Residential Real Estate, Risk, Return and the Benefits of Diversification: Some Empirical Evidence

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Abstract: Residential real estate is a key component of household wealth. While we have some insight into the aggregate returns of this asset class—thanks to real estate price indexes—we have little understanding of the characteristics of investment in individual properties. This paper outlines and applies a methodology for estimating and examining the variation in risk and return for unique homes. We use large data sets of home prices and rents for Sydney, Australia, from 2002-14, to estimate flexible spline hedonic models which incorporate spatial and characteristics smoothing. Using these models we estimate total returns—the sum of capital gains and rental yield—for a large sample of properties for each time period. This enables use to consider the risk and return of investment in individual parcels of residential real estate and explore the benefits of diversification. As a reference point, we contrast housing with investment in equities. We find that there is dispersion in returns and their volatility—though significantly less than shares—and that this is tied to certain home characteristics. However, when we investigate the benefits of holding a diversified portfolio of homes over a single home we find they are small compared with the corresponding case for equities.

Keywords: Residential real estate; Hedonic regression; Risk and Return; Diversification.

JEL Classification Codes: C23, C43, G12, R30

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1 Introduction

Globally residential real estate is a key store of wealth for households and investors. In the US for example, the Federal Reserve's Flow of Funds statistics estimate that households' holding of residential real estate is around $23 billion in the fourth quarter of 2016 (Federal Reserve Board, 2016, Table B.101 Balance Sheet of Households and Nonprofit Organizations, p. 138). This is the largest asset class held by households by a significant margin. Work by Case and Shiller (1989, 1990), amongst others, has increasingly made available information on the returns to housing, in the form of capital gains, over extended periods of time. Integral here was the development of the S&P Case-Shiller House Price Index (Standard & Poor's, 2015) constructed for the US as a whole and certain metropolitan areas. Similar indexes have appeared in other countries. The increasing availability of information on historical housing price trends has in turn has meant we can better understand the role of real estate in the household's investment portfolio and how it performs relative to other asset classes over the cycle (see for example, Flavin and Yamashita, 2002; Gelain and Lansing, 2014).

However, unlike other assets, such as stocks or bonds—where it is relatively easy to own a well diversified portfolio of such assets—it is usually the case that most households own a single home. Moreover, each home is unique in its mix of locational and structural characteristics. This begs the question; what are the risk and return profiles of the various individual home-types that are actually owned by households? Just as certain stocks are likely to perform differently over time—perhaps as a result of their industry of operation, geographic footprint, the company's size and so forth—so potentially are different types of homes. In fact there is strong evidence for significant heterogeneity in price trends across homes. For example, Case and Shiller (1989) found a weak correlation between the price movements of individual homes and those at the city-level. This implies that there are significant price dynamics which are occurring at a disaggregated level. Others, who have explicitly modeled housing prices at a disaggregated level, have found significant levels of heterogeneity in price dynamics. Bourassa, Hoesli and Peng (2003) found strong evidence of geographic housing submarkets within a city. McMillen (2003)—who estimated house price indexes at the census tract level for Chicago—found large differences in appreciation rates across the city. Melser and Lee (2014) looked at various market segments, not only those defined by geography, and also found evidence of distinct home price trends. While more recently Melser (2017a, 2017b) has outlined a repeat sales models which reveals significant characteristics-driven appreciation profiles for homes.

While disaggregated house price trends appear to be important there has not been

comprehensive analysis of how this variation impacts on the returns to households and how it varies compared with the overall index. For example, do houses have higher returns than apartments and are they more volatile; how important is the regional component in driving risk and return and what is the impact of other characteristics—such as price level and momentum—in driving risk and returns? Such questions are obviously integral to homeowners and housing investors. But they are also important for the banking industry. The credit risk of a mortgage will depend, along with other factors, on the dynamics of rental yields and particularly home prices. If these differ by property type then this implies that loans should be structured and/or priced differently for different types of homes.

This paper makes two broad contributions. First, it outlines a methodology for constructing the dynamics of the returns to housing at a disaggregated level and applies this approach to data for Sydney—Australia's largest city—from 2002-14. We make use of a large database of housing transactions prices and characteristics, from 2000-14, as well as a database of home rents starting in 2002. The data sets are comprehensive. The rental database includes 1,143,534 observations on 452,803 unique properties while the housing transaction data includes 549,504 observations on 435,501 unique properties over the respective periods. In order to analyse the drivers of individual home price movements we must first know what those movements are. This is a perennial problem with housing as each home is unique and they transact infrequently. Hence observed data will be insufficient. We show how the requisite indexes of residential real estate prices can be constructed for each house in our sales database, using transactions prices, characteristics data and flexible smoothing spline hedonic regression methods. These models are then used to impute individual home price and rental levels for a random sample of 10,000 homes. For these properties we construct the total return for a given home in each quarter of our data.

Second, we explore the risk and returns for individual homes and examine the benefits of holding a portfolio of homes. We approach this issue from a number of directions. We examine return and risk—the standard deviation of returns–as well as calculating Sharpe ratios for each property. This allows us to examine the dispersion across each of these components. As a point of comparison we contrast the risk-return profiles for properties with those for individual shares. We find that while the average total return is much lower for housing than shares on a risk-adjusted basis housing on average has a higher Sharpe ratio than equities. This is after accounting for the running costs of homes. We also estimate regression models which allow us to identify the factors which have driven risk, return and the Sharpe ratio. We find houses tend to have both higher returns and a higher Sharpe ratio than do apartments. Moreover, there is significant regional variation

in returns, risk and Sharpe ratios. Moreover, we found that more expensive properties had weaker risk-adjusted returns while the size of the structure—reflected in the number of bedrooms—had limited impact. Thus our results paint a picture of a high degree of dispersion in the investment returns across property types. This points towards the potential benefits to homeowners of diversifying their property holdings across different homes. We investigate this issue and, as a point of comparison, contrast the benefits of housing diversification with those for shares. First we calculate the Sharpe ratio for different-sized portfolios of homes and shares. This illustrates the much steeper rise in the Sharpe ratio for shares compared with homes; the Sharpe ratio for shares doubles for a portfolio of 200 compared with a single share while for homes it increases by just under a third. A further way of exploring the benefits of diversification is to investigate the portfolio weights and utility obtained when homeowners have access to a housing index compared with when they do not. We solve a number of mean-variance portfolio optimisation problems for different levels of risk aversion. We also undertake a similar analysis for shares. Interestingly, we find fairly modest gains in utility for homeowners from accessing a diversified portfolio of homes compared with share investors.

In the next section we discuss the data that is used in estimating the disaggregated housing return dynamics. Integral to our ability to estimate the market model for housing is the existence of a price and rent series for each dwelling. We also introduce the equity data used in our study. Section 3 develops a flexible hedonic smoothing spline model which gives us the ability to impute prices and rents for homes in our sample. Section 4 analyses the total returns for housing and presents the results. Section 5 briefly concludes.

2 Sydney Housing and Equity Data

The approach outlined in this article is applied to large housing price and rent datasets for Sydney, Australia. Sydney is the country's largest city with a population of more than 4.5 million. Our first dataset is for housing transaction prices and includes 549,504 observations on 435,501 unique homes from first quarter of 2000 to the final quarter of 2014. The second data set is for rents. This includes 1,143,534 observations on asking rents in Sydney for 436,130 different properties from 2002 to the end of 2014. The rental data is from a major Australian listing website. While they are not necessarily the actual rent paid they are likely to closely approximate it given that there is limited negotiation over rents in Australia. Mostly the rent asked at the time of advertising is the rent received when the property is let.

Our data comes from a private provider of housing transaction data, Australian

Property Monitors (APM). They source a large amount of the data from the state Valuer General, a government agency which records property transactions. However, they supplement this information with extensive searches through real estate advertising websites and newspapers for property characteristics. The characteristics data we have available to us to estimate the hedonic equation for both selling prices and rents includes; number of bedrooms, number of bathrooms, dwelling structure—whether the property is an apartment or a house—land area for houses (apartments do not involve the individual ownership of land by definition) and the latitude and longitude of the home.[1] Together these characteristics provide a solid basis upon which to model dwelling prices and rents.

The data we use in our estimation and imputation was drawn from a larger data set which was filtered somewhat to ensure that unusual transactions, or transactions with incomplete information, were not included. Any homes selling for more than $5 million or less than $50,000 were removed. As were properties that rented for less than $100 or more than $2,000 per week. We also dropped any dwellings with more than 7 bedrooms or more bathrooms than bedrooms. Given the hedonic approach taken to the estimation of house prices and rents we also removed any properties where any of the characteristics listed above were missing. This limited the set of usable observations, particularly early in the sample when the availability of characteristics information was more limited. However, the sample of home sales, and particularly rents, is significant and encompasses a large number of observations across the regions of Sydney and a wide range of property types.

⟨⟨ *Insert Table 1 and Figure 1 here* ⟩⟩

Table 1 presents some summary statistics for the sample by structure-type, year and some key regions for both selling prices and rents. The regions listed are statistical subdivisions from the Australian Bureau of Statistics (see for example, ABS, 2006) and represent meaningful sub-city regions—similar segmentations are used on real estate listing websites for example. The location of these regions can be seen in Figure 1. The Inner Sydney region includes the CBD area and surrounds while regions such as Central Northern Sydney, Blacktown, Fairfield-Liverpool and St George-Sutherland represent outlying areas.

Both the sale price and rent datasets are large and reflect significant variation across time and regions. This makes them useful for estimating price and rental trends. However, there are some clear differences in the composition of the data sets which influences

[1] Note here that our definition of a house is somewhat broader than a single family freestanding dwelling. We also include; terrace or row houses, villas, duplexes, semis or townhouses. These properties are in most cases more similar to freestanding dwellings than to an apartment, in that they involve the ownership of land, hence we include them together.

the way we proceed. For the home sales data, 351,809 (64.02%) of the observations are for houses while apartments make up the remaining 35.98% with 197,695 observations. This is significantly different from the rental data set which has 59.42% apartments. The two data sets also differ along other dimensions. The rental data has a much higher proportion of observations in the central areas of Sydney, particularly Inner Sydney and Lower Northern Sydney. These compositional differences primarily reflect differences between the rental and owner-occupied stock of houses. Rental units tend to be smaller and more centrally located compared with owner occupied units.

Our objective in this paper is to understand the return dynamics for the stock of housing. Hence, in order to best represent the stock of homes in Sydney we focus on those dwellings in the sales data set. It is more likely that the sold homes represent an accurate sample of the housing stock than do those homes which are rented. Hence, in the hedonic estimation which follows we use the rental data to estimate the rental hedonic function but only impute rents for the properties observed in the sales data set.

As outlined above, in the succeeding sections we make use of equity data to contrast the risk and return profile of housing. The equity data we use is for the 200 largest companies listed on the Australian Stock Exchange (ASX) for which we could obtain data from 2002 to 2014.[2] These companies are those which are most often traded on the ASX and which can be readily invested in by households. The data we use reflects the total returns from owning these stocks—that is it includes both the capital gains and any distributions.[3] We now turn to the hedonic estimation of housing prices using the available data.

