referred to as capitalization rates. Net yields are computed as described here in Figure A.1.

**Figure A.1:** Net yield (or capitalization rate) calculation, source: CoreLogic




**Subprime Originations** We get data on subprime originations from CoreLogic's Loan-Performance dataset, which covers non-agency loans at origination and in subsequent performance by zip code.

**Zip code-level covariates from the Census Bureau** When discussing observables correlated with house price appreciation in the section on zip code-level returns, we look at age of housing stock by zip code. We also get this and other demographic data from the Census Bureau. They provide zip code-level demographic data from the 1990 and 2000 Census. They also provide 5-year American Community Survey ("ACS") estimates from 2011-2013.

[40] Zillow data are publicly-available at `http://www.zillow.com/research/data/`

**AHS from Housing and Urban Development** Our primary data provides us with the cost of rent for rental units and an estimated home value for owner-occupied units. This home value is based upon the home owner estimating what they could sell the home for when surveyed. Using the sample described above, we divide the sample into owner-occupied and renter subsamples. The two subsets of housing are significantly different. For example, the mean number of bedrooms in an owner occupied home is 3.2, while it is 2.0 in a renter occupied home. This is one reason that we use the AHS for a hedonic regression to calculate characteristic-adjusted rent-to-price ratios.

# B Internet Appendix: For Online Publication Only

## B.1 Robustness Checks

We provide several versions of Table 1 in order to show the small effects from several data choices. First, we show that the pattern of house price appreciation (HPA) across price quintiles is robust to using different CoreLogic house price index (HPI) series (covering different subsets of house prices and distress levels), and to using biannual data. Second, we show that volatility is lower for net yields even with different time aggregation methods. Third, we show results for different time subsamples, and illustrate the effect of the higher volatility of HPA on the decomposition of total returns. Finally, we conduct a sensitivity analysis of our main expense assumptions, and show that our main findings remain robust under these alternative scenarios.

**Alternative HPA Measures** In the main text, we use annual observations of house price appreciation when computing city-level averages, since we have annual data for house price appreciation, but not for rental yields. The third column of Table B.1 shows that the results are nearly identical using biannual data for house price appreciation. We also match the house price appreciation data to the yield data by using CoreLogic's Tier 2 house price index, which focuses on homes with prices between 75% and 100% of the median. Column 4 of Table B.1 using Tier 11 from CoreLogic computed using all price levels shows that, unlike for yields, house price appreciation is not substantially affected by which CoreLogic HPI series we use. We weight lower-price-tier homes more heavily in the main analysis for yields and house price appreciation because of the much greater representation of rental homes in lower price tiers.

**Table B.1:** Robustness Check: Alternative measures of HPA

| Price Quintile | Table 1 Baseline: Tier 2, annual HPA | Alternative A: Tier 2, biannual HPA | Alternative B: Tier 11 annual HPA |
|---|---|---|---|
| 1 | 3.1% | 3.3% | 3.1% |
| 2 | 3.5% | 3.9% | 3.5% |
| 3 | 4.2% | 3.9% | 3.9% |
| 4 | 5.2% | 5.3% | 5.1% |
| 5 | 5.5% | 5.3% | 5.5% |

**Alternative volatility measures** Table B.2 addresses the possible effects of measuring the volatility of house price appreciation using annual vs. biannual observations. The top panel reports annualized return volatility using annual Tier 2 CoreLogic HPA observations, and annual yield estimates from AHS, where even years use interpolated data. The bottom panel reports annualized return volatility using biannual observations of Tier 2 CoreLogic HPA observations, and the biannual yield estimates from the AHS. Comparing the top panel, which uses annual house price appreciation observations, with the bottom panel, which uses biannual observations, confirms that the effect of using biannual observations, as we do in

**Table B.2:** Robustness Check: Alternative measures of Volatility

| Table 1 Baseline: Tier 2 annual HPA, interpolated yields | | | |
|---|---|---|---|
| Price Quintile | Net Rental Yield vol | HPA vol | Total Return vol |
| 1 | 1.8% | 5.7% | 6.3% |
| 2 | 1.5% | 7.6% | 8.0% |
| 3 | 1.4% | 9.1% | 9.6% |
| 4 | 1.6% | 10.4% | 10.8% |
| 5 | 1.4% | 11.1% | 11.6% |

| Alternate Method: Tier 2 biannual HPA, biannual measurement of yields | | | |
|---|---|---|---|
| Price Quintile | Net Rental Yield vol | HPA vol | Total Return vol |
| 1 | 1.9% | 5.0% | 5.8% |
| 2 | 1.5% | 6.9% | 7.4% |
| 3 | 1.4% | 8.1% | 8.8% |
| 4 | 1.6% | 9.7% | 10.3% |
| 5 | 1.5% | 10.3% | 10.9% |

Table 2 in the main text, yields very similar results to using annual observations. The volatility of yields is slightly lower using annual observations with interpolated data for even years. The volatility of HPA is slightly higher using annual observations. However, these differences are small and the overall conclusion that returns are less volatile in price tiers in which returns have a larger contribution from net yields robustly holds.

