ARC Centre of Excellence in Population Ageing Research

Working Paper 2011/18

House Price Risk Models for Banking and Insurance Applications

Katja Hanewald and Michael Sherris *

* Hanewald is a Senior Research Associate in the School of Risk and Actuarial at the University of New South Wales (UNSW) and an Associate Investigator at the ARC Centre of Excellence in Population Ageing Research (CEPAR). Sherris is Professor of Actuarial Studies at UNSW and a CEPAR Chief Investigator.

House Price Risk Models for Banking and Insurance Applications

Katja Hanewald* and Michael Sherris†

18th November 2011

Abstract

The recent international credit crisis has highlighted the significant exposure that banks and insurers, especially mono-line credit insurers, have to residential house price risk. This paper provides an assessment of risk models for residential property for applications in banking and insurance including pricing, risk management, and portfolio management. Risk factors and heterogeneity of house price returns are assessed at a postcode-level for house prices in the major capital city of Sydney, Australia, over the period 01-1979 to 03-2011. The paper shows how a significant proportion of house price variability is due to heterogeneity requiring broader risk assessment than market-wide house price indices. Although time series models of market price indices capture the temporal risks of house prices, panel data models with random effects and variable slopes are required to capture cross-sectional heterogeneity and to quantify the risk of postcode-level house prices compared to the market price index. Macroeconomic and financial variables, as well as geographic and socio-demographic postcode characteristics are shown to be important house price risk factors.

Keywords: house price risk, statistical models, risk management

JEL Classifications: G21, G22, G32, R31, L85

*Risk and Actuarial Studies and ARC Centre of Excellence in Population Ageing Research (CEPAR), Australian School of Business, University of New South Wales, k.hanewald@unsw.edu.au

†Risk and Actuarial Studies and ARC Centre of Excellence in Population Ageing Research (CEPAR), Australian School of Business, University of New South Wales, m.sherris@unsw.edu.au

1 Introduction

The recent international credit crisis has highlighted the significant exposure that banks and insurers, especially mono-line credit insurers, have to residential house price risk. In the crisis, a number of major banks collapsed and a number of insurers, including mono-line mortgage and bond insurers, suffered financial distress. Harrington (2009) discusses the causes of the financial crises and the impact on insurers. This recent international experience reinforces how residential house price fluctuations over short time horizons present a substantial risk to private and institutional real estate investors as well as lenders such as pension funds, investment banks, commercial banks, and insurance companies. Insurers writing property insurance including flood and earthquake coverage are exposed to claims costs related to house price values.

Despite this, the nature of house price risk attracts limited analysis in the risk and insurance literature beyond models for a market-wide index. House price risk not only reflects market-wide movements. Cross-sectional heterogeneity is a significant factor to consider especially since few banks hold well diversified housing exposures and mortgage insurers also face similar risk concentrations. Recent experience clearly demonstrates that real estate investors and providers of housing-related financial products can benefit from a deeper understanding of the risk factors driving house price returns and variability.

There are many financial and insurance products including residential housing loans that are exposed to house price risk. Equity release products, such as reverse mortgages, have received significant interest as a means to fund retirement financial needs (see, e.g., Davidoff, 2009; Chen *et al.*, 2010a; Li *et al.*, 2010; Sun and Sherris, 2010). Securitization of reverse mortgages is also an area of study (see, e.g., Wang *et al.*, 2008). Banks providing mortgage loans are exposed to house price risk through borrower default on the loan. Default on the mortgage loan has the features of a put option on the house value reflecting volatility in the underlying house value (see, e.g., Ambrose and Buttimer, 2000) and thus house price risk is a significant factor in default rates on home mortgages (see, e.g., Case *et al.*, 1996). Mortgage default risk also depends on a household's income and employment status. Mian and Sufi (2009) show that in the recent financial crisis the sharp increase in mortgage defaults observed in the United States in 2007 was significantly higher in postcode areas with a low median household income, high poverty rates, low levels of education, and high unemployment rates.

Insurance risk management solutions have been proposed for managing these risks but are not widely available beyond mortgage insurance. Mortgage insurance protects a mortgage lender against a loss in the event a mortgage borrower defaults on his home loan and the net proceeds of the sale are insufficient to cover the balance outstanding on the loan (Chen *et al.*, 2010b; Chang *et al.*, 2010). This shifts house price risk to the mortgage insurer. Shiller and Weiss (1999) discussed the development of home equity insurance to insure homeowners against declines in the prices of their homes. In 2004, a pilot project on home equity insurance was undertaken in Syracuse, NY, under the name "Home Equity Protection" with insurance payments linked to postcode-specific house price indices (Caplin *et al.*, 2003; Englund, 2010). A recent study of housing market transactions in Melbourne finds that index-based insurance schemes would be unattractive from a homeowner perspective because of the large idiosyncratic component of house price risk (Sommervoll and Wood, 2011). Derivatives such as the housing futures and options traded at the Chicago Mercantile Exchange are based on aggregate market indices and provide an imperfect hedge.

This paper develops and compares models for the risks inherent in housing portfolios and in housing-related financial products. House price risk and returns are analyzed based on a large micro-level data set. The analysis of postcode-level house prices demonstrates that a large proportion of house price risk is due to heterogeneity across suburbs and that sub-markets show very different risk-return profiles over time. Models of house price risk that allow for both temporal and cross-sectional risks in housing markets are considered that can be applied for pricing, risk management, and portfolio management of house price products and portfolios in banking and insurance.

Multivariate time series models quantify temporal properties of house price risks. They capture autoregressive and moving average patterns in the house price series accounting for overall price index trends and variability. Multivariate auto-regressive integrated moving average (ARIMA) models describe the time series properties of house prices at a finer detail than the market price index.

Panel data models allow us to relate postcode-level house prices to socio-demographic variables and macroeconomic factors as well as the market index. Random effects and variable slope parameters in panel data models very effectively capture cross-sectional heterogeneity and allow quantification of this heterogeneity. They allow a quantification of how house prices in different postcode areas vary with the Sydney market house price index, yielding the equivalent of a house price beta. They identify the impact of exogenous factors on house price returns and volatility, including macroeconomic and financial variables, geographic and seasonal indicators, and postcode-level socio-demographic indicators. These are shown to be important risk factors required to assess residential house portfolios.

The main research questions addressed in this study are: What are the best models to use for house price risk and how do they vary for different risk applications? What is the significance of time variations in house prices and how do these differ across postcode areas compared to the market-wide index. How important is the heterogeneity that arises from cross-sectional variations in house prices and what are the major factors driving this? What are the exogenous factors driving house price dynamics over time? What models are most suited to the differing banking and insurance applications?

The paper is organized as follows. Section 2 provides some background on house price indices and risk models and describes the data. Section 3 develops and compares the different statistical models. Applications of the models are discussed in Section 4. Section 5 concludes.

2 Data for house prices and explanatory risk factors

The analysis is based on house price indices for the postcode areas in the Sydney Statistical Division over the period Jan-1979 to Mar-2011. Postcode level data provides a level of detail that allows an assessment of heterogeneity and the significance of risk factors on house prices including geographical location. Postcode-level geographic characteristics and socio-demographic data were collected from the censuses of 1981 to 2006. Monthly and quarterly macroeconomic and financial time series were obtained from the Reserve Bank of Australia. All analyses in the paper were performed with SAS 9.2 and the SAS Enterprise Guide 4.2.

2.1 House price indices and risk factors

House price indices are used to reflect the risk and return characteristics of the underlying housing market. Median measures of house prices are easy to calculate but do not account for changes in the composition and quality of houses over time. Hedonic measures overcome this problem by modeling the price of a house as a function of its physical characteristics and other factors such as neighborhood characteristics and macroeconomic variables (see, e.g., Malpezzi, 2002; Sirmans *et al.*, 2005). Spatial hedonic analysis is a variant of this approach that accounts for spatial autocorrelation and spatial heterogeneity often observed in real estate markets (see, e.g., Case *et al.*, 2004; Chernih and Sherris, 2004; Páez, 2009; Bourassa *et al.*, 2010). Repeat-sales house price indices are an alternative less data-intensive method based on price changes of houses that have sold more than once. A recent comparison of hedonic and repeat-sales measures based on Australian data shows that the two methods provide similar estimates of house price growth (Hansen, 2009).