3 Hedonic Estimation

There are two key difficulties in constructing real estate sale price and rent indexes and hence in calculating total returns. The first is the underlying heterogeneity of residential real estate; no two homes are quite the same. The second is that homes sell or list for rent only infrequently. This makes the construction of constant quality price and rent indexes very difficult. To overcome this problem, and derive indexes for specific properties, we use hedonic regression methods. This relates the price and rent of homes to their characteristics and to time. This function can then be used to impute values for homes which did not transact in a given period.

[2] A listing of the 200 companies used, and the industry in which they operate, can be found in the Online Appendix A for this article.

[3] The data was obtained from the Securities Industry Research Centre of Asia-Pacific (SIRCA). SIRCA is a research collaboration amongst Australian universities originating in 1997 in order to provide comprehensive data for research in Finance. They have significant expertise in sourcing and constructing financial data.

However, a key issue with using hedonic methods in this context is that most standard hedonic techniques are not flexible enough to estimate unique prices, and hence price trends, for individual homes. In many hedonic studies strong assumptions are made regarding the pricing function and how it evolves over time, across space and over dwelling characteristics. Consider the following general additive hedonic function for home prices,

$$\ln p_{it} = \tau_{i[r]t} + \sum_{c=1}^{C} f(z_{i[r]tc}) + \epsilon_{it}, \qquad t = 1, 2, ..., T,\ i = 1, 2, ..., I \tag{1}$$

Here there are $c = 1, 2, \ldots, C$ characteristics which take on the value $z_{i[r]tc}$ in time t for property i in geographic region r. Consider the function which mediates the impact of the characteristic on price. Most standard hedonic models impose rather simple relations. The time-dummy method (see for example; de Haan and Diewert, 2013) supposes that $\tau_{i[r]t} = \tau_t$ and $f(z_{i[r]tc}) = \delta_c z_{i[r]tc}$. That is, the impact of the characteristics is fixed across time and across homes and any difference in price is reflected in a time-varying intercept. More flexible hedonic methods have been used which allow for temporal flexibility in the quality characteristics, $f(z_{i[r]tc}) = \delta_{ct} z_{i[r]tc}$ or variability across discrete regions where they can be identified, e.g. $f(z_{i[r]tc}) = \delta_{crt} z_{i[r]tc}$ and $\tau_{i[r]t} = \tau_{rt}$ (for a fuller discussion see Hill and Melser, 2008). For our purposes, it is vital that the hedonic function accurately represents any differences in prices trends in individual homes. This requires a hedonic function which is flexible both in terms of the temporal dimension but also in the way that location and dwelling characteristics relate to price.

3.1 Penalized Smoothing Spline Hedonic Models

Our approach is to estimate a generalized additive model (GAM) with smoothing spline effects for each of the variables in terms of how they change over time. This builds on earlier work, such as Bao and Wan (2004), and reflects growing interest in the hedonic housing literature on the use of spline methods (see for example, Hill and Scholz, 2014; Melser, 2017b). Each of the variables—land area, bedrooms, bathrooms and each of the dwelling types (apartment or house)—are included using a multi-dimensional smoother interacted with time (t) and latitude (lat) and longitude (long). For bedrooms, for example, we denote the effect as, $s_1(bedrooms, t, lat, long)$. What this means is that the effect of the number of bedrooms on price can be non-linear and, furthermore, can evolve both over time and across space (latitude and longitude). For the structure variables we include a separate spline for each but estimate a common smoothing parameter and denote this $s_3([apartment][house], t, lat, long)$. The effect of location on price is modelled

by a trivariate spline between latitude, longitude and time.

Smoothing spline models require estimates of the smoothing parameters—that is, the relative weight given to the smooth evolution of the parameters compared with the fit of the data. In our application the smoothing parameters are endogenously selected in conjunction with the data using the Generalized Cross Validation (GCV) approach.[4] The model is shown below,

$$\begin{aligned}\ln p_{it} = {} & s_1(bedrooms, t, lat, long) + s_2(bathrooms, t, lat, long) \\ & + s_3([apartment][house], t, lat, long) + s_4(land\ area, t, lat, long) \\ & + s_5(t, lat, long) + \epsilon_{it}, \quad t = 1, 2, ..., T,\ i = 1, 2, ..., I \end{aligned} \tag{2}$$

This approach to the estimation of hedonic prices is new and highly flexible in that it utilizes multidimensional splines for each of the property's characteristics. The existing prior work on the use of splines for hedonic estimation has primarily focused on using splines to estimate the impact of geographic factors—latitude and longitude—only (Bao and Wan, 2004). However, our approach does have some antecedents in the literature. Gelfand et al. (1998) and Gelfand et al. (2004) propose a model of the evolution of home prices which is similar in spirit to ours. Their model is formulated on the basis of stochastic spatio-temporal processes and estimated using Bayesian methods. While ostensibly the use of random effects and splines appear quite different there is a close relationship between these two approaches (see Ruppert, Wand and Carroll, 2003). Perhaps one of the benefits our approach in this context is the fact that cross validation is used to select the smoothing parameters. This is based on the ability of the model to forecast out of sample. This is important as our imputations will effectively be out of sample predictions of what prices would have been had a property been sold or rented. Also related to our spline approach is the structural time series model proposed by Francke and Vos (2004). This constructs price estimates using a state space formulation conditioned on different groups of properties. This allows a high degree of flexibility in modelling how prices evolve through time. However, the cross section is treated differently and clustered rather than allowing the characteristics to explicitly drive cross sectional variation in prices. Our approach treats time and the other characteristics somewhat more symmetrically.

The smoothing spline price and rent models fit the data very well when compared with standard hedonic methods and other potential smoothing spline models. We explored whether the spatial interactions with bedrooms, bathrooms, dwelling type and land area

[4]The GAM smoothing spline estimation is implemented using the approach of Wood (2004, 2011) reflected in the `mgcv` package in R.

were required—that is we removed latitude and longitude from $s_1(.) - -s_4(.)$ in (2). This gives what we call the Time Smooth model—as opposed to the model in (2) which is both temporally and spatially smooth. The results are more supportive of the full smoothing model. This model has a statistically significantly higher R^2 and a lower AIC for both prices and rents as shown in Table 2.

⟨⟨ *Insert Table 2 here* ⟩⟩

We also fit several different, more standard, hedonic formulations and compared the in-sample model fit for both prices and rents. The results are shown in Table 2. The time-dummy method—in equation (1) where $f(z_{itc}) = \delta_c z_{itc}\ \forall c = 1, 2, \ldots, C$—has an R^2 of 0.6878 compared with 0.8171 for our preferred Time-Spatial Smooth spline model for prices and 0.6716 compared with 0.7839 for rents. There are comparable differences in RMSE and MAE. The time-region dummy model, where the intercept in (1) changes every time period in each of the eleven regions listed in Table 1, has a marginally higher R^2 of 0.6909 for prices and 0.6746 for rents. We consider three further models; the time flexible model—which allows shadow prices to vary across time as well as including time-region dummy variables—the region flexible model—which allows parameters to change across regions—and finally the time-region flexible model which estimates separate parameters for each time and region. The R^2 for each of these models respectively is well below that for our preferred spline model for both prices and rents. This gives us some confidence that the more sophisticated Time-Spatial Smooth spline model is providing the best possible imputations of temporal price and rent trends for a diverse range of homes.

3.2 Hedonic Imputation Results

We used the estimated Time-Spatial Smooth spline hedonic model to impute sales and rental prices. This was done for a random sample of 10,000 properties drawn from the homes that are observed to sell in Sydney over our sample. The complexity of the models and size of the data meant that it was infeasible to impute prices for all 435,501 unique properties which were observed to sell. Our sample of 10,000 properties is significant however. Prices and rents were imputed from 2002Q1 up until 2014Q4.

We construct aggregate city-wide indexes by taking the mean of imputed log price and rent changes each period. We also construct total returns—the sum of the quarterly price gain and the rental yield. Note that unlike shares or bonds there are running costs (e.g. maintenance and repairs, insurance and taxes) associated with home ownership. Harding, Rosenthal and Sirmans (2007) estimate these at around 2.5% per annum for

homeowners in the US. Unfortunately there has not been comparable work done for Australia—though our inclination is that the running costs are likely to be broadly similar. Given this we use Harding, Rosenthal and Sirmans (2007) estimate of 2.5% running costs per annum and adjust our calculated total returns accordingly.

The quarterly log price and rent changes, and the total returns each quarter, are shown in Figure 2 and also in index form. These are averages across the 10,000 homes for which we imputed prices and rents. We explored various methods of averaging these values across homes—such as value weighting or taking the median—but it made very little difference to the resulting numbers.[5]

⟨⟨ *Insert Figure 2 here* ⟩⟩

It can be seen that over the period, from 2002Q1 to 2014Q4, Sydney exhibited some significant house price dynamics. There was a boom in prices in the early 2000s followed by a modest decline from 2004 through to 2007. There was a small rise in prices in late 2007 and then a dip as a result of uncertainty around the global financial crisis (GFC) in 2008. Australia's economy was only modestly effect during the GFC and house prices jumped as this became apparent. Prices were relatively stable from 2010 but rose strongly starting in 2012. These trends in Sydney house prices are consistent with other publicly available indexes of the city's real estate prices. For example, the ABS (2016) index of house prices is quite similar in terms of trends to the index we have constructed. The cycles in housing prices are echoed in rents though they grow at a much steadier rate than do prices. Overall, rents and housing prices increased by broadly similar amounts from 2002Q1 to 2014Q4—prices rose by 90.84% while rents increased 80.22%. But this masked significant deviations at different points as a result of the more haphazard growth in prices. The index of total returns rose by 133.13% over the period or an impressive 6.64% per year.

Now turning to the disaggregated price trends. The estimated spline model provides unique imputations for price and rent trends, and hence total returns, for each of the 10,000 sampled homes. These imputations do vary, often quite significantly, based on the characteristics of the home. We can illustrate the diversity of price trends across property types by considering the cross-sectional distribution of price changes at different points in time. Figure 3 plots histograms of price change, rent change and total returns for two quarters; 2008Q3 and 2010Q3. It can be seen that there is significant dispersion in the imputations and moreover the distribution of price and rental changes, as well as total returns, shifts over time.

[5] This is consistent with the results in Melser (2017b) who finds that weighting has only a modest impact on aggregate price change in housing price indexes.

⟨⟨ *Insert Figures 3 here* ⟩⟩

We can also consider the diversity of price trends by looking at average price changes, rental yields and total returns for specific types of dwellings. Figure 4 plots changes for four regions for houses with 3 bedrooms, 2 bathrooms and land area between $400m^2$ and $1000m^2$. It can be seen that while the overall dynamics are quite similar there are some quite large differences in certain quarters. For example, price growth was strongest in Lower Northern Sydney and Canterbury-Bankstown, rental growth was strongest in the Eastern Suburbs and total returns were highest in St George-Sutherland though, interestingly, were quite similar across regions.