**Subsamples by Time Period** Table B.6 displays total returns, net yields, and HPA by time period. The results are consistent with the idea that net yields are fairly stable, while HPA is much more volatile. On average, net rental yields and HPA contribute equally to total returns, however, during the boom of the early 2000's, total returns were driven up by higher-than-average HPA. Subsequently, in the bust, total returns were driven down by the negative realization of HPA. During both periods, net yields were slightly lower than their full-sample average, but the variation is small relative to that of HPA. The fact that yields appear very stable supports our zip code-level analysis combining zip code-level yields from recent years in which they became available, with the longer available series for zip code-level HPA data.

**Table B.3:** Robustness Check: Alternative time periods

| Total Return | | | | | |
|---|---|---|---|---|---|
| Price quintile | 1986-1993 | 1994-2000 | 2001-2007 | 2008-2014 | TS avg. |
| 1 | 9.3% | 11.6% | 11.0% | 5.0% | 9.2% |
| 2 | 8.9% | 10.3% | 10.6% | 5.1% | 8.7% |
| 3 | 8.4% | 9.1% | 15.1% | 1.0% | 8.4% |
| 4 | 9.7% | 8.5% | 14.5% | 0.6% | 8.4% |
| 5 | 9.0% | 10.0% | 11.7% | 0.6% | 7.9% |
| All cities avg. | 9.1% | 9.9% | 12.6% | 2.4% | 8.5% |

| Net Yield | | | | | |
|---|---|---|---|---|---|
| Price quintile | 1986-1993 | 1994-2000 | 2001-2007 | 2008-2014 | TS avg. |
| 1 | 5.8% | 6.7% | 6.4% | 5.7% | 6.1% |
| 2 | 5.3% | 5.5% | 4.4% | 5.7% | 5.2% |
| 3 | 4.4% | 4.8% | 4.0% | 3.5% | 4.2% |
| 4 | 3.7% | 4.2% | 2.6% | 1.9% | 3.1% |
| 5 | 2.7% | 3.5% | 1.6% | 1.5% | 2.4% |
| All cities avg. | 4.4% | 4.9% | 3.8% | 3.7% | 4.2% |

| HPA | | | | | |
|---|---|---|---|---|---|
| Price quintile | 1986-1993 | 1994-2000 | 2001-2007 | 2008-2014 | TS avg. |
| 1 | 3.6% | 4.8% | 4.6% | -0.8% | 3.1% |
| 2 | 3.5% | 4.8% | 6.3% | -0.6% | 3.5% |
| 3 | 4.0% | 4.4% | 11.1% | -2.6% | 4.2% |
| 4 | 5.9% | 4.3% | 11.9% | -1.3% | 5.2% |
| 5 | 6.3% | 6.4% | 10.1% | -0.9% | 5.5% |
| All cities avg. | 4.7% | 4.9% | 8.8% | -1.2% | 4.3% |

**Results including more recent sample, 15 City Series** Due to budgetary constraints, the Census stopped regularly sampling all 30 of the top MSA's in each survey. From 2015 onwards, only 15 MSA's are sampled with certainty. Table B.4 shows that, for the full sample from 1986 to 2020 our main results from 1 look very similar. Table B.5 shows results by subperiod, including for the most recent subperiod from 2015 to 2020. For other subperiods, the results are similar to the 30-city analysis in Table B.6. The recent sample displays yields in line with other subperiods, but higher HPA due to the recovery after the Great Financial Crisis.

**Table B.4:** Average Net Rental Yields, house price appreciation, and Total Returns by pooled time series, cross-section annual city Price Quintile from 1986-2020. Top 15 MSA's.

| Price Quintile | Net Rental Yield | House Price Appreciation | Total Return |
|---|---|---|---|
| 1 | 6.2% | 4.0% | 10.3% |
| 2 | 5.1% | 4.4% | 9.5% |
| 3 | 4.2% | 4.9% | 9.1% |
| 4 | 3.5% | 5.2% | 8.8% |
| 5 | 2.4% | 5.5% | 7.9% |