Australian housing markets have shown strong growth rates in the past few decades. Economic factors have been recognised as important in explaining house price trends in Australia. Bodman and Crosby (2004) estimate the effect of macroeconomic factors on house prices in Sydney and Brisbane in 2002 and 2003. Abelson *et al.* (2005) model changes in real house prices in Australian capital cities from 1970 to 2003. In the long run, real house prices are determined by real disposable income, the consumer price index, the unemployment rate, real mortgage rates, equity prices and the housing stock. Otto (2007) studies real house prices in Australia's capital cities over the period 1986 to 2005. The mortgage rate has an important impact on growth rates in all eight capital cities while other variables, such as the real interest rate, property tax rates, subsidies to housing, cost of maintenance and depreciation, and expected capital gains, are found to be significant factors depending on city. Hatzvi and Otto (2008) shows that real rent growth only accounts for a small fraction of the variations in residential property prices in a study of the interaction of property prices and rents for Sydney's Local Government over the period 1991-2006. A recent study by Street (2011) concludes that low interest rates and low unemployment impact Australian house prices.

House price dynamics in submarkets are assessed in Bourassa *et al.* (1999, 2003, 2009); Knight and Cottet (2011). Bourassa *et al.* (2009) investigate the reasons for variations in price changes among houses within a market. Studying repeat-sales data from three New Zealand metropolitan areas, they show that investing in an atypical house is riskier than purchasing a standard house, demonstrating that mortgage lenders should take property characteristics into account. Knight and Cottet (2011) use income as a socio-demographic factor to classify Sydney suburbs to take into account spatial variability. Three studies using data for the cities of Perth and Adelaide find no significant seasonal variations in house prices (Costello, 2001; Rossini, 2000, 2002). Rossini (2000) shows there is seasonality in volume sales, with more sales in summer and autumn, and that this seasonality depends on the property's location.

2.2 Postcode-level house price indices

Postcode-level price indices for residential properties were provided by the Sydney-based company Residex for all postcode areas in the Sydney Statistical Division for the period Jan-1979 to Mar-2011. Not all postcodes in the postcode range of the Sydney Statistical Division (2000-2263, 2555-2574, 2745-2787) are actually allocated or contain houses for which sales are observed, for example, because they are assigned to universities. In total, there is data available at a monthly frequency for both houses and units (apartments) for 243 postcodes, ranging from postcode 2007 to 2787. The analysis is based on houses since these are a major component of the Sydney market.

The method used to calculate the Residex' "Non-Revisionary Repeat Sales Indices" is an extension of the repeat sales index approach taking into account median sales prices for properties that do not sell in a period. Early values of the index, prior to December 2004 are computed using the repeat sales approach. Anomalous records are removed and smoothing is used to ensure consistency through time and to limit the impact of outliers and data errors. The indices are computed using all sales data in the market, not just the sales on properties with repeat sales improving the accuracy of the index and avoiding the need for revision of the indices when new sales data are available.[1] The method of index calculation is a hybrid of a repeat sales index and a median sale index that includes the best features of both methodologies.

Figure 1 plots all postcode-level house price indices over time. House prices have shown positive trends over time with considerable variations around these trends. There is also a large cross-sectional variability observed in house price trends. A market-wide index will not capture these differences in postcode-level indices.

2.3 Comparison with national and international house price data

Residex provides aggregate house price indices for all Australian capital cities free of charge on their website.[2] The "Residex House Price Trading Indices" for houses in Sydney is used as an aggregate measure for the Sydney housing market. Figure 2 and Table 1 show a comparison of this index with the quarterly Sydney house price index

[1] See http://www.residex.com.au/index.php?content=article060606.

[2] See http://www.residex.com.au/index.php?content=get_indices.

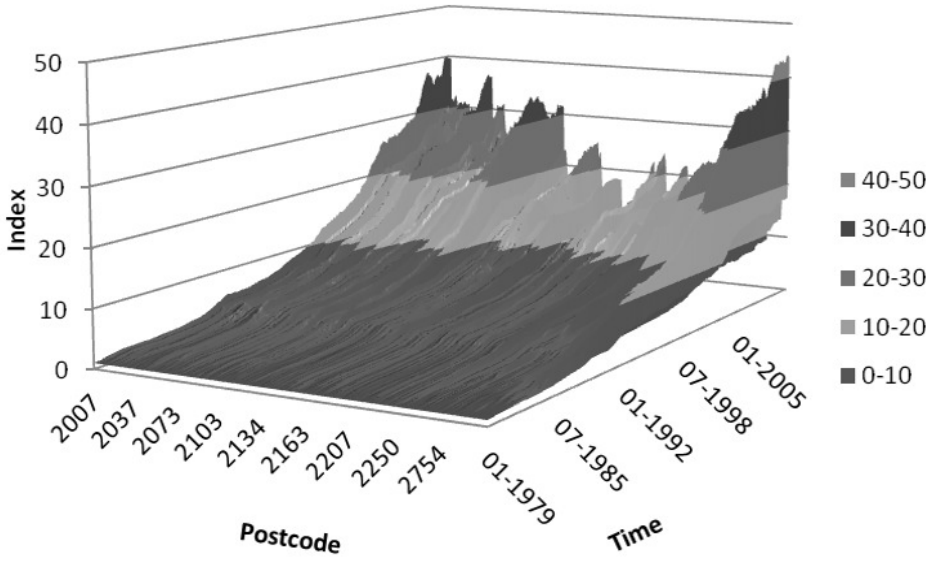

Figure 1: House prices of postcodes in the Sydney Statistical Division, Jan-1979 to Mar-2011.

published by the Australian Bureau of Statistics, which is available for the period I-2002 to II-2011 (with I and II denoting the first and second quarter of the year).[3] The two indices have very similar growth rates and volatility over time. The Residex index covers a much longer time period (starting in Jan-1979) and provides disaggregated postcode-level house price indices.

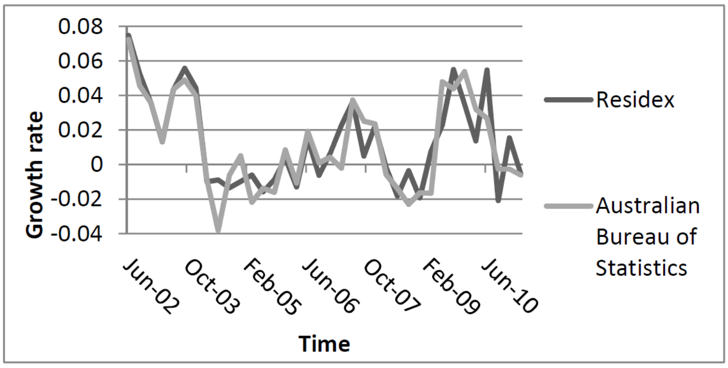

Figure 2: Comparison of the "Residex House Price Trading Indices" for Sydney with the Sydney house price index published by the Australian Bureau of Statistics, I-2002 to II-2011.

Table 1 and Figure 3 compare the "Residex House Price Trading Index" against house price indices for major U.S. cities. Quarterly house price indices for three metropolitan statistical areas over the period I-1991 - I-2011 were obtained from the U.S. Federal

[3]See http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/6416.0Jun%202011?OpenDocument

Frequency	Source	Region	Sample period	Mean	Std. Dev.	N
Quarterly	Residex	Sydney	I-2002 - II-2011	1.32%	2.59%	36
Quarterly	ABS	Sydney	I-2002 - II-2011	1.18%	2.70%	36
Quarterly	Residex	Sydney	I-1991 - II-2011	1.64%	2.23%	81
Quarterly	FHFA	New York-White Plains-Wayne, NY-NJ	I-1991 - I-2011	1.03%	2.03%	81
Quarterly	FHFA	Los Angeles-Long Beach-Glendale, CA	I-1991 - I-2011	0.68%	3.37%	81
Quarterly	FHFA	Philadelphia, PA	I-1991 - I 2011	0.88%	1.74%	81
Monthly	Residex	Sydney	Jan-1987 - Mar-2011	0.64%	1.23%	290
Monthly	S&P/CSI	New York, NY	Jan-1987 - Mar-2011	0.27%	0.80%	290
Monthly	S&P/CSI	Los Angeles, CA	Jan-1987 - Mar-2011	0.36%	1.27%	290
Monthly	S&P/CSI	Washington, DC	Jan-1987 - Mar-2011	0.35%	1.01%	290

Table 1: Summary statistics for the growth rates of different Australian and U.S. house price indices. *Notes:* Data was obtained from Residex, from the Australian Bureau of Statistics (ABS), from the Federal Housing Finance Agency (FHFA), and from S&P/Case-Shiller (via MacroMarkets LLC)

Housing Finance Agency (FHFA).[4] Monthly S&P/Case-Shiller Indices for three major U.S. cities over the period Jan-1987 - Mar-2011 were taken from MacroMarkets LLC.[5]

Housing markets perform differently across cities and countries. They also share certain characteristics. There are extended periods of upward and downward trends and there is considerable variation around these trends, with standard deviations of more than two or three times the average growth rates.