⟨⟨ *Insert Figures 4, 5 and 6 here* ⟩⟩

Figure 5 illustrates price trends for 2- and 5-bedroom houses in the Eastern Suburbs. The overall appreciation rate is broadly similar—at least until the last couple of years. However, it can be seen that prices for smaller homes appear to be more volatile than for larger houses, particularly early in the sample. Figure 6 considers the price trends for houses and apartments in the Lower Northern Sydney region. Houses appear to have had a considerably higher appreciation rate compared with apartments but they also look to be significantly more volatile. There is also a large difference in the yield for houses compared with apartments—the latter has a considerably higher rental yield.

In Table 3 we provide summary statistics for the price and rent changes as well as the total return and rental yield across various dimensions from 2002Q1 to 2014Q4. We can see here that the dynamics of the total return is mostly driven by the capital gain—on average more than half of total return comes from price change, which is relatively volatile. The rental yield contributes a smaller, though certainly non-trivial, amount to total returns but is an order of magnitude more stable. These aggregate statistics also provide more general evidence for a significant difference between the rental yields on houses compared with apartments. For houses the rental yield averages around 3.83% per year whereas for apartments it is 4.59% per annum. This differential is broadly consistent with what others have found. Both Bracke (2013), for a matched sample of London homes, and Hill and Syed (2012), for Sydney, find lower yields for houses than apartments. Bracke (2013) finds that the rental yield for houses is around half a percent lower than for apartments. This is similar, though a bit smaller, than our estimate of 0.76%. However, note that the capital appreciation has been lower for apartments than housing. This means we find that the average total return over the entire period was roughly comparable for the two property types—7.33% for apartments compared with 7.97% for apartments.

⟨⟨ *Insert Table 3 here* ⟩⟩

There are very significant differences in returns over time. In 2002 returns averaged 21.69% per annum—2013 and 2014 were also very good years. But the worst year saw total returns of -3.43% per annum in 2004. The regional aggregates are also interesting because they illustrate non-trivial differences in total returns. Fairfield-Liverpool had the highest return over the period of 10.62% per year while the lowest return was for the Eastern Suburbs which returned 6.65%.

Overall these results are strongly suggestive of housing return dynamics which are driven systematically by the nature of the property. It is the underlying drivers of the dispersion in real estate returns and issues of diversification to which we now turn.

4 Housing Risk, Return and Diversification

We use the imputed total returns for each of the 10,000 homes randomly selected from our data to examine the investment characteristics of housing. It is particularly instructive to do this in the context of the returns to shares. Because much prior analysis of the sort we are doing for housing has been done in the context of shares the analogy is useful. Contrasting the results for housing with shares also provides a basis for considering the relative magnitudes of risk and return and the benefits to diversification.

With housing and equity returns data we turn to three issues. We first consider the dispersion in the total returns to housing and compare this with that for shares. In doing so we use the (ex post) Sharpe ratio as a way of efficiently summarizing risk and return into a single measure (Sharpe, 1963). This is calculated for asset i as,

$$SR_i = \frac{\bar{R}_i - \bar{R}_f}{\sigma_{if}} \tag{3}$$

Here $\bar{R}_i$ is the return on asset i (which may be a particular home or share). The risk free rate ($\bar{R}_f$) that is used is the total return on the 3-Month Overnight Index Swap Rate.[6] The standard deviation of the net return, $\bar{R}_i - \bar{R}_f$, is represented by σ_{if}. Second, in addition to examining dispersion in returns we decompose risk, return and the Sharpe ratio based upon the characteristics of the home. This enables us to identify the drivers of differences in these investment outcomes. Third, we explore the benefits of diversification of housing investment holdings and contrast these benefits to that for equities.

[6]The data is also from SIRCA, like the equity data. This is the series chosen by SIRCA to best represent the risk free rate of return in Australia.

4.1 Dispersion in Risk and Return

The average rate of return on housing outlined above conceals a very significant degree of dispersion in returns. This can be seen by examining the distribution of the cross section of total returns across the 10,000 homes in our sample. Table 4 reports the mean as well as various percentiles of the distribution of quarterly total returns and the Sharpe ratio over the period 2002Q1 to 2014Q4.

⟨⟨ *Insert Table 4 here* ⟩⟩

While the mean quarterly total return was 1.74% there was considerable variation. The 5th percentile was 1.20% while the 95th percentile was 2.33%. In contrast, the distribution of total returns for the 200 largest companies listed on the ASX has a much higher mean, 4.45% and an even greater spread in total returns. The 5th percentile is 0.77% while the 95th percentile is 10.43%. As outlined, a useful way to compare the risk-adjusted return on housing and shares is to examine the Sharpe ratio. This paints an interesting picture of the relative attractiveness of housing compared with shares. On average housing has a higher risk-adjusted return than do individual shares; 0.2294 compared with 0.1573. This reflects the much lower variance in housing returns compared with shares. However, housing has a roughly comparable dispersion in the Sharpe ratio to that for shares. The 5th percentile is 0.0213 compared with -0.0173 for shares while the 95th percentiles are 0.4275 and 0.3562 respectively. This is an interesting feature of the investment profile of housing. The fact that the spread in total returns is higher for shares than housing but that this is reversed for the Sharpe ratio implies a weaker correlation between risk and return for housing than shares. This fact was noted by Han (2013) who examined the puzzling divergence between risk and return in certain housing markets. She argued that this can be explained by the fact that housing fulfils the dual roles of an investment and consumption good. Because everyone requires somewhere to live households may be willing to accept a lower return now if buying a home hedges them against future shelter price risk. Our results for Sydney housing returns reinforce those of Han (2013).

4.2 The Drivers of Risk and Return

There is clearly significant dispersion in the total returns, variance of total returns and Sharpe ratios, for different homes. For investors and prospective homeowners it is important to understand the investment characteristics of different property types before they make a decision to purchase. This is even more so the case given the large transaction costs involved in buying and selling a property—related both to information acquisition

and transaction taxes. We now investigate, using a regression framework, the observable drivers of the investment characteristics of individual homes.

There are two general types of regressors in our models; physical characteristics and financial characteristics. Included in the former grouping are structural and locational characteristics—house or apartment, property size (reflected in the number of bedrooms and land area) and region. While the financial characteristics are the lagged price level of the home and dependent variable. We estimate models for the three key investment characteristics; total return, the standard deviation of total return and the Sharpe ratio. In each case we estimate two models. The first, called model [A], includes just the physical characteristics of the properties. The second, model [B], includes both the physical and financial characteristics. In order to avoid simultaneity we estimate this latter model over total returns, standard deviation and the Sharpe ratio calculated from 2003Q1 onwards. The value of the lagged price and lagged dependent variable included in these models are from 2002Q1 to 2002Q4. The advantage of model [B] is that it enables us to examine whether liquidity plays a role—for example, whether higher priced homes have higher returns because there is less ability of investors with limited means to arbitrage. Including the lagged value of the dependent variable also enables us to examine whether momentum or mean reversion plays a role.

Importantly, we account for the estimation uncertainty in the dependent variable in each of these regressions using a bootstrap approach. We have an estimate of the variance of total returns for each home in each period. This is used to randomly simulate errors which are added to total returns, the various variables are calculated using the bootstrapped dependent variable and the model is estimated. This is done 1,000 times and the confidence intervals are derived using the distribution of estimated coefficients. The results are shown in Table 5.

⟨⟨ *Insert Table 5 here* ⟩⟩

Let us examine the results by the particular characteristic. First to the effect of structure type and the related effect of land area. In both models [A] and [B] for total returns there is a positive, and significant, coefficient on houses indicating they experienced a higher returns than did apartments. However, when considering the effect of houses we also need to take account of the fact that houses—by definition—have land associated with them whereas apartments do not. We have included a land area coefficient in our model and for total returns it has a negative coefficient. This indicates that houses with larger land areas had weaker returns. The question then is the size of the net effect. The average land area (refer to Table 1) is 0.31. This means that according to our model the average house recorded returns which exceeded those for apartments

with a net effect equal to around 0.0008 ($= 0.0012 - 0.0013 \times 0.31$). Examining the model of the standard deviation of returns, there is some evidence that the risk was higher for houses. This reflects a positive coefficient on the houses dummy in [A] and a positive coefficient on land area in [A] and [B]. However, when we examine the drivers of the Sharpe ratio we find somewhat ambiguous effects for houses compared with apartments. We again need to take account of the fact that houses are associated with land as the coefficients on the house dummy and on land have opposite signs. In model [A] for the Sharpe ratio we find a net effect for the average house of -0.0093 ($= 0.0144 - 0.0765 \times 0.31$) while for [B] it is 0.0197 ($=0.0413 - 0.0698 \times 0.31$). Thus while risk and return appears clearly higher for houses the effect of structure on the risk-adjusted return—reflected in the Sharpe ratio—is somewhat ambiguous.

Turning to region; the effects of this variable are clearly important judging by the size and significance of the coefficients. However, the coefficients are somewhat volatile across the [A] and [B] models. This is likely to primarily reflect the large differences in average price levels across these regions. What is clear, however, is that there are big region effects. For example, in model [A] for the Sharpe ratio the effect of -0.0874 for the Eastern Suburbs compared with 0.0904 for Inner Sydney. These are large effects in the context of an average Sharpe ratio for housing of 0.2294 (refer to Table 4). The other non-financial characteristic is the number of bedrooms—a proxy for the size of the structure. Interestingly, this does not appear to have played a particularly strong role in driving either risk or return. Though the coefficients are significant in all cases the size of the effect is not economically significant.

The financial characteristics—the price level and dependent variable for 2002—play important roles. Their inclusion leads to a large jump in the R^2 (though note the models are not nested as they use different data as discussed above). The log price level variable in particular has a very clear impact. It lowers returns, raises risk and lowers the Sharpe ratio. Remember, from Table 1, that the average price of a home is around $740,000 meaning the average log price is roughly 13.5. This means that a home which costs $1,000,000 (or 35.14% more than the average) has a Sharpe ratio which is lower by around -0.0928. This is clearly significant in the context of an average Sharpe ratio for housing of 0.2294. The other financial characteristics are the average value of the dependent variable in 2002 while the models are estimated over data from 2003. They provide some insight into whether mean reversion of momentum plays a role in the housing market. Interestingly, we find the coefficient on lagged total returns is negative while it is positive for the standard deviation and the Sharpe ratio. All coefficients are significant. This implies that total returns are somewhat mean reverting while momentum appears to play a greater role for the two other characteristics. However, overall these effects

appear somewhat limited. For the Sharpe ratio the coefficient of relatively small at just 0.0014. When multiplied by the average Sharpe ratio this leads to a small effect on the future Sharpe ratio.

4.3 Housing and Diversification

A key issue with housing investment is the question of diversification. As noted, housing is usually a significant part of most households portfolios. Yet the housing asset holding is invariably a single home meaning that household's holdings of housing are highly undiversified. This reflects the fact that there are few products which enable owners to diversify their holdings. Of course if the household is particularly wealthy then they can purchase a number of properties. This option is unlikely to be available to most households. Another possibility is Real Estate Investment Trusts (REITs), which are increasingly available as investment vehicles for households who may wish to hold a wider portfolio of property. However, there are two problems with REITs in this context. First, REITs often invest in non-residential property such as commercial, retail or industrial real estate. There is less clarity about price movements and returns for these asset classes than for residential. Second, for most homeowners, because they have such a large amount already invested in their home, it will likely be more prudent to invest in another asset class than real estate. Related options to limiting housing exposure have been explored. For example, Case, Shiller and Weiss (1993) proposed a housing insurance contract for owners where they would receive any shortfall between the purchase price and the selling price predicted by an aggregate housing index. But such contracts have proved surprisingly unpopular with homeowners.