**Table B.5:** Robustness Check: Alternative time periods. Top 15 MSA's

| Total Return | | | | | | |
|---|---|---|---|---|---|---|
| Price quintile | 1986-1993 | 1994-2000 | 2001-2007 | 2008-2014 | 2015-2020 | TS avg. |
| 1 | 10.0% | 12.4% | 9.7% | 5.8% | 14.1% | 10.3% |
| 2 | 9.5% | 10.8% | 11.2% | 4.7% | 11.6% | 9.5% |
| 3 | 8.4% | 9.1% | 16.2% | 0.5% | 11.7% | 9.1% |
| 4 | 10.2% | 8.8% | 14.9% | 0.3% | 9.6% | 8.8% |
| 5 | 8.7% | 9.1% | 12.4% | 0.7% | 8.6% | 7.9% |
| All cities avg. | 9.4% | 10.0% | 12.9% | 2.4% | 11.1% | 9.1% |

| Net Yield | | | | | | |
|---|---|---|---|---|---|---|
| Price quintile | 1986-1993 | 1994-2000 | 2001-2007 | 2008-2014 | 2015-2020 | TS avg. |
| 1 | 5.8% | 7.0% | 5.7% | 6.7% | 6.2% | 6.2% |
| 2 | 5.6% | 5.8% | 4.1% | 4.9% | 4.8% | 5.1% |
| 3 | 4.2% | 4.8% | 4.1% | 3.7% | 4.0% | 4.2% |
| 4 | 4.2% | 4.3% | 3.3% | 2.3% | 3.5% | 3.5% |
| 5 | 2.7% | 3.8% | 1.9% | 1.7% | 1.8% | 2.4% |
| All cities avg. | 4.5% | 5.2% | 3.8% | 3.9% | 4.1% | 4.3% |

| HPA | | | | | | |
|---|---|---|---|---|---|---|
| Price quintile | 1986-1993 | 1994-2000 | 2001-2007 | 2008-2014 | 2015-2020 | TS avg. |
| 1 | 4.2% | 5.4% | 4.0% | -0.8% | 7.9% | 4.0% |
| 2 | 3.9% | 5.0% | 7.1% | -0.2% | 6.7% | 4.4% |
| 3 | 4.2% | 4.2% | 12.2% | -3.2% | 7.6% | 4.9% |
| 4 | 6.0% | 4.4% | 11.6% | -2.0% | 6.2% | 5.2% |
| 5 | 6.0% | 5.3% | 10.5% | -1.1% | 6.8% | 5.5% |
| All cities avg. | 4.9% | 4.9% | 9.1% | -1.5% | 7.1% | 4.8% |

**Alternative Gross to Net Rent Assumptions** Our baseline cost assumptions are as detailed in the main Appendix and repeated here for convenience:

- Insurance: 0.375% of price
- Repairs: 0.6% of price
- Capex: 1.15% of price
- Property manager: 5.9% of rent
- Credit loss: 0.73% of rent
- Tax: state-level data, % of price
- Vacancy: MSA-level data, % of rent

We conduct a robustness check on the effect of cost increases on median net yields by price quintile, and find that these effects are fairly small. We use actual data for taxes and vacancy costs. The remaining costs are either computed as a fraction of rent or a fraction of house prices, but netted out of yields in both cases when moving from gross to net yields. Here, we choose the largest cost from each category, and display the effect on net yields of increasing each of these costs by 25%, as well as the effect of increasing both costs by 25%. The overall effect on yields of increasing both repair costs (% of price) and management fees (% of rent) is to reduce the net yield by about 25 basis points, or 0.25% across all price tiers. Thus, we conclude that at calibrated values, reasonable changes in costs are unlikely to alter our main conclusions.

**Table B.6:** Robustness Check: Increase Costs

| | Net yields with increased costs | | | | |
|---|---|---|---|---|---|
| Price quintile | Base case Net Yield | Repair Costs Net Yield | Mgmt Fees Net Yield | Increase both costs Net Yield | Change in yield with both cost increases |
| 1 | 6.1% | 6.0% | 6.0% | 5.9% | -0.28% |
| 2 | 5.2% | 5.1% | 5.1% | 5.0% | -0.27% |
| 3 | 4.2% | 4.1% | 4.1% | 4.0% | -0.25% |
| 4 | 3.1% | 3.0% | 3.1% | 2.9% | -0.23% |
| 5 | 2.4% | 2.2% | 2.3% | 2.1% | -0.22% |
| Average | 4.2% | 4.1% | 4.1% | 4.0% | -0.25% |

**Alternative Hedonic Method: Actual Rents, Estimated Prices** We present results for an alternative hedonic method using actual rents from single family rental homes, and estimated prices. In the main text, we use the model-implied rents, and actual prices. This is because the sample of rented single-family homes represents a small fraction of homes in the AHS. In particular, in a few MSA's (for example in Newark) the fraction of observations that are rentals is only around 5%. We confirmed that there is no relation in our data between the net yields we estimate, and the fraction of unit observations that are rentals. Table B.8 presents the results using prices estimated using the analogous hedonic regression used in the baseline estimation to estimate rents for the larger sample of owned homes:[41]

$$\ln\left(\text{Price}_i\right) = \beta_{0,j} + \beta_{0,t} + \beta_1 \text{Rooms}_i + \beta_2 \text{Beds}_i + \beta_3 \text{Baths}_i + \\ \beta_4 \text{AirSys}_i + \beta_5 \text{UnitType}_i + \beta_6 \text{Age}_i + \beta_7 \text{Ln(SqFt)} \epsilon_i.$$