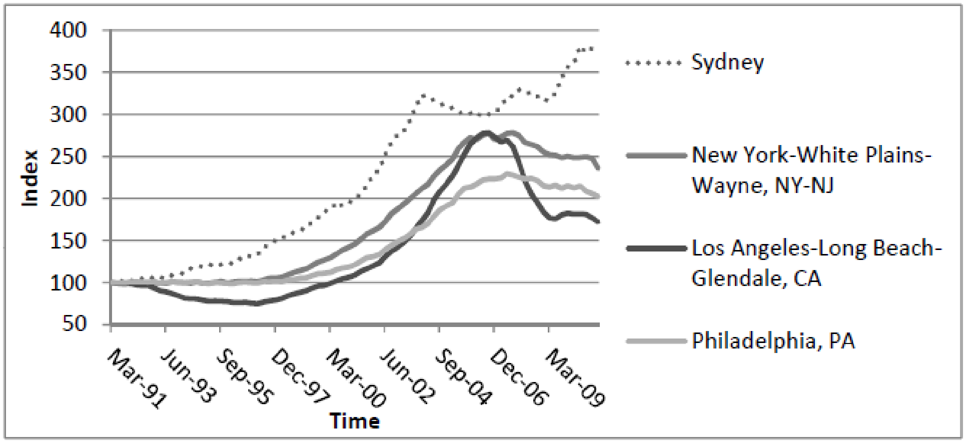

Figure 3: Comparison of the "Residex House Price Trading Index" for Sydney with house price indices for three metropolitan U.S. statistical areas obtained from the Federal Housing Finance Agency, I-1991 - II-2011.

[4]See http://www.fhfa.gov/Default.aspx?Page=87
[5]See http://www.macromarkets.com/csi_housing/index.asp

2.4 Cross-sectional distribution and time series properties of house price growth rates

Growth rates of the postcode-level house price indices are calculated as the differences of the log time series (using the natural logarithm ln). The logarithmic transformation normalizes the data and differencing generates a stationary series for analysis. The house price indices are available on a monthly basis. Monthly, quarterly, and yearly growth rates are compared. Quarterly growth rates are calculated from using the index for December, March, June, and September. Yearly growth rates are calculated from December in one year to December in the next year. This is also the month with highest sale volume (see Figure 7).

Table 3 gives the descriptive statistics for monthly, quarterly, and yearly growth rates in postcode-level house price indices in the Sydney Statistical Division. The summary statistics are calculated across time and postcode areas. Over the period Jan-1979 to Mar-2011, the average monthly growth rate in house prices in Sydney was 0.73% per month, 2.16% per quarter and 8.26% per year. There are substantial variations around these mean values. The third column in Table 4 gives the coefficient of variation. For monthly data, the standard deviation is 151.04% of the mean value, 111.93% for quarterly data, and 87.24% for annual data. There is also a high level of auto-regression in the series.

Frequency	Mean	Std. Dev.	CV	AR(1) parameter	p value	N
Monthly	0.73%	1.10%	151.04%	0.759	<.0001	93798
Quarterly	2.16%	2.42%	111.93%	0.821	<.0001	31104
Yearly	8.26%	7.21%	87.24%	0.881	<.0001	7533

Table 2: Summary statistics for the growth rates in postcode-level house price indices at different frequencies over the period Jan-1979 to Mar-2011. *Notes:* CV denotes the coefficient of variation. The autoregressive AR(1) parameter and the corresponding p value were estimated using a linear regression model with an intercept.

House price growth exhibits very large variations over short time horizons and these variations reduce for longer time horizons. House price growth measured over longer time periods reflect the impact of auto-regression in the series.

The analysis will use quarterly growth rates from Jan-1979 to Mar-2011. Some of the economic and financial time series are only available on a quarterly basis. The quarters of the year are denoted by I, II, III, and IV. Stationarity of the growth rates was tested using the Phillips-Perron unit root test. For each postcode, the Phillips-Perron test statistic was computed based on an autoregressive model with up to four lags and a constant. All quarterly growth rates are stationary at the 5% level.

Figure 4 plots the growth rates over time for five selected postcodes and compares them against the Sydney market index. The postcodes are located at the harbor (2009-Pyrmont), at the coast (2095-Manly), in the Inner West city (2150-Enmore, Newtown), in the Outer West (2150-Harris Park, Parramatta), and near the Blue Mountains National Park (2780-Katoomba, Leura, Medlow Bath). The plot and the summary statistics provided in Table 3 show how house price growth varies across postcode areas. A histogram for the quarterly growth rates is provided in Figure 5. The skewness of the distribution is positive (0.756) and slightly skewed to the right. The distribution has a more acute peak around the mean and fatter tails than the normal distribution with a kurtosis of 1.494.

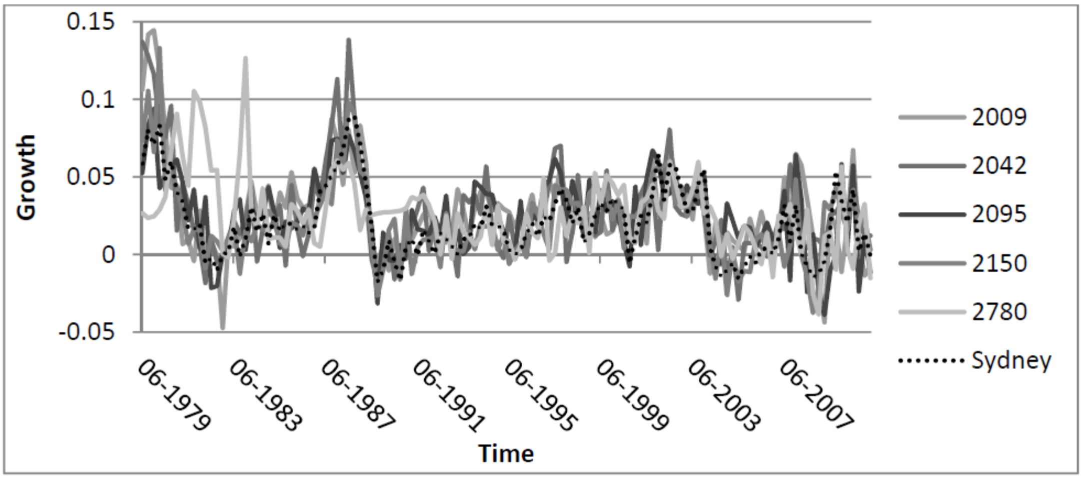

Figure 4: Quarterly growth rates of the house price indices for five selected postcodes and for the Sydney market index, I-1979 to I-2011.

Region	Postcode	Mean	Std. Dev.	AR(1) parameter	p Value
Pyrmont	2009	0.028	0.029	0.644	<.0001
Enmore, Newtown	2042	0.027	0.031	0.596	<.0001
Manly	2095	0.025	0.025	0.439	<.0001
Harris Park, Parramatta	2150	0.022	0.026	0.624	<.0001
Katoomba, Leura, Medlow Bath	2780	0.026	0.025	0.506	<.0001
Sydney		0.021	0.023	0.784	<.0001

Table 3: Summary statistics for the quarterly growth rates of the house price indices for five selected postcodes and for the Sydney market index, I-1979 to I-2011. *Notes:* The autoregressive AR(1) parameter and the corresponding p value were estimated using a linear regression model with an intercept.

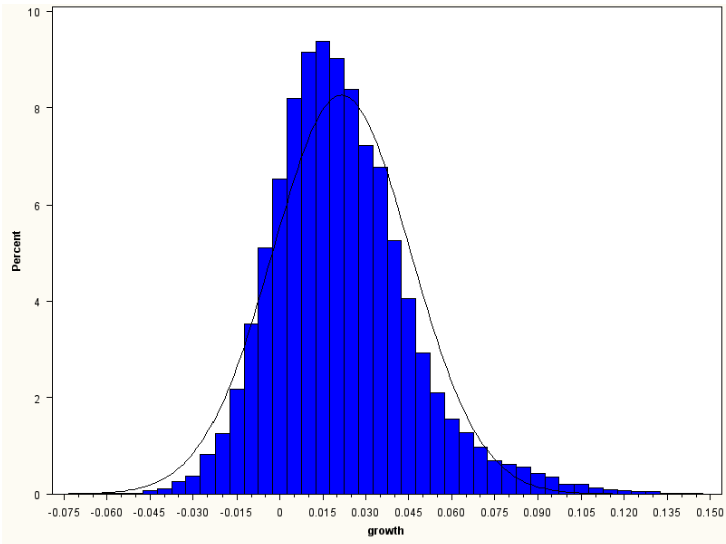

Figure 5: Histogram for quarterly growth rates of postcode-level house price indices.

2.5 Long-term returns to housing

Residential property is an asset class that investors typically hold over long time periods. The average annualized return in the Sydney Statistical Division over the 32-year sample period was 9.1%. The standard deviation of this average return across postcodes is 1.3% reflecting a large variability over long time horizons. The highest returns to housing were realized in the central business district (CBD) and along the harbor with an annualized return of 10.6% in both regions.