The fact that homeowners, for the most part, do not diversify, insure or hedge their housing holdings raises a number of issues about the benefits of such contracts. An important question is the extent to which this lack of diversification imposes costs on households. Viewed from another perspective, the lack of such diversifying products—and the limited uptake of those that do exist—may reflect the limited benefits to homeowners of diversification. We investigate this.

A useful way of exploring the benefits of diversification is to look at how the Sharpe ratio changes as the portfolio size increases. The Sharpe ratio provides a summary measure of the risk-adjusted return. A higher Sharpe ratio means that a higher return can be achieved at a given variance. For both housing and equities we randomly select either homes or shares to create a portfolio of different sizes for each asset class. From this we construct the Sharpe ratio for each portfolio. We do 1,000 replications for each portfolio size and then average the Sharpe ratios. These are presented in Table 6

⟨⟨ *Insert Table 6 here* ⟩⟩

The results are particularly instructive regarding the benefits of diversification for homeowners. For those who own a single home the Sharpe ratio is on average 0.1977. This compares with 0.1614 for shares. As we increase the size of the portfolio of homes or shares the Sharpe ratio invariably increases. The most insightful feature of the results is the relative extent to which it increases for homes compared with shares. For our largest-sized portfolio of 200 holdings the Sharpe ratio for housing has risen to 0.2558 compared with 0.3214 for shares. This amounts to a 29.37% rise in the Sharpe ratio for housing compared with a 99.13% for shares. This points to the relatively modest gains from diversification in the area of housing compared with that for shares.

Another way of examining the benefits of diversification for homeowners is to look at this issue within a portfolio allocation framework. In particular we consider how much the owner gains from access to the opportunity to invest in a diversified portfolio of homes compared with only being able to invest in a single home.

Consider an investor who can choose the shares of the following portfolio elements in order to maximise their expected utility; (1) housing, (2) equities, (3) a risk free asset. We proceed in two steps. First we suppose that an investor has access to; (1A) an individual home, (2B) an equity index, and (3) a risk free asset. Given these three assets we calculate the optimal portfolio weights for each asset and the utility level which results. We do this for each home in our data set. In the second step we add a fourth asset; (1B) a diversified portfolio of homes. Given this we again run the optimisation for each home in our data set and obtain the optimal weights and utility level. We can compare the weight of housing in the first case, which we call case [A], with that in the second step, case [B]. We also examine the gain in utility in [B] compared with [A]. This provides some insight into the gains from being able to diversify one's real estate holdings. For a point of comparison we proceed analogously for shares. First we allow investors access to the following assets; (1B) a diversified portfolio of homes, (2A) an individual share, and (3) a risk free asset—this is called case [C]. In a second step, case [D], we add (2B) a diversified portfolio of shares.

The portfolio optimisation framework we develop is fairly standard. We base it on the widely used power utility function. This has the Constant Relative Risk Aversion (CRRA) property which means that portfolio allocation decisions are independent of the level of wealth. It also has the advantage of being tractable. That is, we suppose the utility function over wealth (W) has the following form where γ is the parameter which

determines the level of risk aversion,

$$\mathrm{U}\left(W\right) = \begin{cases} \frac{W^{1-\gamma}}{1-\gamma}, & \gamma \neq 1 \\ \ln(W), & \gamma = 1 \end{cases} \tag{4}$$

The literature points towards a value of γ that is greater than one and less than around 10 (see Attanasio, Banks and Tanner, 2002; Vissing-Jorgensen, 2002). According to Hasanov and Dacy (2009) a value of 4 or 5 leads to portfolios that are broadly similar to those observed in practice. Given this we will undertake our portfolio allocation problem for various values of γ equal to; 2, 4 and 8. The higher the value of γ the larger is the degree of risk aversion.

In the Online Appendix B we show that this results in a mean-variance portfolio optimisation problem where the object we seek to maximise is shown below,

$$\log \mathrm{E}_t \left[U(W_{t+1})\right] = \mathrm{E}_t \left[\log(1 + r_{pt+1})\right] + \frac{(1-\gamma)}{2} \mathrm{Var}\left(\log(1 + r_{pt+1})\right) \tag{5}$$

In the case that we will consider there are multiple assets yielding the portfolio return, r_{pt+1}, with the choice parameters being the weights vector ($\mathbf{w}$),

$$r_{pt+1} = \mathbf{w}^T \mathbf{r}_{t+1} \tag{6}$$

For take an ex post approach to portfolio optimisation of (5) and use historical returns and covariances in the model. This leads to a nonlinear optimisation problem. Though it can be solved quite quickly given the small number of unknown parameters.

The portfolio allocation problem is run several times. First, in case [A], we consider the problem of portfolio weights when each of the individual homes in our data form the role of the housing asset. This yields 10,000 different sets of weights—one for each housing series we examine. Second, in [B], we undertake the same exercise but with the addition of a aggregate housing index as an investment option. We proceed similarly for shares. In [C] we include an aggregate housing index along with a risk free asset and each individual shares in turn. This gives 200 sets of portfolio weights. Finally in [D] we add a aggregate share index to the set of investment options in [3]. These scenarios are run for each value of γ The results are reported in Table 7.

⟨⟨ *Insert Table 7 here* ⟩⟩

The results provide some insight into the benefits of diversification for housing. Let us focus on the results for $\gamma = 4$. In the case of [A]—where the assets are each individual property (of which there are 10,000), an aggregate share index and a risk free asset—we

see the average weight for individual homes being 36.20%, 61.74% for the aggregate share index and 2.06% for the risk free asset. When we make an aggregate index of homes available to investors in [B] the share of individual homes drops to 25.19% with 16.82% being invested in the aggregate index on average and the amount invested in the share index and the risk free asset dropping somewhat. While there are significant changes in portfolio weights—with the total weight on housing rising to 42.01%—the gain in utility in [B] compared with [A] is small; just 0.03%. This is readily compared with the gain in utility in [C] compared with [D]. In the former case investors can allocate their portfolio between an aggregate housing index, individual shares (of which there are 200) and a risk free asset. For [C] the weight on individual shares is equal to 15.00% on average. When investors also have available a share index in [D] the weight on individual shares drops to 7.09% but the weight on aggregate shares is equal to 55.59 on average—a massive rise in the combined allocation to equities. Importantly, this leads to a rise in an investor's utility of 0.41% on average. This is an order of magnitude larger than the gain from housing diversification. These results provide support for the conclusion that the gains from diversifying residential real estate holdings are somewhat limited in comparison with that for equities.

The results for the other values of γ—2 and 8—further support this conclusion. In both cases the utility gains are much larger in terms of diversification for shares than they are for housing. The gains are particularly large for more risk tolerant investors, those with $\gamma = 2$, who are able to access a share index. This is because such investors will have a high proportion of their assets in the high risk-high return asset which in shares. Risk averse investors, those with $\gamma = 8$, gain relatively less from accessing a share portfolio and relatively more from the portfolio of homes than was the case for $\gamma = 4$. Though in absolute terms the gains from having access to the share portfolio are still much larger than for the portfolio of homes.

5 Conclusion

The emergence of housing bubbles around the world—and their subsequent crash—has shown just how important an asset class is residential real estate and just how poor is our understanding of it. The purpose of this paper has been to show that it is possible to construct real estate price indexes at a disaggregated level—in fact at the level of the individual home. Using these indexes we can understand the financial characteristics of home ownership. This enables us to answer some of the most basic questions around residential real estate; what is the risk and return for different types of housing investments and what are the benefits to diversification.

Using sale price and rent price data from Sydney, Australia's largest city, we estimated total returns for a sample of homes from 2002Q1 to 2014Q4. Using this data we investigated housing risk, return and the possible benefits of diversification. Our results show that there is significant heterogeneity in housing returns across properties. Though this is not as significant as the heterogeneity seen for shares which are both higher risk and higher return. However, on a risk-adjusted basis the average Sharpe ratio for housing exceeded that for shares over our sample. Though, interestingly, we find a weaker correlation between risk and return for housing than for shares. In order to try and identify the drivers of housing risk and return we estimated models of these factors on the characteristics of each property. This showed that houses exhibit both higher returns and also higher risk than do apartments. There was significant variation in returns across regions indicating diversity in the role that amenities are likely to play over time in determining returns. With this data we were also able to explore the key issue of diversification in housing markets. A key question is the financial cost imposed on households as a result of the fact that they usually hold a highly undiversified portfolio of residential real estate—i.e. usually a single home. We construct various portfolio optimisation problems where we compare utility and allocation weights when households are able to, first, invest just in a single home and, second, invest also in an aggregate portfolio of homes. A similar problem is setup for shares. Interestingly, we find that the benefits of being able to invest in a portfolio of homes are small compared with the benefits of being able to invest in a portfolio of shares. This explains the relatively modest success of investment products aimed at diversifying or insuring household's residential real estate holdings. Overall, the approach outlined and the illustration provide some useful insights to prospective homebuyers and investors who must decide what property to buy and hence what risk and return profile to enjoy.