**Table B.7:** Hedonic regression coefficients, alternative method

| | coefficient | t value |
|---:|---:|---:|
| condo | 0.00 | 0.59 |
| detached home | 0.20 | 36.21 |
| rooms | 0.06 | 43.38 |
| bedrooms | 0.00 | -0.87 |
| bathrooms | 0.16 | 59.36 |
| airsys | 0.10 | 25.24 |
| age | -0.38% | -51.62 |
| log sqft | 0.11 | 38.84 |
| $n$ | 153,787 | |
| $R^2$ | 59.88% | |

The results in Table B.8 display the same cross sectional pattern as those in Table 1. Yields decline with price tier. Yields are, however, lower on average using actual rents and estimated prices. This is mainly due to lower yields in the lower price tiers, and is expected since the prices of owned homes are likely higher than those on rented homes. Indeed, both methods likely understate yields since, in the baseline estimation, rents are likely *lower* on actual rented units than on owned homes. However, comparing the two results suggests that the bias is larger for estimated prices.

**Table B.8:** Average Net Rental Yields, house price appreciation, and Total Returns by pooled time series, cross-section annual city Price Quintile from 1986-2014. Alternative Hedonic method using actual rents, estimated prices.

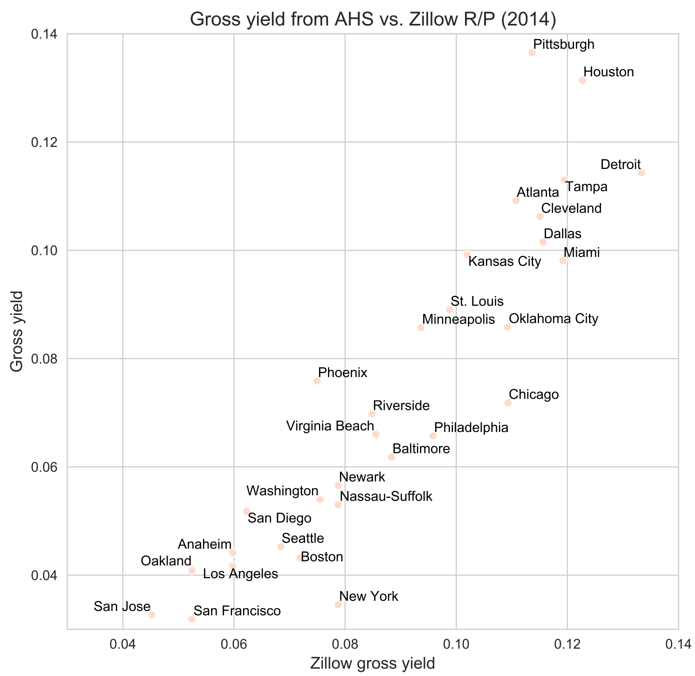
| Price Quintile | Net Rental Yield | House Price Appreciation | Total Return |
|---|---|---|---|
| 1 | 4.3% | 3.1% | 7.4% |
| 2 | 4.0% | 3.5% | 7.5% |
| 3 | 4.0% | 4.2% | 8.2% |
| 4 | 2.9% | 5.2% | 8.1% |
| 5 | 2.3% | 5.5% | 7.8% |

[41] As in the baseline estimation, we apply the Goldberger correction to account for the biased introduced by the log specification.

## B.2 Comparison of rental yields across data sources

We present scatter plots of our estimates vs. Zillow's and CoreLogic's. The figures show that our yield estimates using AHS data which we can construct over a long sample, line up well with data from Zillow and Core Logic, which cover only recent years. Figure B.1 plots our estimated gross yields against those from Zillow for 2013, and Figure B.2 plots our estimated net yields against Core Logic's cap rates in 2013.