Figure 6 plots the annualized returns on postcode-level house price indices against the standard deviations in monthly house price growth rates observed in the same postcode areas over the period Jan-1979 to Mar-2011 showing a positive relationship with higher long-term growth associated with higher volatility.

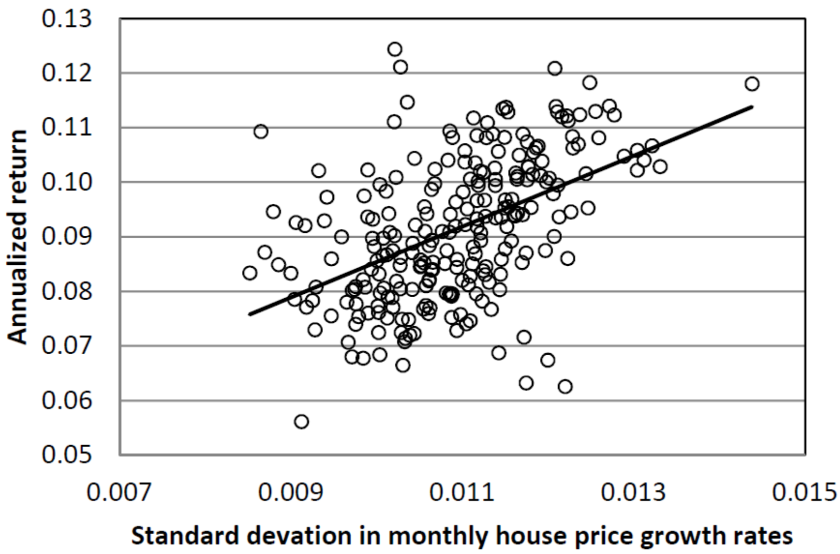

Figure 6: Scatter plot of the annualized returns on postcode-level house price indices over the period Jan-1979 to Mar-2011 against standard deviations in the monthly growth rates of postcode-level house price indices.

2.6 Seasonal effects in house price growth and in sale volumes

Figure 7 compares the average growth in postcode-level house prices with the average sale volume. The two graphs at the top are based on monthly data; the two graphs at the bottom use quarterly data. Panel data analysis was used to test whether growth rates and sale volumes in a given month or quarter are significantly different from the annual average.[6]

A number of significant seasonal effects are found for both growth and sales volumes. Significant above-average house price growth is observed in the months April to June and September to November. Significant below-average growth is observed in February, March, August, and December. On a quarterly basis, above-average growth is observed in the second quarter and below-average growth in the first quarter. House prices in Sydney grow on average fastest in the month of April, with an average growth

[6]Tests were done by first subtracting the mean growth rate from the postcode-specified series of house growth. Then, a panel data model without intercept but with dummy variables for the twelve months or the four quarters of the year was fitted to the demeaned time series. A t test is used to test whether the growth rate in a given month or quarter is statistically different from the mean.

rate of 0.86% but sale volumes peak in December, with on average 19.40 transactions per postcode area. There are significant above-average sales in the second and fourth quarter and significant below-average sales in the first quarter. Similar seasonal patterns are observed in monthly and quarterly house price growth rates.

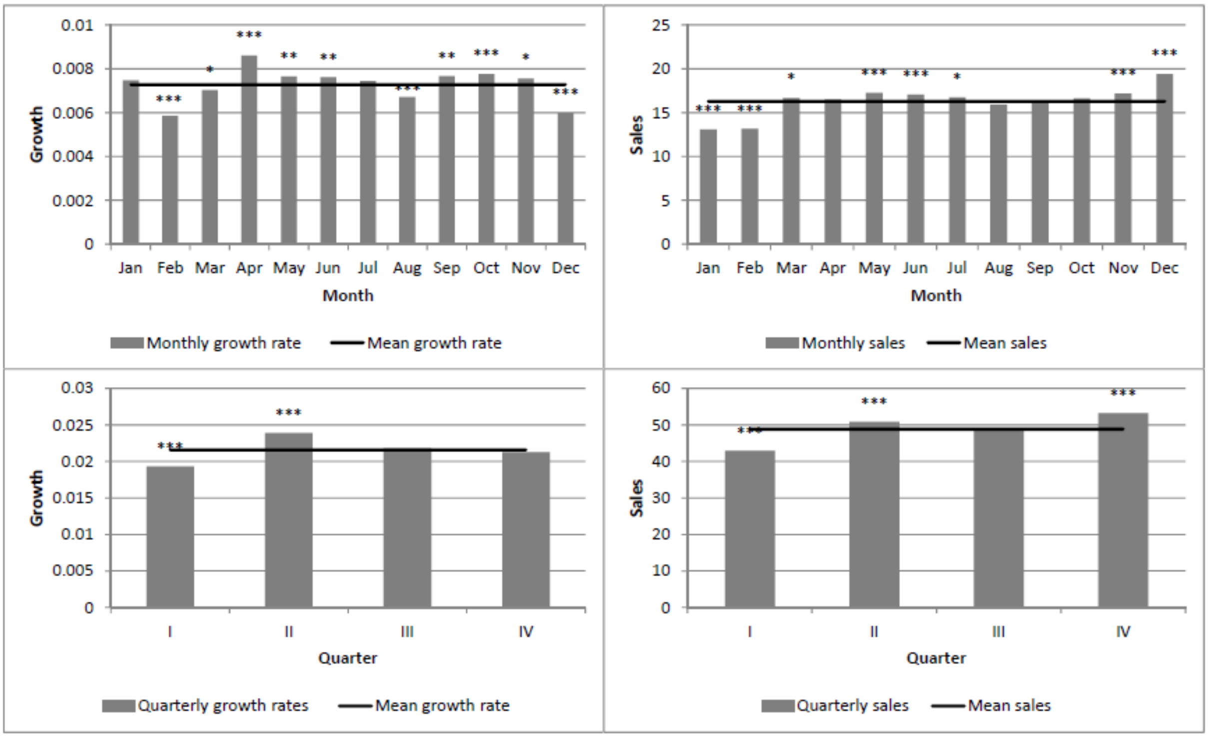

Figure 7: Average growth in postcode-level house prices and average sale volumes, monthly and quarterly data. *Notes:* * symbols indicate the months or quarters with significant above-average or below-average growth (* p-value < .05, ** p-value < .01, *** p-value < .001).

2.7 The impact of geographic characteristics on postcode-level house price growth

Two different measures of a postcode's geographic characteristics are used. For each postcode the distance in kilometers is calculated between the postcode area's central location and Sydney's central business district (CBD). The central location of a postcode is the average of the latitude and longitude of all houses in that postcode and the central location in the CBD is the General Post Office building in No. 1 Martin Place. Regional dummy variables were created using a postcode map of Sydney to indicate whether a postcode area is adjacent to the CBD, the harbor, the coastline, or the airport. Postcode areas can be in more than one regional category, when, for example, bordering the harbor and the CBD.

The average distance to the CBD is 23.79 kilometers for 243 all postcode areas in the Sydney Statistical Division. This distance is 2.07 kilometers for the seven postcode areas located in or adjacent to the CBD, 5.09 kilometers for the 25 postcodes located at the harbor, 7.60 kilometers for the seven postcode areas next to the airport, and 18.69 kilometers for the 22 postcodes that are adjacent to the coast. Sydney's airport is located in relatively close proximity to the city center. The airport also is well connected to the transportation infrastructure. As a result, the postcode areas near to the airport are also attractive residential areas. This can be seen in Figure 8 which gives average house price indices for the different regions. Above-average returns to housing are realized in the postcode areas near the central business district, along the harbor, near the airport, and at the coast. The corresponding average quarterly growth rates are given in Table 4.

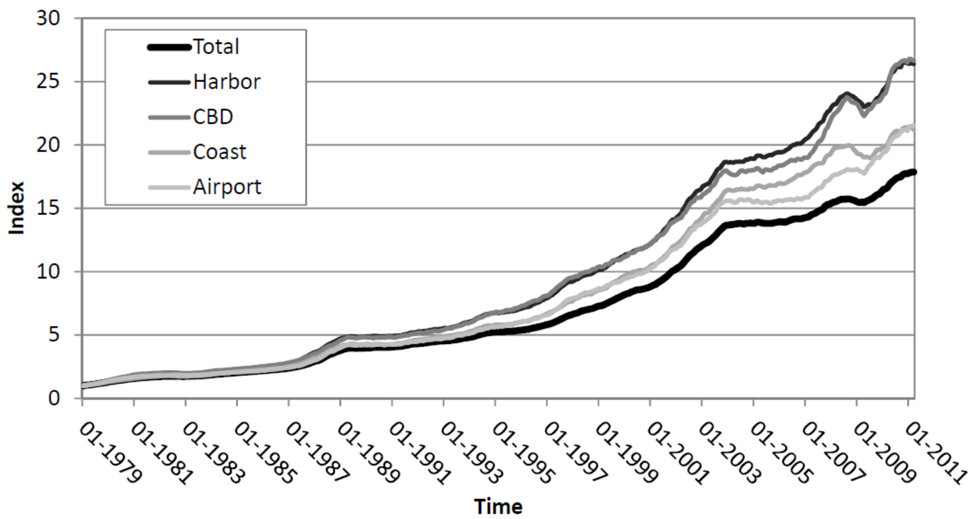

Figure 8: Average house price indices in different regions of the Sydney Statistical Division over the period Jan-1979 to Mar-2011.