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Table 1: Summary Statistics

By	Dimension	No. of Obs.	House		Price ($)†		Land Area (1000m^2)		Bedrooms		Bathrooms	
			Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
					Home Sale Prices							
Structure	Apartment	197,695	0.00	0.00	541,807	362,895	0.00	0.01	1.99	0.62	1.35	0.51
	House	351,809	1.00	0.00	852,357	565,614	0.73	0.61	3.41	0.90	1.79	0.79
Years	2000	4,783	0.80	0.40	750,027	516,386	0.55	0.52	3.43	0.99	2.11	0.71
	2001	8,692	0.78	0.41	759,385	514,045	0.53	0.52	3.34	1.01	2.05	0.72
	2002	9,470	0.76	0.43	885,159	591,799	0.50	0.53	3.26	1.05	2.00	0.75
	2003	11,833	0.73	0.44	896,499	593,100	0.48	0.52	3.21	1.05	1.93	0.74
	2004	13,511	0.71	0.45	843,589	571,507	0.48	0.53	3.14	1.03	1.85	0.75
	2005	31,631	0.67	0.47	666,928	488,207	0.45	0.54	2.92	1.03	1.61	0.73
	2006	39,837	0.66	0.47	651,853	498,514	0.45	0.56	2.89	1.03	1.59	0.72
	2007	50,118	0.65	0.48	676,242	527,377	0.45	0.57	2.87	1.03	1.58	0.71
	2008	44,019	0.63	0.48	639,523	492,758	0.45	0.59	2.82	1.04	1.56	0.71
	2009	59,595	0.61	0.49	641,654	471,943	0.45	0.62	2.80	1.04	1.55	0.70
	2010	55,643	0.63	0.48	741,221	526,352	0.46	0.61	2.86	1.06	1.59	0.72
	2011	58,962	0.59	0.49	709,052	484,806	0.45	0.64	2.79	1.06	1.58	0.71
	2012	48,063	0.64	0.48	753,540	487,796	0.48	0.63	2.91	1.07	1.64	0.73
	2013	57,178	0.63	0.48	822,419	528,410	0.48	0.64	2.92	1.09	1.66	0.74
	2014	56,169	0.63	0.48	939,390	570,605	0.47	0.63	2.93	1.10	1.66	0.74
Region	Blacktown	32,791	0.94	0.24	402,845	144,860	0.70	0.68	3.31	0.75	1.46	0.59
	Canterbury-Bankstown	36,256	0.73	0.44	512,831	221,607	0.53	0.62	2.95	0.92	1.46	0.66
	Central Northern Sydney	71,326	0.85	0.36	842,500	461,231	0.81	0.64	3.59	0.98	2.09	0.78
	Central Western Sydney	47,089	0.62	0.49	461,719	192,857	0.53	0.74	2.78	0.90	1.49	0.62
	Eastern Suburbs	51,809	0.46	0.50	1,087,151	785,816	0.19	0.33	2.64	1.05	1.59	0.76
	Fairfield-Liverpool	32,501	0.85	0.36	426,801	160,586	0.60	0.60	3.26	0.89	1.55	0.68
	Inner Sydney	65,068	0.47	0.50	733,939	449,366	0.14	0.33	2.21	0.93	1.42	0.58
	Inner Western Sydney	29,788	0.52	0.50	790,407	484,271	0.33	0.49	2.74	1.02	1.62	0.70
	Lower Northern Sydney	63,873	0.51	0.50	950,088	676,416	0.37	0.55	2.70	1.07	1.63	0.73
	Northern Beaches	48,506	0.61	0.49	920,464	567,839	0.45	0.53	2.97	1.14	1.77	0.78
	St George-Sutherland	70,497	0.65	0.48	659,791	361,712	0.51	0.61	2.95	1.03	1.62	0.74
Total		549,504	0.64	0.48	740,631	523,846	0.46	0.60	2.90	1.06	1.63	0.73
					Home Rents							
Structure	Apartment	679,464	0.00	0.00	470	212	0.00	0.00	1.82	0.61	1.25	0.44
	House	464,070	1.00	0.00	581	302	0.76	0.73	3.06	0.87	1.53	0.68
Years	2002	10,430	0.40	0.49	416	237	0.27	0.57	2.28	0.93	1.34	0.56
	2003	26,764	0.43	0.49	396	228	0.31	0.60	2.32	0.93	1.33	0.55
	2004	41,043	0.44	0.50	381	216	0.34	0.63	2.37	0.92	1.34	0.56
	2005	81,621	0.41	0.49	392	222	0.32	0.61	2.33	0.92	1.34	0.55
	2006	89,820	0.41	0.49	409	236	0.31	0.61	2.32	0.94	1.34	0.56
	2007	83,272	0.44	0.50	455	253	0.33	0.61	2.36	0.95	1.37	0.58
	2008	84,766	0.45	0.50	519	276	0.34	0.61	2.38	0.97	1.39	0.59
	2009	105,090	0.41	0.49	520	255	0.30	0.58	2.32	0.96	1.37	0.59
	2010	105,569	0.41	0.49	534	249	0.30	0.59	2.32	0.95	1.35	0.57
	2011	126,201	0.39	0.49	559	256	0.30	0.61	2.30	0.95	1.37	0.57
	2012	126,106	0.40	0.49	571	255	0.31	0.59	2.32	0.96	1.37	0.58
	2013	128,353	0.39	0.49	580	250	0.29	0.58	2.30	0.95	1.37	0.57
	2014	134,499	0.37	0.48	591	245	0.28	0.57	2.28	0.95	1.37	0.56
Region	Blacktown	49,363	0.88	0.33	352	108	0.73	0.81	3.05	0.75	1.33	0.51
	Canterbury-Bankstown	61,539	0.54	0.50	383	127	0.41	0.61	2.53	0.82	1.24	0.49
	Central Northern Sydney	91,598	0.70	0.46	580	278	0.71	0.77	3.11	1.03	1.80	0.72
	Central Western Sydney	105,332	0.47	0.50	379	118	0.45	0.75	2.44	0.79	1.36	0.54
	Eastern Suburbs	147,227	0.23	0.42	628	319	0.10	0.30	2.10	0.84	1.28	0.53
	Fairfield-Liverpool	49,270	0.74	0.44	364	109	0.57	0.68	2.89	0.85	1.32	0.53
	Inner Sydney	213,459	0.29	0.45	547	249	0.10	0.33	1.83	0.81	1.27	0.48
	Inner Western Sydney	75,346	0.32	0.47	489	198	0.24	0.52	2.26	0.82	1.38	0.55
	Lower Northern Sydney	175,505	0.26	0.44	558	288	0.21	0.54	2.12	0.89	1.34	0.55
	Northern Beaches	74,127	0.36	0.48	635	316	0.28	0.51	2.35	1.04	1.44	0.66
	St George-Sutherland	100,768	0.45	0.50	454	165	0.39	0.62	2.45	0.86	1.36	0.57
Total		1,143,534	0.41	0.49	515	259	0.31	0.60	2.32	0.95	1.36	0.57

† For rents the price is measured as dollars per week.

Table 2: Hedonic Model Fit Statistics

	Time Smooth	Time-Spatial Smooth	Time-Dummy (τ_t,δ_c)	Time-Region Dummy (τ_{rt},δ_c)	Time Flexible (τ_{rt},δ_{tc})	Region Flexible (τ_{rt},δ_{rc})	Time-Region Flexible (τ_{rt},δ_{rtc})
				Home Sale Prices			
No. Obs.	549,504	549,504	549,504	549,504	549,504	549,504	549,468
No. Parms.	701	2,450	74	664	900	704	3,223
AIC	35,005	-24,001	264,959	260,537	246,426	188,010	177,374
R^2	0.7950	0.8171	0.6878	0.6909	0.6940	0.7079	0.7129
RMSE	0.2495	0.2357	0.3079	0.3063	0.3048	0.2978	0.2953
MAE	0.1785	0.1667	0.2253	0.2238	0.2226	0.2164	0.2147
% of Absolute Errors: <0.15	55.06	58.72	44.82	45.14	45.43	46.73	47.06
<0.30	83.50	85.45	74.08	74.40	74.64	76.15	76.47
<0.50	95.04	95.62	91.19	91.30	91.34	91.80	91.95
				Home Rents			
No. Obs.	1,143,534	1,143,534	1,143,534	1,143,534	1,143,534	1,143,534	1,143,531
No. Parms.	814	2,505	65	564	764	604	2,792
AIC	-368,203	-439,825	33,877	24,253	-5,713	-126,763	-154,874
R^2	0.7692	0.7839	0.6716	0.6746	0.6769	0.6887	0.6919
RMSE	0.2058	0.1992	0.2456	0.2444	0.2436	0.2391	0.2379
MAE	0.1501	0.1438	0.1797	0.1787	0.1780	0.1743	0.1733
% of Absolute Errors: <0.15	61.76	64.08	54.08	54.44	54.65	55.65	55.99
<0.30	88.73	89.53	82.71	82.91	82.97	83.72	83.86
<0.50	97.18	97.44	95.11	95.14	95.17	95.41	95.46

Note: No. Obs.=number of observations used in the estimation, No. Parms.=number of parameters in the model (or equivalent in the smoothing splines), R^2= the squared correlation coefficient between estimated and actual log prices, RMSE=Root Mean Squared Error, MAE=Mean Absolute Error, AIC=Akaike Information Criterion.

Table 3: Housing Return Summary Statistics for Sydney (% per annum)

			Price Change		Rental Yield		Total Return	
By	Dimension	No. of Obs.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Structure	Apartment	163,072	5.14	9.53	4.59	0.74	7.33	9.83
	House	356,928	6.55	16.13	3.83	0.75	7.97	16.50
Regions	Blacktown	31,772	7.94	31.82	4.62	0.86	10.24	32.79
	Canterbury-Bankstown	36,972	6.65	13.34	4.12	0.95	8.37	13.54
	Central Northern Sydney	76,180	6.24	11.80	3.96	0.59	7.77	11.91
	Central Western Sydney	43,420	6.42	12.30	4.38	0.95	8.41	12.54
	Eastern Suburbs	40,508	5.28	10.25	3.81	0.68	6.65	10.41
	Fairfield-Liverpool	33,800	8.39	21.87	4.55	1.11	10.62	22.60
	Inner Sydney	52,156	5.99	8.30	4.27	0.72	7.85	8.46
	Inner Western Sydney	28,704	5.51	10.66	3.65	0.81	6.72	10.80
	Lower Northern Sydney	54,236	5.50	9.24	3.76	0.65	6.81	9.35
	Northern Beaches	49,868	5.19	12.79	4.11	0.66	6.87	12.98
	St George-Sutherland	72,384	5.51	12.59	3.88	0.74	6.96	12.77
Years	2002	40,000	20.07	32.79	3.87	1.01	21.69	33.79
	2003	40,000	11.61	17.25	3.49	0.66	12.70	17.51
	2004	40,000	-4.28	10.42	3.36	0.63	-3.43	10.72
	2005	40,000	-2.97	7.54	3.66	0.57	-1.83	7.68
	2006	40,000	0.02	5.63	3.89	0.62	1.42	5.66
	2007	40,000	7.86	6.54	4.14	0.71	9.59	6.40
	2008	40,000	-2.89	6.28	4.50	0.85	-0.90	6.85
	2009	40,000	11.71	8.43	4.57	0.78	13.98	8.56
	2010	40,000	7.21	8.26	4.33	0.79	9.16	8.46
	2011	40,000	-0.07	6.37	4.41	0.72	1.87	6.72
	2012	40,000	2.68	4.92	4.49	0.69	4.73	5.07
	2013	40,000	14.31	6.32	4.33	0.68	16.34	6.31
	2014	40,000	14.12	7.14	3.87	0.65	15.64	7.25
Total		520,000	6.11	14.41	4.07	0.83	7.77	14.74

Table 4: The Distribution of Total Returns and the Sharpe Ratios (Quarterly)

		Housing	Shares
No. Obs		10,000	200
		Total Returns (%)	
Mean		1.74	4.45
Percentiles:	5th	1.20	0.77
	25th	1.54	2.52
	50th	1.74	3.59
	75th	1.95	5.40
	95th	2.33	10.43
		Sharpe Ratio	
Mean		0.2294	0.1573
Percentiles:	5th	0.0213	-0.0173
	25th	0.1470	0.0882
	50th	0.2344	0.1475
	75th	0.3085	0.2281
	95th	0.4275	0.3562