**Figure B.1:** Gross yields estimated from AHS vs. Zillow gross yields 2013.

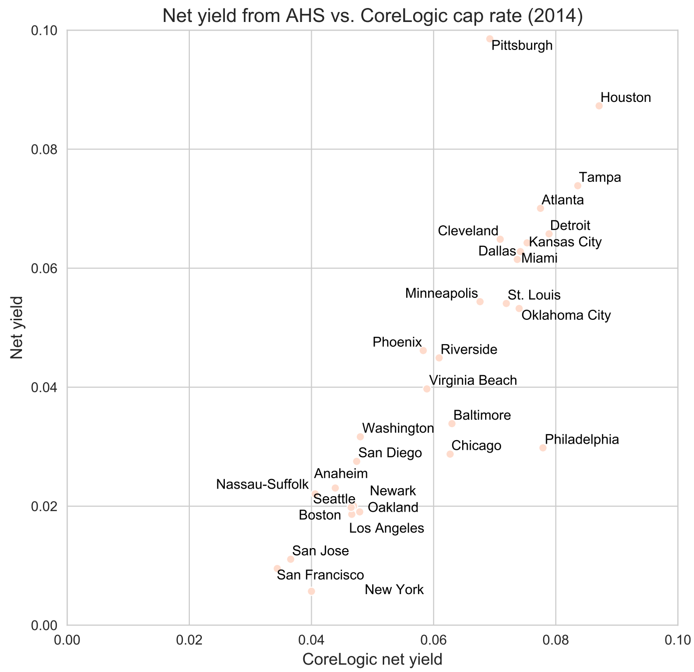



## B.3 Single family rental IRR example

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 single family rental investment in order to illustrate the typical composition, timing and magnitudes of cash inflows and outflows. Figure B.3 presents our spreadsheet model and the associated assumptions for the purchase and sale of a typical buy-to-rent (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

**Figure B.2:** Net yields estimated from AHS vs. Core Logic cap rates (net yields) 2013.




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 B.3 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).[42] Looking at the rows describing the expenses in the top panel of Figure B.3, one can see that expenses linked to home value are on average over four times the magnitude of those linked to rents. Most of the variation in rental yields is driven by variation in house prices, as carefully documented in Campbell, Davis, Gallin, and Martin (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 B.4. We use three sets of assumptions, detailed in Table B.9. In particular, we use an all equity

[42]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.

investment, an example small investor investment from a multi-borrower-backed single family rental bond, and an example large investment from a single-borrower-backed single-family-rental bond, defined by their leverage ratios and borrowing constraints as detailed in the caption to Figure B.4. Importantly, note that all IRR's are approximately (and undetectably different from) linear in the two inputs into total returns, namely net yields and house price appreciation, 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 single family rental homes.[43] In sum, our example closely represents the actual collateral owned by institutional investors, and the either assumed or incurred expenses associated with them. We use similar assumptions when computing net yields in our city-level analysis.

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

**Figure B.3:** Pro Forma Example: All Equity Single Family Rental 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%** | | | | | |

**House Characteristics**

| | Assumptions highlighted | Assumptions or Implied Percentages | |
|---|---|---|---|
| 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 |