Figure 9 shows house price growth rates in a postcode area against the corresponding postcode area's distance in kilometers from Sydney's central business district. This is done for the average quarterly growth rates observed in a suburb. The graph indi-

Region	Mean	Std. Dev.	Minimum	Maximum	N
Total	2.16%	2.42%	-7.40%	15.12%	31104
CBD	2.49%	2.67%	-4.73%	14.45%	896
Harbor	2.50%	2.60%	-7.40%	14.64%	3200
Airport	2.34%	2.39%	-4.56%	12.62%	896
Coast	2.33%	2.53%	-6.39%	12.68%	2816

Table 4: Descriptive statistics for the quarterly growth rates of postcode-level house price indices in different regions of the Sydney Statistical Division, I-1979 to I-2011.

cates an U-shaped relationship between house price growth and distance with lowest growth rates in postcode areas located approximately 40-50 kilometers away from the city.

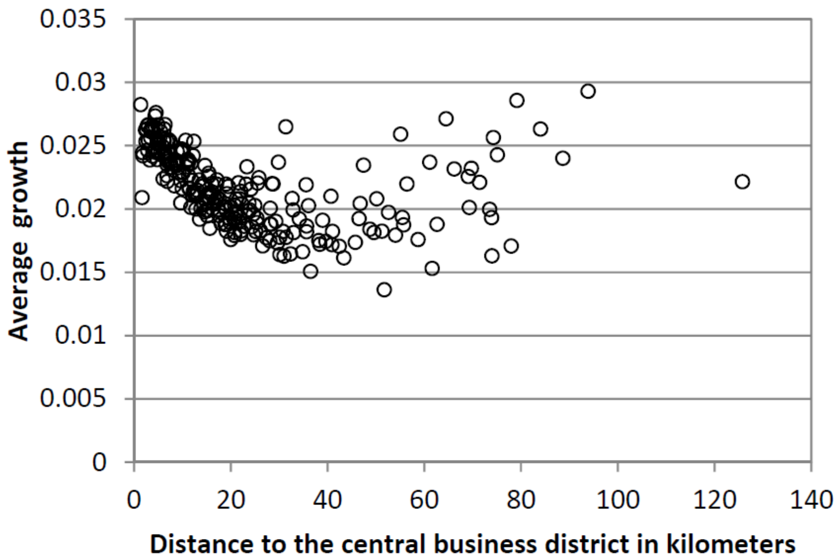

Figure 9: Scatter plot of average quarterly growth rates of postcode-level house price indices against the corresponding postcode area's distance in kilometers from Sydney's central business district, I-1979 to I-2011.

2.8 Macroeconomic and financial variables

Time series for real Gross Domestic Product (GDP), unemployment rates, interest rates, mortgage rates and inflation are sourced from the Reserve Bank of Australia for the same time period for which house price data is available (Jan-1979 to Mar-2011). Real GDP and unemployment rates are available as quarterly series, the other variables are monthly series.[7] A monthly time series for the Australian stock market index "ASX All Ordinaries Index" was obtained from the Australian Stock Exchange, Wren Research. All monthly time series are converted to a quarterly frequency by extracting the series values for December, March, June, and September. This applies to unemployment rates, interest rates, mortgage rates, and the ASX index. Time series with trends (real GDP and the ASX index) were transformed to growth rates using first differences of the ln series. Unemployment rates, interest rates, mortgage rates, and inflation rates were used directly.

Table 5 gives the descriptive statistics for the macroeconomic and financial time series on a quarterly basis. The average quarterly growth rate of the ASX index was 1.95%, which is lower than the average quarterly growth rate of 2.16% of postcode-level house price indices (see Table 4). High significant correlations are found between mortgage rate, interest rates, and inflation (89% for mortgage rate-interest rate, 67% for inflation-interest rate, and 54% for mortgage rate-inflation) based on pairwise Pearson correlation coefficients calculated for all bivariate associations between the macroeconomic and financial variables and two-sided t tests to test the null hypothesis that the correlation is zero. These three variables have the potential to cause multi-collinearity problems if included together as explanatory variables.

Variable	Mean	Std. Dev.	Minimum	Maximum	N
Real GDP growth	0.88%	0.98%	-1.59%	4.01%	128
Unemployment rate	7.18%	1.85%	4.05%	11.21%	128
Interest rate	8.94%	4.54%	3.16%	19.56%	128
Mortgage rate	10.00%	3.18%	5.80%	17.00%	128
Inflation rate	1.15%	0.93%	-0.50%	4.20%	128
ASX growth	1.95%	9.59%	-57.19%	22.98%	128

Table 5: Descriptive statistics for the macroeconomic and financial variables based on quarterly data for I-1979 to I-2011.

[7] The series names are "Real gross domestic income" from the table "G10 Gross Domestic Product", "Unemployment rate, per cent" from the table "G7 Labour Force", "Bank accepted bills (90 days)" from the table "F1 Interest Rates and Yields - Money Market", "Housing Loans, Banks, Variable, Standard" from the table "F5 Indicator Lending Rates", and "Consumer price index - All groups" from the table "G1 Measures of Consumer Price Inflation".

2.9 Socio-demographic postcode characteristics

Census data was obtained from the Australian Bureau of Statistic for the census years 1981, 1986, 1991, 1996, 2001, and 2006. This data is provided for all Postal Areas in the Sydney Statistical Division (2006 boundaries). Postal Areas used in the Census approximately match postcode areas. From the census data files, the variables “Median Household Income”, “Unemployment Rate”, “Median Age”, and “Average Household Size” are used. Table 6 gives the mean values for each variable calculated across all postcode areas for each census year between 1981-2006. The median weekly household income has increased from AUD 327.19 to AUD 1294.00. The unemployment rate has varied between 5.04% in 1981 and 9.92% in 1991. The average median age has increased from 30.5 years to 36.1 years and the average household size has decreased from 2.98 to 2.70 persons.

Variable	1981	1986	1991	1996	2001	2006
Median household income	327.185	492.227	706.173	797.054	1,065.610	1,294.000
Unemployment rate	5.036	8.411	9.917	7.015	5.804	5.078
Median age	30.531	31.727	32.562	33.858	34.892	36.081
Average household size	2.977	2.846	2.793	2.713	2.724	2.700

Table 6: Descriptive statistics for socio-demographic postcode area characteristics based on data for the Census years 1981-2006.

3 Risk models for house prices

3.1 Model frameworks

The growth rates of postcode-level house price indices are modeled over time and for the cross-section of postcode areas. The models are characterized as “longitudinal models” or “panel data models” (Frees, 2004) (Chap. 1). Time series models in the class of auto-regressive integrated moving average (ARIMA) models use past values of the dependent variable and past random errors to explain future values. Modeling the growth rates (calculated by differencing the log (ln) house price indices) ensures stationarity of the data. Longitudinal modeling techniques for modeling heterogeneity are panel data models and these include variable effects allowing the intercept and/or slope parameters to vary. Heterogeneity can also be modeled using random variables instead of fixed parameters. Random-effects and fixed effects models are covered in Frees (2004) (Chap. 3).

3.2 Summary and comparison of models

Table 7 compares the models for house prices including models with both time series and cross sectional characteristics. Selected models are discussed in the following subsection. Models are estimated for the quarterly growth rates in postcode-level house price indices except for models that use socio-demographic postcode area characteristics which are only available for census years. In these models, growth rates of postcode-level house price indices are calculated by taking the difference between the ln index value observed in December of one census year minus the ln index value observed in December of the previous census year. The variability of the dependent variable, $\hat{\sigma}^2$, is estimated as the standard deviation of house price growth rates over time and over the cross-section. The percentage of this variability explained by the model is calculated by comparing the variability of the dependent variable to the variability of the model error terms.