Table 5: Drivers of Risk and Return

Variable	Total Returns		Std. Dev. Total Returns		Sharpe Ratio	
	[A]	[B]	[A]	[B]	[A]	[B]
No. Obs.	10000	10000	10000	10000	10000	10000
R^2	0.3676	0.7247	0.3822	0.5000	0.3123	0.6421
Log Lik.	44504	48072	31232	35822	8273	10198
Dwelling Type						
Apartment	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
House	0.0012***	0.0024***	0.0005***	0.0000***	0.0144***	0.0413***
	(0.0003)	(0.0003)	(0.0004)	(0.0003)	(0.0037)	(0.0039)
Region						
Blacktown	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Canterbury-Bankstown	−0.0010	0.0008	−0.0163***	−0.0003***	0.0346***	0.0296***
	(0.0007)	(0.0005)	(0.0013)	(0.0006)	(0.0068)	(0.0071)
Central Northern Sydney	−0.0017**	0.0032***	−0.0224***	−0.0029***	0.0513***	0.1750***
	(0.0007)	(0.0005)	(0.0012)	(0.0006)	(0.0062)	(0.0067)
Central Western Sydney	−0.0007	0.0012**	−0.0170***	−0.0003***	0.0434***	0.0562***
	(0.0007)	(0.0005)	(0.0013)	(0.0006)	(0.0066)	(0.0068)
Eastern Suburbs	−0.0048***	0.0040***	−0.0181***	0.0019***	−0.0874	0.1624***
	(0.0007)	(0.0006)	(0.0012)	(0.0007)	(0.0065)	(0.0085)
Fairfield-Liverpool	0.0026***	0.0007	−0.0039	0.0022***	0.0412	−0.0543***
	(0.0008)	(0.0005)	(0.0017)	(0.0008)	(0.0068)	(0.0069)
Inner Sydney	−0.0019***	0.0050***	−0.0223***	−0.0005***	0.0904***	0.2603***
	(0.0007)	(0.0005)	(0.0012)	(0.0007)	(0.0062)	(0.0076)
Inner Western Sydney	−0.0046***	0.0022***	−0.0188***	0.0019***	−0.0688	0.1177***
	(0.0007)	(0.0005)	(0.0012)	(0.0007)	(0.0067)	(0.0079)
Lower Northern Sydney	−0.0041***	0.0039***	−0.0224***	−0.0011***	−0.0310***	0.2034***
	(0.0007)	(0.0005)	(0.0012)	(0.0007)	(0.0064)	(0.0081)
Northern Beaches	−0.0044***	0.0027***	−0.0190***	−0.0007***	−0.0396	0.1571***
	(0.0007)	(0.0005)	(0.0012)	(0.0007)	(0.0066)	(0.0078)
St George-Sutherland	−0.0042***	0.0005	−0.0162***	0.0001***	−0.0744*	0.0388***
	(0.0007)	(0.0005)	(0.0012)	(0.0006)	(0.0061)	(0.0068)
Land Area						
Apartment	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
House	−0.0013***	−0.0013***	0.0083***	0.0061***	−0.0765***	−0.0698***
	(0.0003)	(0.0003)	(0.0004)	(0.0004)	(0.0027)	(0.0028)
No. Bedrooms	−0.0004***	0.0015***	0.0000***	0.0001***	−0.0069***	0.0557***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0014)	(0.0018)
Log Price Level (in 2002)	—	−0.0084***	—	0.0012***	—	−0.3082***
	—	(0.0003)	—	(0.0004)	—	(0.0048)
Total Return (in 2002)	—	−0.0369***	—	—	—	—
	—	(0.0045)	—	—	—	—
Std. Dev. TR (in 2002)	—	—	—	0.1169***	—	—
	—	—	—	(0.0064)	—	—
Sharpe Ratio (in 2002)	—	—	—	—	—	0.0014***
	—	—	—	—	—	(0.0003)
Constant	0.0208***	0.1189***	0.0403***	0.0015***	0.2816***	3.9301***
	(0.0007)	(0.0041)	(0.0013)	(0.0049)	(0.0065)	(0.0554)

Table 6: Sharpe Ratio and Portfolio Size

	Portfolio Size							
	1	2	5	10	20	50	100	200
Homes	0.1977	0.2125	0.2254	0.2329	0.2378	0.2511	0.2542	0.2558
	(0.1486)	(0.1336)	(0.1060)	(0.0779)	(0.0618)	(0.0412)	(0.0283)	(0.0198)
Shares	0.1614	0.1885	0.2328	0.2728	0.2894	0.3095	0.3181	0.3214
	(0.1200)	(0.1031)	(0.0809)	(0.0603)	(0.0479)	(0.0301)	(0.0181)	(0.0000)

†Note: The mean Sharpe ratio is shown with its standard error in brackets.

Table 7: Portfolio Weights and Utility Gain

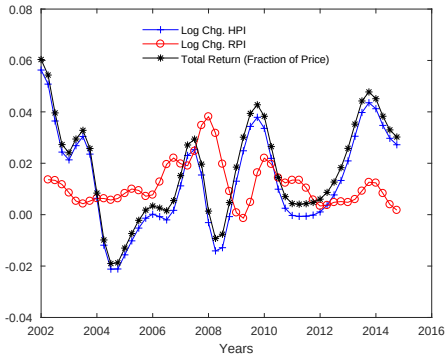
	$\gamma = 2$				$\gamma = 4$				$\gamma = 8$			
	[A]	[B]	[C]	[D]	[A]	[B]	[C]	[D]	[A]	[B]	[C]	[D]
Portfolio Weights (%)												
Homes	0.58	0.58	—	—	36.20	25.19	—	—	51.09	33.89	—	—
Aggregate Homes	—	0.00	60.66	0.00	—	16.82	85.00	37.33	—	37.28	87.53	70.41
Shares	—	—	39.34	17.62	—	—	15.00	7.09	—	—	6.88	3.09
Aggregate Shares	99.42	99.42	—	82.38	61.74	57.98	—	55.59	29.96	28.50	—	26.23
Risk Free Asset	0.00	0.00	0.00	0.00	2.06	0.00	0.00	0.00	18.95	0.33	5.59	0.27
Utility Gain (%)†		0.00		0.81		0.03		0.41		0.06		0.21

† This compares the utility from [B] vs [A] and from [D] vs [C].

Figure 1: Sydney's Regions

Figure 2: Aggregate Series for Sydney

(a) Changes



(b) Indexes

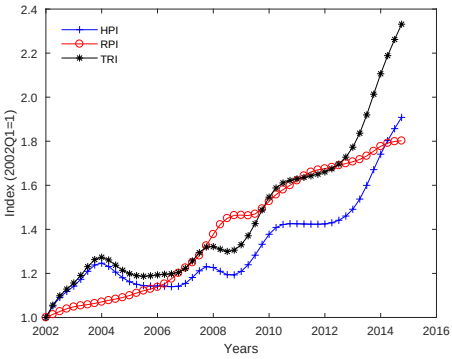
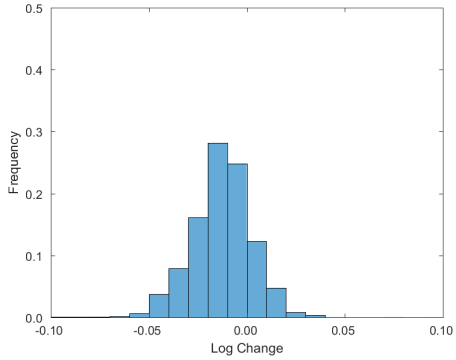
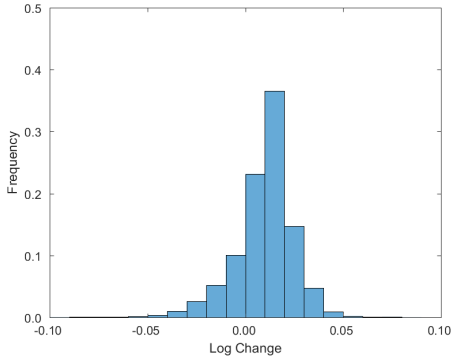


Figure 3: Histogram of Price and Rent Changes and Total Returns

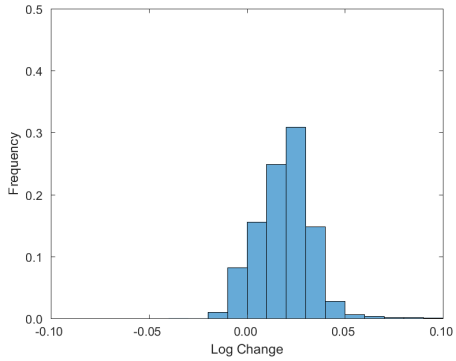
(a) 2008Q3: Log Price Change



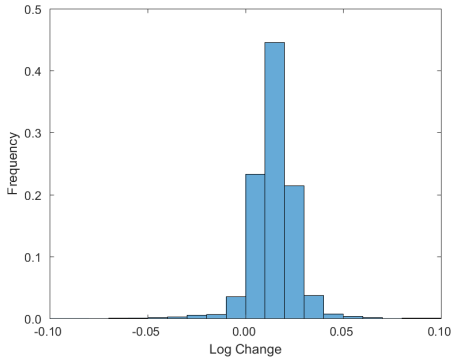
(b) 2010Q3: Log Price Change



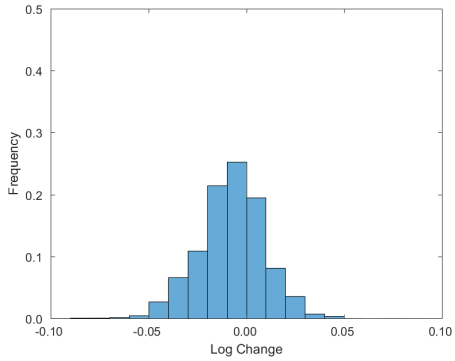
(c) 2008Q3: Log Rent Change



(d) 2010Q3: Log Rent Change



(e) 2008Q3: Total Returns



(f) 2010Q3: Total Returns

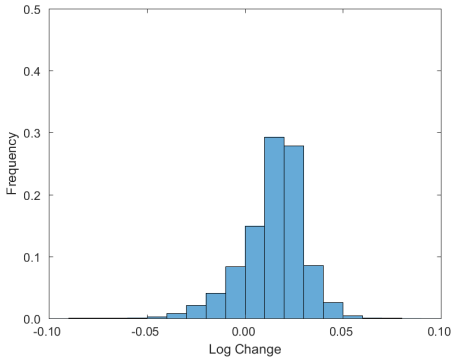
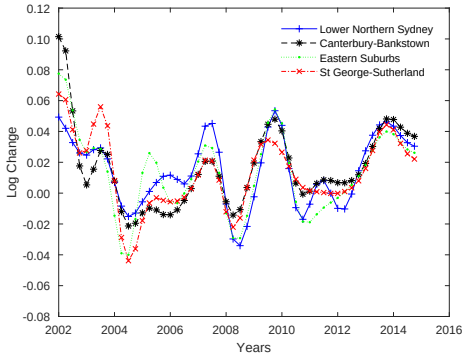
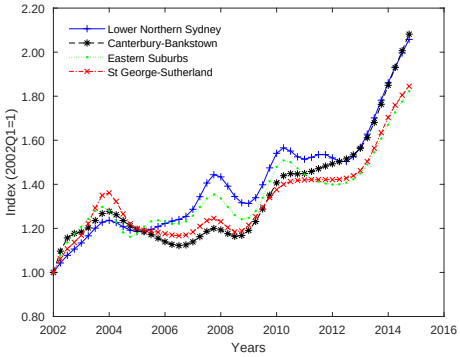


Figure 4: Comparing Houses Across Regions
(Mean for: House=1, Bedrooms=3, Bathrooms=2, Land Area $\in$ [400,1000])