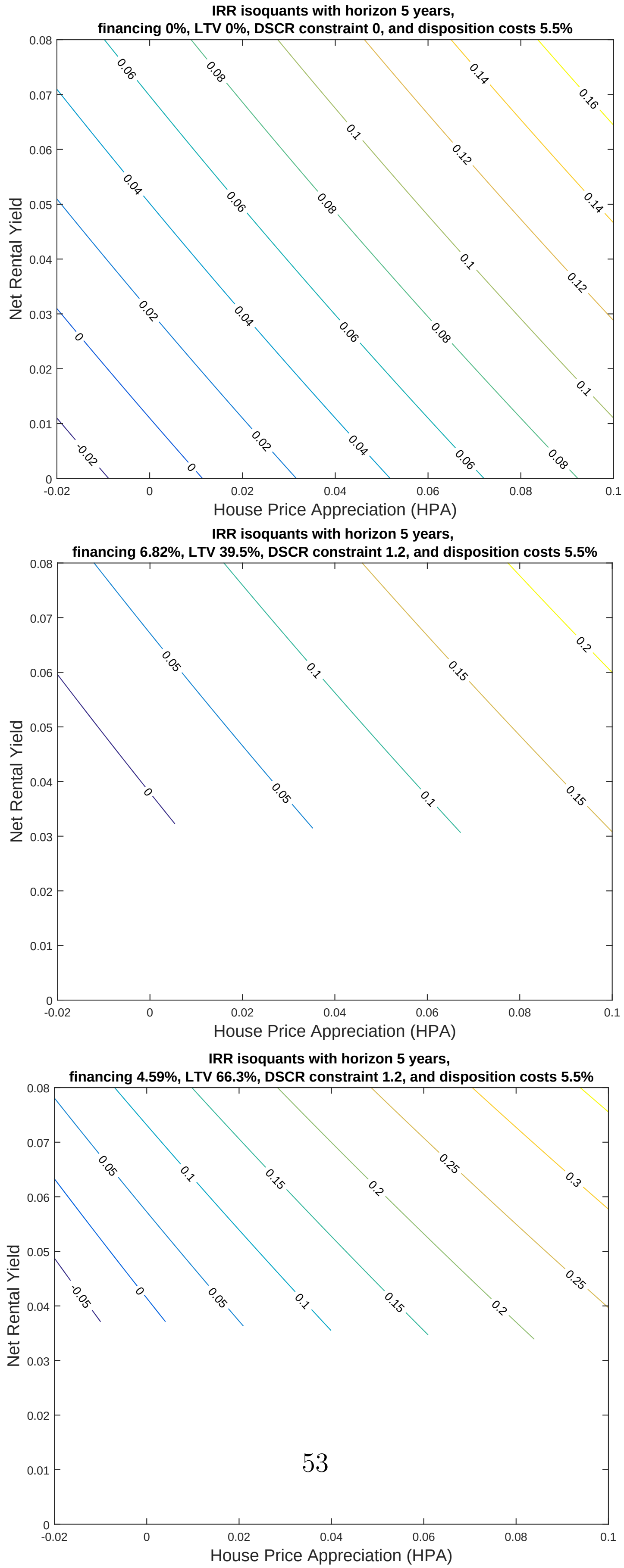
**Annual Assumptions:**

| | | | |
|---|---|---|---|
| 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 |

**Table B.9:** 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 |

**Figure B.4:** Internal Rates of Return are Approximately Linear in Yields and House Price Appreciation.



# C House-Level Net Rental Yields

We discuss returns at the house level, using bond annex data from existing securitizations of single family rental portfolios. House-level variation allows us to study the continuous effect of house price on net rental yields. In addition, the data from these recent securitizations verify that the expense ratios and net yields we construct from AHS survey data, and Core Logic data, conform to data from actual investor collateral. Finally, the bond collateral data allow us to document the properties of existing investors' operating efficiencies and portfolio choice. We find evidence of a significant operator fixed effect in collateral performance. In terms of portfolios, we show that institutional investors' assets are somewhat concentrated in cities which experienced greater subprime lending activity prior to the financial crisis. However, we find little evidence that institutional investments succeeded in capturing the greatest ex-post trough to peak gains in house prices.

We examine the houses operated by large single family rental institutions. We collected data from bond prospectuses on the fourteen single family rental issuances as of January 2015. Each issuance comes with an appendix listing every property in the collateral, its acquisition prices, its net rent, and other characteristics. We also reference the reports on these issuances produced by Kroll Brothers Rating Agency. The fourteen single-borrower single-family-rental 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 billion in notional bond value.[44] We examine the total returns to single family rentals at the house level in order to provide a robustness check on our net yield estimates derived from AHS at the city level, and Core Logic data at the zip code level, as well as to provide evidence on the collateral underlying the institutional portfolios backing bond issuances, as well as on operator performance.

In the bond annex data, we observe underwritten gross rents, net income, and broker-price opinions (BPOs) on each property.[45] Although higher broker-price opinions increase collateral values, they also drive down yields and future capital gains. Thus, we treat the BPOs as an unbiased estimate of the market value. The fourteen issuances come from seven different institutional single family rental operators.[46] To provide a house-level 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 single family rental properties.[47] This seems roughly comparable to our average estimated net yield of 4.3% from the 2013 AHS data and 6.0% from 2013 CoreLogic RentalTrends. Recall that we compare yields from these two sources in Figure B.2.

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

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

[45] 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.

[46] These operators have since merged to form three larger operators.

[47] 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.

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 C.10 and we view the similarity across separate issuances from the same single family rental operators as evidence of the reliability of the estimates.

We estimate $\beta_1$ 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. Of course, in practice the positive intercept is due to the indivisibility of housing. The regression $\text{Annual Income}_i = \beta_0 + \beta_1 \text{BPO VALUE}_i$ yields an estimate for $\beta_0$ of \$4,472.[48] Figures C.5 and C.6 provide illustrative scatter plots of the bond annex data. Figures C.5 clearly displays the positive intercept. Figure C.6 shows the resulting downward-sloping net income ratio.[49]

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%. This expense ratio is close to our estimated expense ratio computed using AHS data to construct city-level net yields. We demonstrate the heterogeneity in Figure C.7, which plots the distribution of expense ratios. Consistent with our findings in the time series for city-level net yields estimated using AHS data, we find that (possibly because costs which scale with house prices act like larger fixed costs relative to rents for higher priced homes) 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 single family rental 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 single family rental 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 house price appreciation per-