The multivariate ARIMA model was selected based on the model fit using the Akaike information criterion (AIC), the number of significant parameters, and the time series properties of the model's errors. Models were estimated using conditional least squares estimation. The time series model that represents the series best, given as Model 1, is an ARIMA(3,1,1) model with three autoregressive terms and one moving average term. Model 1 explains 73.4% of variability in house price growth rates.

Panel data models for quarterly postcode-level house price growth rates with growth rates of the Sydney market price index as the explanatory variable were estimated using restricted maximum likelihood (REML) estimation. Model 2a assumes a ho-

No.	Frequency	Main explanatory variables	Slope	Intercept	Error structure	AIC	$\hat{\sigma}^2$	$\%\hat{\sigma}^2$
1	Quarterly	ARIMA(3,1,1)	.	fixed	diagonal	-184,446	0.00058	73.4%
2a	Quarterly	growth_Sydney	homogenous	fixed	diagonal	-160,649	0.00058	42.8%
2b	Quarterly	growth_Sydney	variable	fixed	diagonal	-160,742	0.00058	44.8%
2c	Quarterly	growth_Sydney	variable	fixed + random	diagonal	-161,003	0.00058	44.4%
2d	Quarterly	growth_Sydney	variable	fixed	ARMA(1,1)	-163,309	0.00058	42.0%
3a	Quarterly	Marcoec. variables	homogenous	fixed	ARMA(1,1)	-157,352	0.00058	1.9%
3b	Quarterly	Macroec. variables	variable	fixed	ARMA(1,1)	-147,862	0.00058	2.5%
3c	Quarterly	Macroec. variables with 5 lags	homogenous	fixed	ARMA(1,1)	-154,631	0.00058	20.8%
3d	Quarterly	Marcoec. variables, growth_Sydney	homogenous	fixed	ARMA(1,1)	-165,973	0.00058	48.8%
4a	5-year	Socio-demog. variables	homogenous	fixed	ARMA(1,1)	-2,065	0.02440	23.1%
4b	5-year	Socio-demog. variables with 1 lag	homogenous	fixed	ARMA(1,1)	-1,805	0.02440	61.5%

Table 7: Comparison of different models for the growth rates in postcode-level house price indices. *Notes:* AIC denotes Akaike's information criterion. $\hat{\sigma}^2$ denotes estimated variability in the dependent variable.

mogenous slope for the Sydney index and explains 42.8% of the variability in the postcode-level growth rates. This increases to 44.8% in Model 2b which assumes a different slope parameter for each postcode. This model quantifies the differential price sensitivity of house prices in different postcode areas towards the market index. Model 2c includes, in addition, a random intercept term for each postcode but this does not improve the percentage of the explained variability with most random intercept terms insignificant. Including an ARMA(1,1) error covariance structure provides the best fit in terms of the AIC criterion.[8] The market-wide growth rate is an important factor explaining variability and growth rates across postcodes. There remains a significant amount of variation in the quarterly postcode growth rates.

To quantify the impact of exogenous variables on house prices, postcode-level house price growth rates are modeled with macroeconomic and financial variables, seasonal dummy variables, and geographic explanatory variables. Model 3a assumes homogenous slope parameters for the macroeconomic and financial variables and an ARMA(1,1) error covariance structure. Although these factors are statistically significant, the model only explains 1.9% of the variability in house price growth rates. Allowing for variable slope parameters in Model 3b improves the model only marginally. Since only a few of the many postcode-specific slope parameters are significant only homogenous slopes are included in subsequent models. Model 3c with lagged values (five lags) of the macroeconomic and financial variables explains 20.8% of the variability in house price growth rates. Model 3c that includes the growth rate of the Sydney index and macroeconomic and financial variables explains 48.8% of house price risk.

Panel data models that quantify the impact of socio-demographic postcode area characteristics on postcode-level house price growth include Model 4a, which is based on current values of the socio-demographic variables and explains 23.1% of postcode-level house price risk, and Model 4b, which explains 61.5% by considering socio-

[8]The ARMA(1,1) covariance structure is defined as $\sigma_{ij} = \sigma^2[\gamma\rho^{(i-j)-1}I(i \neq j) + I(i = j)]$, where σ_{ij} denotes the ijth element in the covariance matrix, ρ is the autoregressive parameter, γ models a moving-average component, and σ is the residual variance. $I(A)$ equals 1 when statement A is true and 0 otherwise.

demographic trends observed in the current census and in the previous census.

3.3 Detailed results for selected models

Multivariate ARIMA(3,1,1) model

Time series models without cross sectional explanatory variables explain a large share of the variability in postcode-level house price growth rates (73.4%). The autoregressive nature of house price growth rates means that the historical values provide information about future trends. Parameter estimates for an ARIMA(3,1,1) are provided in Table 8. All model parameters are statistically significant. The autocorrelation and partial autocorrelation functions show no significant autocorrelation left in the errors. The quarterly lagged growth rates capture any seasonality.

		Parameter estimates			
Effect	Estimate	Standard Error	t Value	Approx Pr > |t|	Lag
Intercept	0.022	0.001	19.27	<.0001	0
$growth_{i,t-1}$	1.145	0.013	85.82	<.0001	1
$growth_{i,t-2}$	-0.074	0.010	-7.66	<.0001	2
$growth_{i,t-3}$	-0.088	0.009	-9.98	<.0001	3
$\varepsilon_{i,t-1}$	0.727	0.012	61.87	<.0001	1
		Fit Statistics			
	AIC	-184,462	BIC	-184,421	

Table 8: Estimation results for the multivariate ARIMA(3,1,1) model based on quarterly data for I-1979 to I-2011.

Time series models are the standard modeling approach for banking and insurance applications when quantifying risk from an asset such as housing as in this study. Modeling the market-wide index does not capture differing trends by postcode. Cross sectional variation is evident in house price growth rate data. To not include this is a substantial weakness of any risk model for a non-homogeneous asset such as housing.

Panel data model with variable slopes for the Sydney house price market index

Panel data models with variable slopes for growth in the Sydney market index quantify the sensitivity of postcode-level house prices towards market movements. Model 2d assumes an ARMA(1,1) covariance structure for the errors. The estimation results are summarized in Table 9. The estimated slope parameters are significant for all 243 postcode areas. The three parameters defining the ARMA(1,1) covariance structure (denoted as ρ, γ, and σ) are all statistically significant. The mean of the estimated slope parameter across all postcode areas is 0.459, with a standard deviation of 0.105, so that sensitivity to overall market growth rates is relatively significant but varies across postcodes. Correlations between postcodes are captured with a single-factor model using the market-wide index. Some postcodes have a higher proportion of variation explained by the market-wide index where there is a higher slope as given by the beta with respect to the market-wide index.

Covariance parameter estimates for the random effects						
Cov. Parameter	Subject	Estimate	Std. Error	Z Value	Pr Z	
ρ	postcode	0.7720	0.0079	97.89	<.0001	
γ	postcode	0.3181	0.0080	39.88	<.0001	
σ		0.0003	0.0000	94.14	<.0001	
Solution for fixed effects						
Effect	Postcode	Estimate	Std. Error	t Value	Pr > |t|	DF
Intercept		0.013	0.000	56.42	<.0001	242
$growth\_Sydney_t * postcode$	2007	0.510	0.063	8.07	<.0001	31,000
$growth\_Sydney_t * postcode$	2008	0.603	0.063	9.54	<.0001	31,000
$growth\_Sydney_t * postcode$	2009	0.606	0.063	9.60	<.0001	31,000
...	...	...	...	...	...	
$growth\_Sydney_t * postcode$	2785	0.245	0.063	3.88	<.0001	31,000
$growth\_Sydney_t * postcode$	2786	0.330	0.063	5.22	<.0001	31,000
$growth\_Sydney_t * postcode$	2787	0.246	0.073	3.89	<.0001	31,000
Fit Statistics						
AIC	-163,309	BIC	-163,299			

Table 9: Estimation results for Model 2d based on quarterly data for I-1979 to I-2011. *Notes:* Parameter estimates for all postcodes are available from the authors upon request. The parameters ρ, γ, and σ define the ARMA(1,1) structure of the error covariance matrix.

Spatial effects are also observed in the growth rates. House prices in different suburbs vary considerably in their sensitivity towards changes in the Sydney market index. Figure 10 shows that house prices are more sensitive towards changes in the Sydney market index the closer the postcode area is located to Sydney's central business district. Table 10 shows that price sensitivity is largest for postcode at the Sydney harbor and near the CBD. These two regions also have the highest house prices growth rates (compare Table 4).