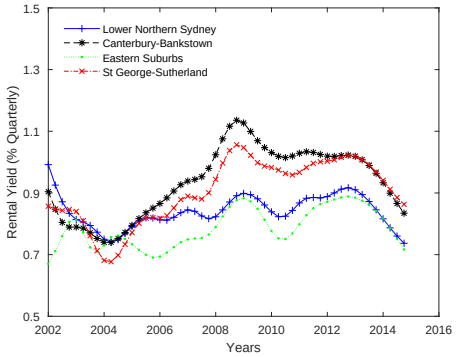
(a) Log Price Change



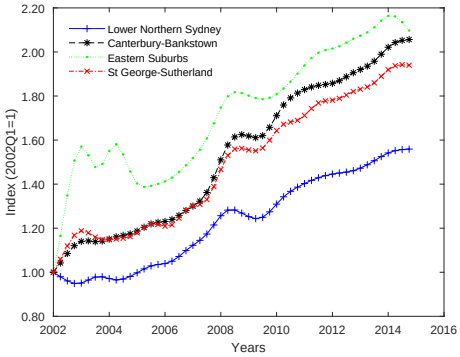
(b) Price Index



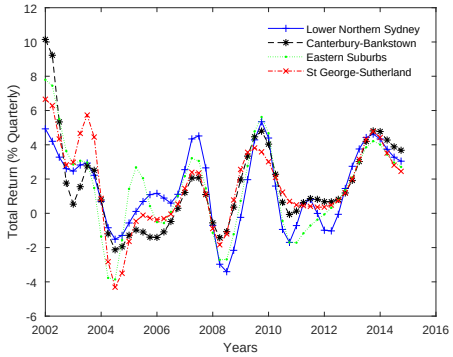
(c) Rental Yield



(d) Rental Index



(e) Total Return (%)



(f) Total Return Index

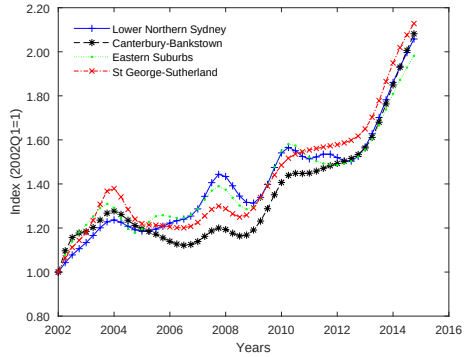
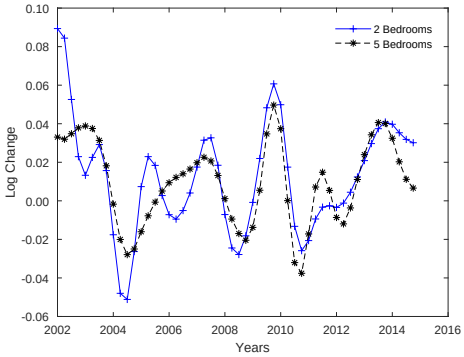
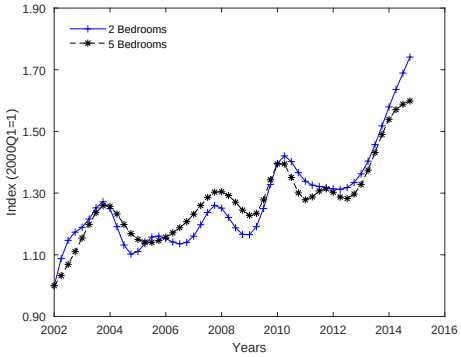


Figure 5: Comparing 2- and 5-Bedroom Houses
(Mean for: House=1, Land Area ∈ [400,1000], Region=Eastern Suburbs)

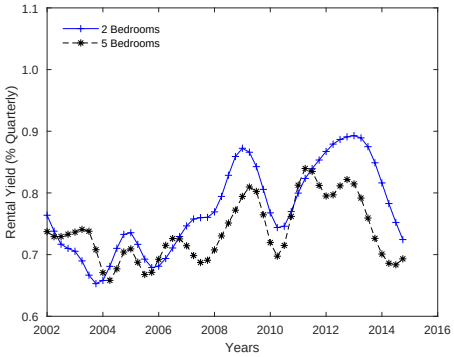
(a) Log Price Change



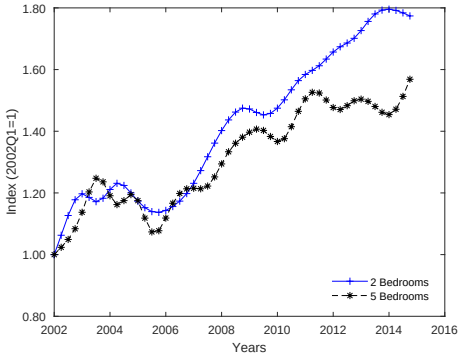
(b) Price Index



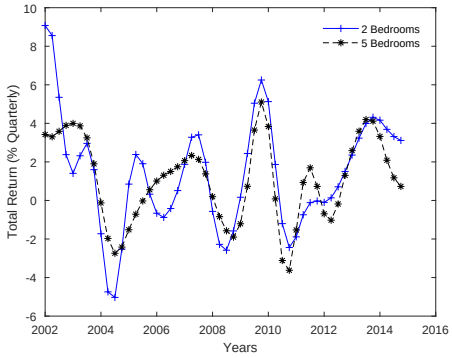
(c) Rental Yield



(d) Rental Index



(e) Total Return



(f) Total Return Index

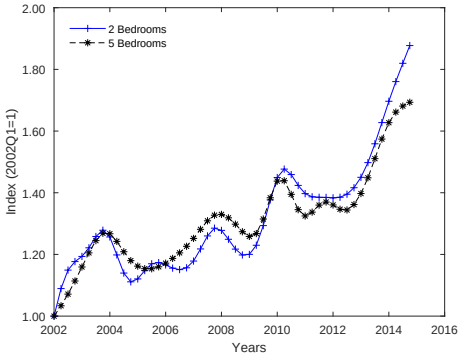
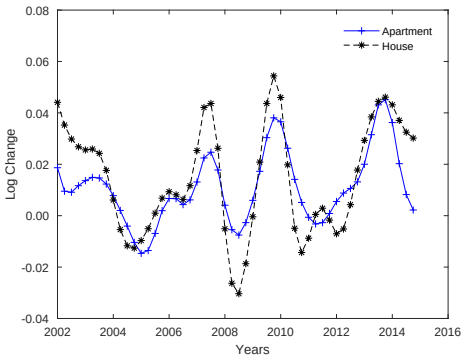
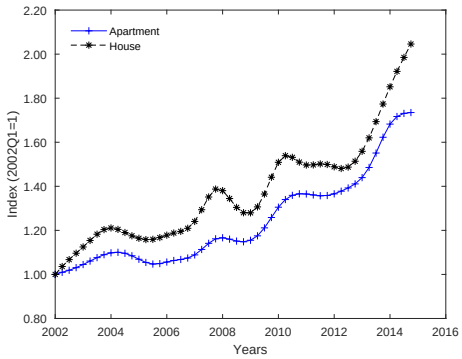


Figure 6: Comparing Houses and Apartments
(Mean for: Bedrooms ∈ [1,4], Bathrooms ∈ [1,2], Region=Lower Northern Sydney)