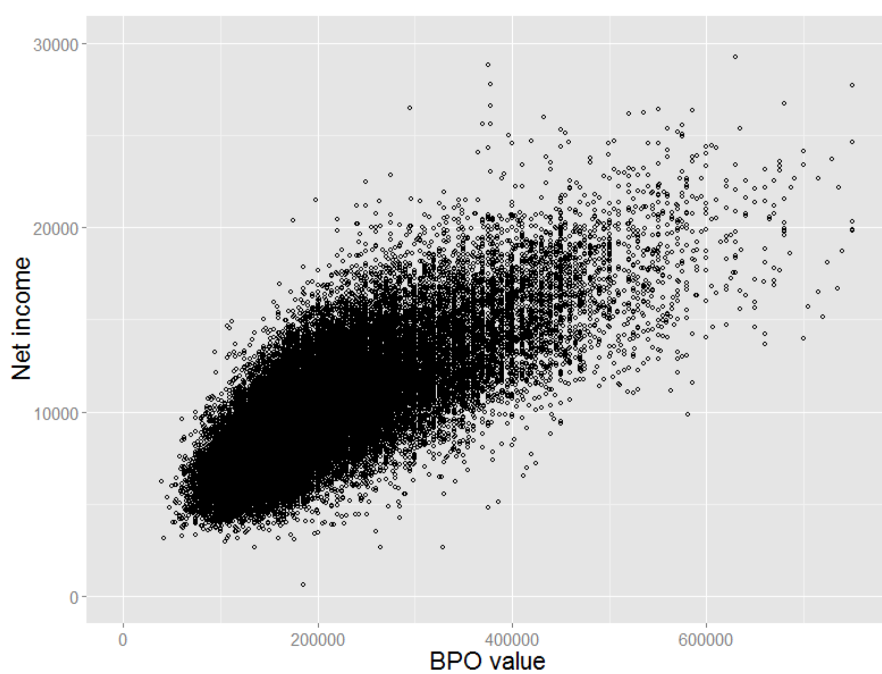
[48]There is certainly some nonlinearity as the value of a house approaches zero. If we estimate on only properties with a value under \$120,000, the estimate of $\beta_0$ drops to \$3,676 and the estimate of $\beta_1$ climbs to 3.1%.

[49]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.

formance of the portfolios of homes collateralizing single family rental backed bonds. Figure C.9 plots peak to trough vs. trough to current house prices for the cities with the largest market share of single family rental collateral, along with a comparison the other largest cities. The CBSAs with the five largest shares of single family rental properties in securitized products are Phoenix (13.9%), Atlanta (12.1%), Tampa (7.3%), Houston (5.2%), and Las Vegas (4.7%). Figure C.9 shows that cities with larger peak to trough losses have tended to experience larger trough to present gains in home values. The figure also provides some evidence that institutional investors in single family rentals chose locations with large peak to trough losses and trough to peak gains.[50]

Finally, we use the bond annex data to investigate the relation between single family rental investment post-crisis and subprime lending pre-crisis. We merge the bond annex data with Core Logic's Loan Performance data on non-agency subprime originations by zip code as follows: We bin the 53,806 properties in our dataset into zip codes and count the number of properties by zip code.[51] We then compute the average monthly subprime originations (by value) between 2003 and 2008 in each zip code in the Loan Performance data. We find some limited support for subprime borrowers being turned into single family rental renters. The correlation between the two variables is 0.37. The two variables are plotted in Figure C.8, showing that the zip codes with the highest property counts tend to have higher past subprime originations.

**Figure C.5:** Underwritten net income is an increasing function of BPO value in single family rental bond collateral.




[50]Malloy et al. (2017) emphasize the related points that institutional investors focused on cities with a large supply of homes for sale, and may have helped to support prices in the neighborhoods they operate in.

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

**Figure C.6:** Underwritten net income ratio is a decreasing function of BPO value in single family rental bond collateral.

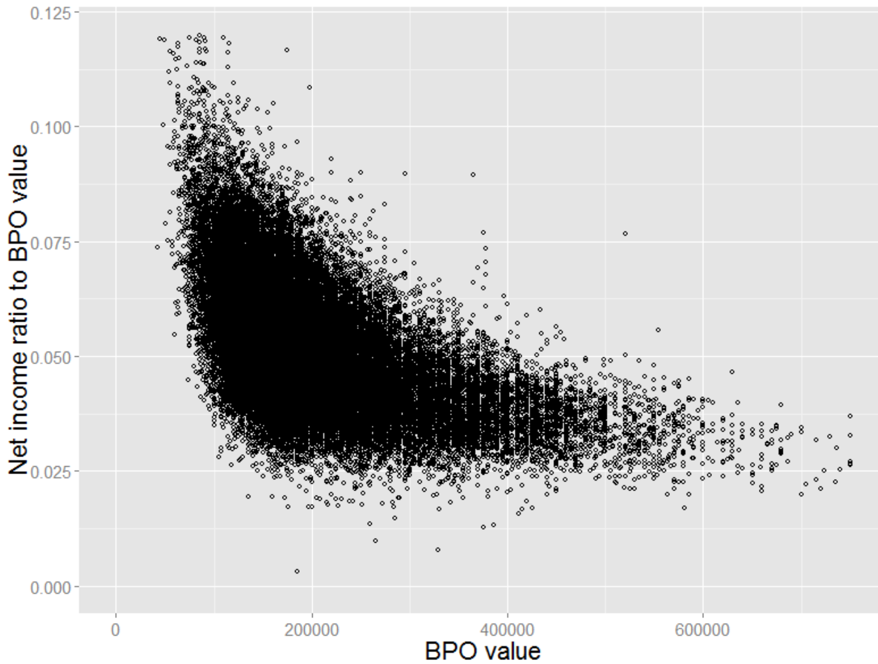



**Figure C.7:** Single family rental securitized assets: house-level expense ratios demonstrate substantial heterogeneity.