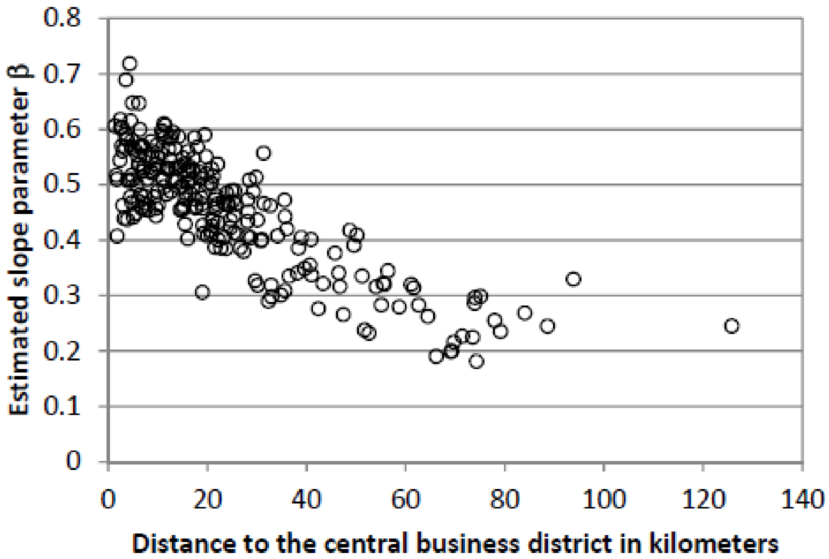

Figure 10: Scatter plot of the estimated postcode-specific slope parameters in Model 2d against the corresponding postcode area's distance in kilometers from Sydney's central business district.

Region	Mean*	Std. Dev.*	N
Total	0.459	0.105	243
CBD	0.518	0.075	7
Harbor	0.532	0.060	25
Airport	0.511	0.070	7
Coast	0.491	0.084	22

Table 10: Descriptive statistics for the estimated postcode-specific slope parameters in Model 2d. *Notes:* * indicates that the summary statistics are calculated for the parameter estimates.

Panel data model with macroeconomic, financial, seasonal, and geographic variables

Model 3c explains the quarterly growth rates in postcode-level house price indices with macroeconomic and financial variables with up to five lags, seasonal dummy variables for the first, second, and third quarter of a year, the postcode's distance in kilometers from Sydney's central business district, and the square of this distance measure. Interest rates are converted to real interest rates using the observed inflation rate and mortgage rates are omitted to avoid estimation issues because of high correlations between mortgage rates, interest rates, and inflation. An ARMA(1,1) error structure is assumed for the errors.

From Table 11 significant effects are found for both current and lagged values of the macroeconomic and financial variables demonstrating that macroeconomic and financial variables are highly significant factors explaining house price growth rates. Interestingly, real GDP growth in the current quarter and growth in the ASX stock market index lagged one quarter are significant explanatory factors for increases in house price growth. A buoyant economy is positive for houses prices. There is a significant negative relationship between house price growth and unemployment rates in the same quarter and between house price growth and real interest rates lagged one quarter. Significant seasonal effects are found for the first and second quarter with below-average house price growth in the first quarter and above-average growth in the second and third quarter. House price growth in a postcode area is significantly related to the distance of the postcode area to Sydney's central business district in a non-linear manner as noted previously in Section 2.

Given the nature of economic variables and the likely impact of the real economy on housing prices lagged values of the economic variables should be included in the model. House prices also have an impact on the real economy and this is a factor that the Reserve Bank of Australia monitors when assessing monetary policy and interest rate settings. Geographic and spatial factors are also significant since capturing variability with economic factors does not explain postcode variability even though the economic effects on house prices may vary by postcode.

Panel data model with socio-demographic and geographic postcode area characteristics

Socio-demographic characteristics are only available from the census date every five years. This limits the usefulness of these variables in practical applications. Model 4a includes an intercept, socio-demographic postcode area characteristics observed in the current census, the postcode's distance in kilometers from Sydney's central business district, and the square of this distance measure. An ARMA(1,1) error structure is assumed for the errors. The socio-demographic characteristics are transformed to rates of change to represent the trends observed in these variables (compare Table 6 in

Covariance parameter estimates for the random effects					
Cov. Parameter	Subject	Estimate	Std. Error	Z Value	Pr Z
ρ	postcode	0.8117	0.0067	121.28	<.0001
γ	postcode	0.5178	0.0076	67.90	<.0001
σ		0.0005	0.0000	67.41	<.0001
Solution for fixed effects					
Effect	Estimate	Std. Error	t Value	Pr > |t|	DF
Intercept	0.0096	0.0016	6.03	<.0001	240
GDP growth$_t$	0.0025	0.0002	16.79	<.0001	30,000
GDP growth$_{t-1}$	0.0015	0.0002	9.31	<.0001	30,000
GDP growth$_{t-2}$	0.0004	0.0002	2.47	0.014	30,000
GDP growth$_{t-3}$	0.0012	0.0002	7.21	<.0001	30,000
GDP growth$_{t-4}$	0.0011	0.0002	6.23	<.0001	30,000
GDP growth$_{t-5}$	0.0011	0.0002	6.52	<.0001	30,000
Unempl. rate$_t$	-0.0038	0.0004	-8.58	<.0001	30,000
Unempl. rate$_{t-1}$	0.0032	0.0005	6.54	<.0001	30,000
Unempl. rate$_{t-2}$	0.0027	0.0005	5.12	<.0001	30,000
Unempl. rate$_{t-3}$	0.0001	0.0005	0.10	0.923	30,000
Unempl. rate$_{t-4}$	-0.0010	0.0005	-1.78	0.075	30,000
Unempl. rate$_{t-5}$	0.0002	0.0005	0.43	0.665	30,000
Real interest$_t$	0.0166	0.0090	1.85	0.064	30,000
Real interest$_{t-1}$	-0.2024	0.0090	-22.46	<.0001	30,000
Real interest$_{t-2}$	-0.0380	0.0087	-4.36	<.0001	30,000
Real interest$_{t-3}$	-0.0300	0.0086	-3.51	0.001	30,000
Real interest$_{t-4}$	0.1246	0.0093	13.35	<.0001	30,000
Real interest$_{t-5}$	0.0754	0.0092	8.17	<.0001	30,000
ASX growth$_t$	0.0000	0.0000	-1.90	0.057	30,000
ASX growth$_{t-1}$	0.0002	0.0000	13.38	<.0001	30,000
ASX growth$_{t-2}$	0.0000	0.0000	2.19	0.029	30,000
ASX growth$_{t-3}$	0.0001	0.0000	5.56	<.0001	30,000
ASX growth$_{t-4}$	0.0000	0.0000	-1.22	0.221	30,000
ASX growth$_{t-5}$	0.0000	0.0000	-3.15	0.002	30,000
QI_dummy	-0.0021	0.0003	-7.90	<.0001	30,000
QII_dummy	0.0020	0.0003	7.16	<.0001	30,000
QIII_dummy	0.0005	0.0003	1.97	0.049	30,000
Distance	-0.0002	0.0000	-5.00	<.0001	240
Distance^2	0.0024	0.0005	4.94	<.0001	240
Fit Statistics					
AIC	-154,631	BIC	-154,621		

Table 11: Estimation results for Model 3 based on quarterly data for I-1979 to I-2011. *Notes:* The parameters ρ, γ, and σ define the ARMA(1,1) structure of the error covariance matrix. Distance^2 was divided by 1000 to obtain parameter estimates.

Section 2).

Significant effects are found for all four socio-demographic variables. The estimated parameters are given in Table 12. Higher house price growth in a postcode is related to an increase in the median household income in this postcode, a decrease in the unemployment rate, a decrease in the median age, and to an increase in the average household size in this postcode. The last two effects indicate that higher house price growth is observed in areas where the population gets younger and household sizes increase, that is, areas that attract young families.[9] Furthermore, house price growth in a postcode area is significantly related to the distance of this postcode area to Sydney's central business district in a non-linear manner.

Covariance parameter estimates for the random effects						
Cov. Parameter	Subject	Estimate	Std. Error	Z Value	Pr Z	
ρ	postcode	-1.0000	0	.	.	
γ	postcode	-0.677	0.025	-26.85	<.0001	
σ		0.018	0.001	14.29	<.0001	
Solution for fixed effects						
Effect		Estimate	Std. Error	t Value	Pr > |t|	DF
Intercept		0.400	0.009	42.87	<.0001	239
Median income growth		0.287	0.025	11.66	<.0001	960
Unempl. rate growth		-0.051	0.009	-5.75	<.0001	960
Median age growth		-0.257	0.069	-3.72	0.0002	960
Household size growth		0.374	0.088	4.25	<.0001	960
Distance		-0.003	0.000	-7.83	<.0001	239
Distance^2		0.034	0.004	8.99	<.0001	239
Fit Statistics						
AIC	-2,065	BIC	-2,058			

Table 12: Estimation results for Model 4 based on data for the Census years 1981-2006. *Notes:* The parameters ρ, γ, and σ define the ARMA(1,1) structure of the error covariance matrix. Distance^2 was divided by 1000 to obtain parameter estimates.