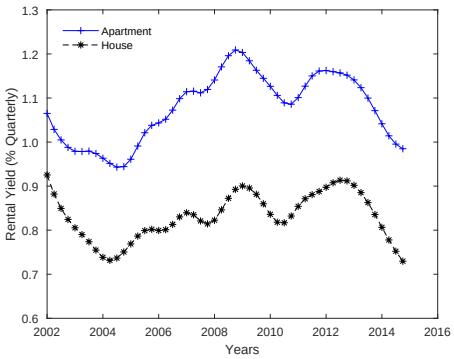
(a) Log Price Change



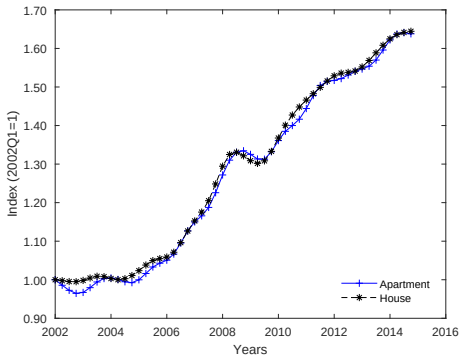
(b) Price Index



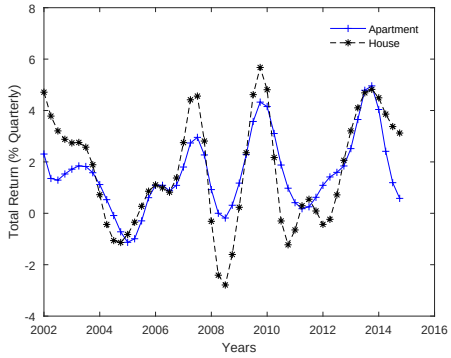
(c) Rental Yield



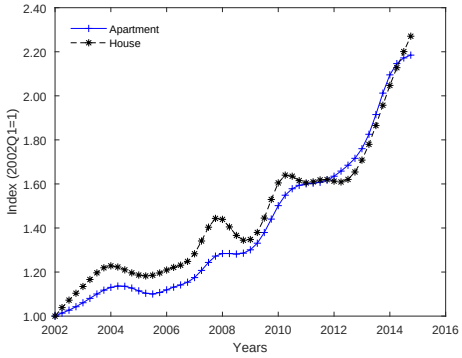
(d) Rental Index



(e) Total Return



(f) Total Return Index



A Online Appendix: List of Companies Used

Ticker	Company	Industry
AAC	Australian Agricultural Company Limited	Con. Staple
ABC	Adelaide Brighton Limited	Materials
AFI	Australian Foundation Investment Company Limited	Not Assigned
AGG	Anglogold Limited	Materials
AGS	Alliance Energy Limited	Materials
AHD	Amalgamated Holdings Limited	Con. Disc.
AIA	Auckland International Airport Limited	Industrials
AIZ	Air New Zealand Limited	Industrials
AJL	AJ Lucas Group Limited	Industrials
ALL	Aristocrat Leisure Limited	Con. Disc.
ALZ	Australand Holdings Limited	Financials
AMC	Amcor Limited	Materials
AMP	AMP Limited	Financials
ANZ	Australia and New Zealand Banking Group Limited	Financials
APA	Australian Pipeline Trust	Utilities
APE	AP Eagers Limited	Con. Disc.
API	Australian Pharmaceutical Industries Limited	Health Care
APN	APN News and Media Limited	Con. Disc.
APZ	Aspen Group Limited	Financials
AQP	Aquarius Platinum Limited	Materials
ARG	Argo Investments Limited	Not Assigned
ARP	ARB Corporation Limited	Con. Disc.
ASB	Austal Limited	Industrials
ASL	Ausdrill Limited	Industrials
ASX	Australian Stock Exchange Limited	Financials
ATR	Astron Limited	Materials
AUI	Australian United Investment Company Limited	Financials
AVJ	Avjennings Homes Limited	Financials
AWE	Australian Worldwide Exploration Limited	Energy
AXI	Axiom Properties Limited	Financials
BBG	Billabong International Limited	Con. Disc.
BEN	Bendigo Bank Limited	Financials
BHP	BHP Billiton Limited	Materials
BKL	Blackmores Limited	Con. Staple
BKW	Brickworks Limited	Materials
BLD	Boral Limited	Materials
BOC	Bougainville Copper Limited	Materials
BOQ	Bank Of Queensland Limited	Financials
BPT	Beach Petroleum Nl	Energy
BWP	Bunnings Warehouse Property Trust	Financials
CAB	Cabcharge Australia Limited	Industrials
CBA	Commonwealth Bank Of Australia	Financials
CCL	Coca-Cola Amatil Limited	Con. Staple
CCP	Credit Corp Group Limited	Industrials
CDP	Carindale Property Trust	Financials
CIN	Carlton Investments Limited	Financials
CMW	Cromwell Corporation Limited	Financials
CND	Candle Australia Limited	Industrials
COE	Cooper Energy Nl	Energy
COF	Coffey International Limited	Industrials
COH	Cochlear Limited	Health Care
CPU	Computershare Limited	IT
CSL	CSL Limited	Health Care
CSR	CSR Limited	Industrials
CTO	Charters Towers Gold Mines Limited	Materials
CTX	Caltex Australia Limited	Energy
CVC	Continental Venture Capital Limited	Financials
CVN	Carnarvon Petroleum Nl	Energy
CWP	Cedar Woods Properties Limited	Financials
DJW	Djerriwarrh Investments Limited	Financials
DOW	Downer Edi Limited	Industrials
DUI	Diversified United Investment Limited	Financials
DVN	Devine Limited	Financials
ENE	Energy Developments Limited	Utilities
ENV	Envestra Limited	Utilities
EQT	Equity Trustees Limited	Financials
ERA	Energy Resources Of Australia Limited	Energy
ESV	Eservglobal Limited	IT
EWC	Energy World Corporation Ltd	Utilities
EZL	Euroz Limited	Financials
FAN	Fantastic Holdings Limited	Con. Disc.
FBU	Fletcher Building Limited	Materials
FLT	Flight Centre Limited	Con. Disc.
FPH	Fisher and Paykel Healthcare Corporation Limited	Health Care
FWD	Fleetwood Corporation Limited	Con. Disc.
FXJ	Fairfax (John) Holdings Limited	Con. Disc.
GBG	Gindalbie Gold Nl	Materials
GNC	Graincorp Limited	Con. Staple
GOW	Gowing Bros Limited	Financials
GPT	General Property Trust	Financials
GRR	Grange Resources Limited	Materials
GUD	G.U.D. Holdings Limited	Con. Disc.
HHL	Hunter Hall International Limited	Financials
HIL	Hills Industries Limited	Industrials
HRR	Heron Resources Limited	Materials
HTA	Hutchison Telecom. (Australia) Limited	Telecom.
HVN	Harvey Norman Holdings Limited	Con. Disc.
IAG	Insurance Australia Group Limited	Financials
IFM	Infomedia Ltd	IT
IGO	Independence Gold Nl	Materials
IIN	Iinet Limited	Telecom.
ILU	Iluka Resources Limited	Materials
IMD	Imdex Limited	Materials
IOF	ING Office Fund	Financials
IRE	Iress Market Technology Limited	IT
JHX	James Hardie Industries N.V.	Materials
KCN	Kingsgate Consolidated Nl	Materials
KSC	K and S Corporation Limited	Industrials
LEI	Leighton Holdings Limited	Industrials
LLC	Lend Lease Corporation Limited	Financials
LYC	Lynas Corporation Limited	Materials
MAH	Macmahon Holdings Limited	Industrials
MCP	McPherson's Limited	Con. Disc.
MCR	Mincor Resources Nl	Materials
MDL	Mineral Deposits Limited	Materials
MEO	Methanol Australia Limited	Energy
MGR	Mirvac Group	Financials
MGX	Mount Gibson Iron Limited	Materials
MIR	Mirrabooka Investments Limited	Financials
MLB	Melbourne It Limited	IT
MLT	Milton Corporation Limited	Financials
MND	Monadelphous Group Limited	Industrials
MPO	Molopo Australia Nl	Energy
MRM	Mermaid Marine Australia Limited	Industrials
NAB	National Australia Bank Limited	Financials
NCM	Newcrest Mining Limited	Materials
NDO	Nido Petroleum Limited	Energy
NPX	Nuplex Industries Limited	Materials
NUF	Nufarm Limited	Materials
NXS	Nexus Energy Limited	Energy
NZO	New Zealand Oil and Gas Limited	Energy
OKN	Oakton Limited	IT
OMH	Om Holdings Limited	Materials
ORG	Origin Energy Limited	Energy
ORI	Orica Limited	Materials
ORL	Oroton International Limited	Con. Disc.
OSH	Oil Search Limited	Energy
PDN	Paladin Energy Ltd	Energy
PGL	Progen Industries Limited	Health Care
PMC	Platinum Capital Limited	Financials
PMP	PMP Limited	Industrials
PMV	Premier Investments Limited	Con. Disc.
PNA	Pan Australian Resources Nl	Materials
PPT	Perpetual Trustees Australia Limited	Financials
PPX	Paperlinx Limited	Industrials
PRG	Programmed Maintenance Services Limited	Industrials
PRT	Prime Television Limited	Con. Disc.
PRY	Primary Health Care Limited	Health Care
PSA	Petsec Energy Limited	Energy
QAN	Qantas Airways Limited	Industrials
QBE	QBE Insurance Group Limited	Financials
RCR	RCR Tomlinson Limited	Industrials
RCT	Reef Casino Trust	Con. Disc.
RDF	Redflex Holdings Limited	IT
REA	Realestate.com.au Limited	Con. Disc.
REH	Reece Australia Limited	Industrials
RHC	Ramsay Health Care Limited	Health Care
RHL	Ruralco Holdings Limited	Con. Disc.
RIC	Ridley Corporation Limited	Con. Staple
RIO	Rio Tinto Limited	Materials
RKN	Reckon Limited	IT
RMD	Resmed Inc	Health Care
ROC	Roc Oil Company Limited	Energy
RSG	Resolute Mining Limited	Materials
SBM	St Barbara Mines Limited	Materials
SDG	Sunland Group Limited	Financials
SGN	Stw Communications Group Limited	Con. Disc.
SGP	Stockland Trust Group	Financials
SGT	Singapore Telecom. Limited	Telecom.
SHL	Sonic Healthcare Limited	Health Care
SHV	Select Harvests Limited	Con. Staple
SKC	Sky City Entertainment Group Limited	Con. Disc.
SKE	Skilled Engineering Limited	Industrials
SLX	Silex Systems Limited	IT
SMM	Summit Resources Limited	Energy
SMX	Sms Management and Technology Limited	IT
SOL	Washington H Soul Pattinson and Company Limited	Financials
SRV	Servcorp Limited	Financials
SRX	Sirtex Medical Limited	Health Care
SST	Steamships Trading Company Limited	Industrials
STO	Santos Limited	Energy
STS	Structural Systems Limited	Industrials
STW	Streettracks Standard and Poors/ASX 200 Fund	Not Assigned
SUN	Suncorp-Metway Limited	Financials
TAH	Tabcorp Holdings Limited	Con. Disc.
TAP	Tap Oil Limited	Energy
TCL	Transurban Group	Industrials
TEN	Ten Network Holdings Limited	Con. Disc.
TGG	Templeton Global Growth Fund Limited	Financials
TLS	Telstra Corporation Limited	Telecom.
TNE	Technology One Limited	IT
TOL	Toll Holdings Limited	Industrials
TOX	Tox Free Solutions Limited	Industrials
TRG	Treasury Group Limited	Financials
TRY	Troy Resources Nl	Materials
TSE	Transfield Services Limited	Industrials
TWR	Tower Limited	Financials
UGL	United Group Limited	Industrials
UOS	United Overseas Australia Limited	Financials
VRL	Village Roadshow Limited	Con. Disc.
WAM	Wam Capital Limited	Financials
WBB	Wide Bay Capricorn Building Society Limited	Financials
WBC	Westpac Banking Corporation	Financials
WES	Wesfarmers Limited	Con. Staple
WHF	Whitefield Limited	Financials
WOW	Woolworths Limited	Con. Staple
WPL	Woodside Petroleum Limited	Energy
WSA	Western Areas Nl	Materials
WTP	Watpac Limited	Industrials
ZIM	Zimbabwe Platinum Mines Limited	Materials

B Online Appendix: CRRA Utility and Mean-Variance Portfolio Optimisation

Before proceeding, let us first note the fact that if x is a log normally distributed random variable then,

$$\log \mathrm{E}\left[x\right] = \mathrm{E}\left[\log(x)\right] + \frac{1}{2}\mathrm{Var}\left[\log(x)\right] \tag{7}$$

Given CRRA utility, our investor's problem is to maximise the expected value of wealth in period $t+1$. The intertemporal evolution of wealth is; $W_{t+1} = (1 + r_{pt})W_t$ where r_{pt} is the return on the portfolio

$$\mathrm{E}_t\left[U(W_{t+1})\right] = \mathrm{E}_t\left[\frac{W_{t+1}^{1-\gamma}}{1-\gamma}\right] \tag{8}$$

We can take logs of both sides and use (7) to write this as follows. This is assuming that W_{t+1} is log normally distributed.[7]

$$\begin{aligned}
\log \mathrm{E}_t\left[U(W_{t+1})\right] &= \log \mathrm{E}_t\left[\frac{W_{t+1}^{1-\gamma}}{1-\gamma}\right] && (9)\\
&= \mathrm{E}_t\left[\log\left(\frac{W_{t+1}^{1-\gamma}}{1-\gamma}\right)\right] + \frac{1}{2}\mathrm{Var}\left(\log\left(\frac{W_{t+1}^{1-\gamma}}{1-\gamma}\right)\right) && (10)\\
&\propto (1-\gamma)\mathrm{E}_t\left[\log\left(W_{t+1}\right)\right] + \frac{1}{2}(1-\gamma)^2\mathrm{Var}\left(\log W_{t+1}\right) && (11)\\
&= \mathrm{E}_t\left[\log\left(W_{t+1}\right)\right] + \frac{(1-\gamma)}{2}\mathrm{Var}\left(\log W_{t+1}\right) && (12)\\
&= \mathrm{E}_t\left[\log(1+r_{pt+1})\right] + \frac{(1-\gamma)}{2}\mathrm{Var}\left(\log(1+r_{pt+1})\right) && (13)
\end{aligned}$$

Note also, we can calculate the variance of the log portfolio return by using the Delta Method. Here Σ_{t+1} is the covariance matrix of the asset returns.

$$\begin{aligned}
\mathrm{Var}\left(\log(1+r_{pt+1})\right) &= \left(\frac{1}{1+r_{pt+1}}\right)^2 \mathrm{Var}\left(r_{pt+1}\right) && (14)\\
&= \left(\frac{1}{1+r_{pt+1}}\right)^2 \mathbf{w}^T\Sigma_{t+1}\mathbf{w} && (15)
\end{aligned}$$

[7] Note that if $\gamma > 1$ then we need to multiply this expression by -1 and minimize rather than maximize it.