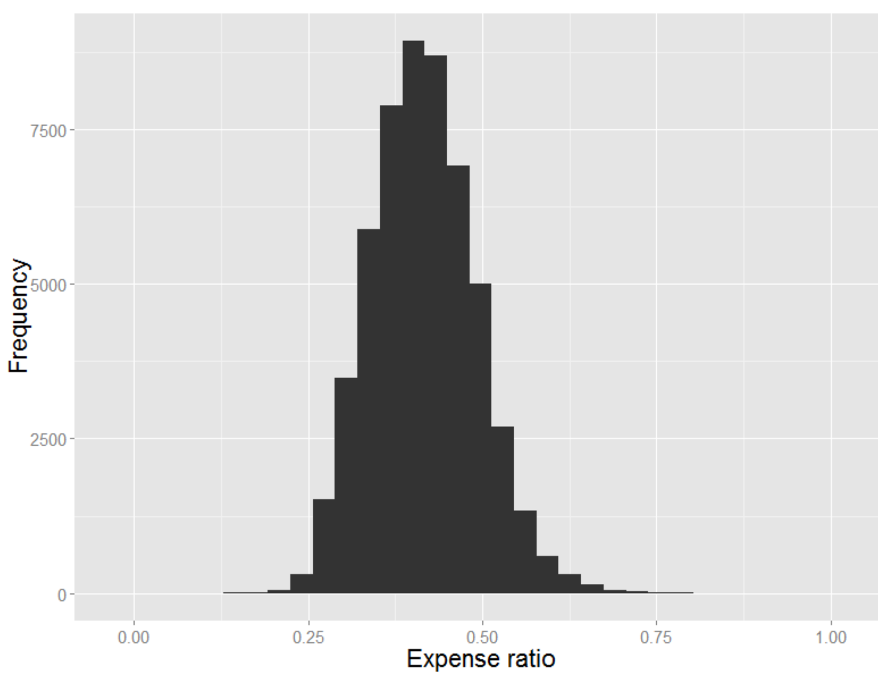


**Figure C.8:** Subprime activity in 2003-2008 is positively related to single family rental presence today.

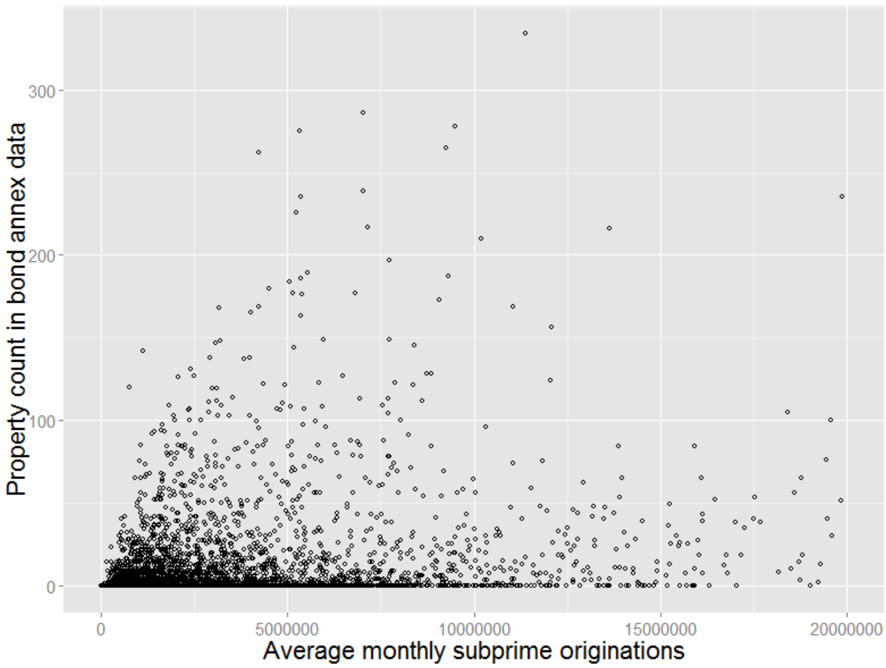



**Table C.10:** Single family rental bond issuer net income dummies

| 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 |

**Figure C.9:** Peak to trough vs. Trough to current HPI. Blue cities have the largest share of properties in securitized products as of January 2015. The four cities with the highest trough to 2014 gains in home values are, from top to bottom, Oakland, Phoenix, Detroit, and Miami. The four cities with the largest peak to trough losses in home values are, from left to right, Detroit, Phoenix, Riverside, and Miami.