[9]Model 4b controls for potential endogeneity between house price growth and the socio-demographic characteristics of a postcode area by including socio-demographic variables observed in the current census and in the previous census. The model confirms the strong positive link between house price growth and income growth.

4 Applications of house price models in banking and insurance

Insurers have major exposures to house price risks through the portfolio of property risks that they underwrite. Banks also have direct exposure through default risk on their mortgage loans secured on residential property. Despite this there is limited detailed analysis of models for quantifying house price risk and limited analysis based on house price data other than at a market-wide level. This reflects the limited availability of such detailed data. This paper is one of the first to provide an assessment of a range of models, to quantify this significant risk and to do this at a postcode level for houses in a major city.

Research on product risk analysis and pricing of housing related financial products, such as reverse mortgages or mortgage insurance, usually models house price risk based on aggregate market indices. From the results in Section 2 house price risk or variability has two main components: temporal variations and cross-sectional heterogeneity. Multivariate time series models effectively capture the autoregressive and moving average patterns observed in the time series but do not explain the cross-sectional variability. Unless a bank or an insurer has exposure to a house portfolio that is representative of the overall market there will be significant risk in the portfolio that is not captured using market-wide indices. The panel data models used here are shown to capture this heterogeneity. The growth rate of houses varies significantly by geographic region and this is shown in the Sydney housing market. Macroeconomic factors are shown to be important in explaining variability in addition to a market-wide index.

Mortgage-related financial products have been a significant component in financial distress faced by banks and insurers as a result of the recent financial crisis. A major risk faced by banks and credit lending institutions providing mortgage loans is mortgage default. Default rates on mortgage loans depend on house price dynamics through the put option-like character of a mortgage loan to the borrower, along with general economic factors, and on the individual borrower's economic situation (see, e.g., Case *et al.*, 1996; Ambrose and Buttimer, 2000; Mian and Sufi, 2009). From the panel data models in Section 3 postcode-level house prices are seen to depend on socio-demographic variables and particularly on macroeconomic factors, including lagged values of these explanatory variables. House price growth was shown to be significantly related to macroeconomic and financial variables including GDP growth, the ASX stock market index, and interest rates. Macroeconomic fluctuations have longer-term, accumulating effects on house price growth since lagged values are significant in explaining house price growth rates. From a borrower risk perspective the analysis of house price growth shows that lower growth occurs in postcode areas with decreasing income levels and an ageing population. In these areas, mortgage loan providers would expect higher mortgage default rates and lower proceeds from selling properties out of foreclosure.

Risk management of house price risk for banks and insurers is more challenging because of the lack of traded instruments to manage the risk. Capital requirements for banks and insurers are increasingly reflecting the risk characteristics of their loans and other assets. Housing exposures are a significant component of the business of many major banks and a significant risk factor for mortgage insurers. Insurance products for housing exposures are not widely available and housing derivatives generally only hedge market-wide risks. The panel models presented in Section 3 show that house price growth rates in a suburb are not fully correlated with the market-wide index. For the house Sydney market, the market index only explained between 42% and 44% of the longitudinal and cross-sectional variation in house price growth rates. The sensitivity of the house price growth rates towards the market index varied significantly across postcodes. The model can quantify and also be used to improve the effectiveness of indexed-based hedging. For Sydney, postcodes near the central business district and at the harbor are closer to the market-wide index. Macroeconomic and financial factors increased the percentage of variability explained up to 49% for houses in the Sydney market. These factors can be used to improve hedging and also inform risk pricing at a finer level than just basing the risk analysis on a market-wide index.

The panel models that relate postcode-level house price growth to the market index can also be used for portfolio management applications in the same way that market betas in the equity market are used. Investors can systematically select postcodes areas that are less correlated with the aggregate housing market when constructing portfolios taking into account expected future growth rates. By taking into account the correlations with macroeconomic and financial variables, investors can use the models to construct portfolios with diversification across asset classes.

This paper has provided a detailed analysis of house price growth rate risks based on a large residential property market in Sydney, Australia. There is limited detailed analysis in the literature of the risks in housing portfolios for banks and insurers provided at the level of analysis in this paper. The models presented and assessed in the paper provide a better understanding of the risks inherent in housing portfolios and in housing-related financial products.

To practically embed these models into risk management or portfolio management processes the models should be estimated for a subset of postcode areas that represent the actual exposure of the specific portfolio. To apply model types that are based on an aggregate market index as the main explanatory variable an index should be used that is close to experience of the respective portfolio. However, the models can also be used to measure the basis risk associated with indexed-based hedging. The models are designed to capture both cross-sectional and longitudinal variations and results are presented based on a very large panel data set. The models can also be applied to data sets with fewer observations in the longitudinal dimension.

5 Summary and conclusions

House price uncertainty presents a substantial risk to private and institutional real estate investors and to the large financial sector providing housing-related financial products such as mortgage loans, equity release products such as reverse mortgages or home reversion schemes, asset-backed securities, and mortgage-backed securities. A comprehensive analysis of house prices in Sydney is used to quantify house price risks. Sydney is a large international city with similar risk factors that would be found in most international cities. The major issues to be considered are the rates of growth and volatility of the whole market since this is the basis of most risk analysis involving products that depend on house prices. House price risks are assessed at a postcode area-level and models appropriate for applications in banking and insurance developed.

The paper shows how sub-markets within a housing market can have quite different risk and return behavior in the housing market and that the risk factors that impact the variability of returns generate heterogeneity in the market. Economic factors and the market-wide index generate systematic changes in house prices but only explain part of the total variability. Individual house price characteristics including the location of the house are important factors. Socio-economic characteristics of a postcode area are also important factors from an insurer or bank perspective.

The detailed statistical analysis of postcode-level house price indices shows that long-term returns to house investments vary considerably across postcode areas and that higher long-term returns are associated with higher risk, as is the case with most investment classes. House price growth exhibits very large variations over short time horizons with standard deviations of up to 150% of average growth rates and that these variations reduce for longer time horizons. Seasonal patterns are documented and an U-shaped relationship is found between house price growth in a suburb and its distance from the city center.

Different approaches to jointly modeling the development of postcode-level house prices over time and over the cross-section are provided. A multivariate auto-regressive moving average (ARIMA) model capturing the data's time series properties provides a good explanation of temporal variations. Panel data models with variable parameters and random effects very effectively capture the cross-sectional heterogeneity observed in house prices at the postcode level. Variable slope parameters quantify how house prices in different postcode areas vary with the Sydney market house price index. The sensitivity of house price growth to the market index is higher for areas with higher growth rates. These are typically postcode areas located close to the city center.

Panel data models are also used to quantify the effects of other exogenous factors on house price growth. A model estimated for quarterly house price growth rates identifies a range of macroeconomic and financial variables as drivers of house price growth: significant positive links are observed between house price growth and GDP growth rates and growth of the ASX stock market index. A negative link is found between house price growth and unemployment rates and real interest rates. Significant effects are also found for seasonal dummy variables and regional characteristics included in the model. The second model uses socio-demographic characteristics observed in the census years 1981-2006. The results from this model show that higher house price growth is observed in postcode areas with increasing average income levels and where the population gets younger.

The models developed are relevant for a many applications in banking and insurance. Applications include the risk assessment and pricing of equity release products, mortgage loans, and mortgage insurance policies. The models can also be used to estimate the basis risk of indexed-linked housing derivatives and indexed-linked home equity insurance.

6 Acknowledgement

The authors acknowledge the financial support of ARC Linkage Grant Project LP0883398 Managing Risk with Insurance and Superannuation as Individuals Age with industry partners PwC and APRA and the ARC Centre of Excellence in Population Ageing Research (CEPAR). Furthermore, data provision by Residex Pty Ltd is kindly acknowledged. John Edwards, Dan Liebke, Chris Fan, and David Lewis from Residex provided valuable technical support and suggestions. Yu Sun provided excellent research assistance.

References

Abelson, P., Joyeux, R., Milunovitch, G., and Chung, D. (2005). Explaining House Prices in Australia: 1970-2003. *Economic Record*, **81**(S1), S96–103.

Ambrose, B. W. and Buttimer, R. J. (2000). Embedded Options in the Mortgage Contract. *The Journal of Real Estate Finance and Economics*, **21**(2), 95–111.

Bodman, P. M. and Crosby, M. (2004). Can Macroeconomic Factors Explain High House Prices in Australia? *Australian Property Journal*, **38**(3), 174–179.

Bourassa, S. C., Hamelink, F., Hoesli, M., and MacGregor, B. D. (1999). Defining Housing Submarkets. *Journal of Housing Economics*, **8**(2), 160–183.

Bourassa, S. C., Hoesli, M., and Peng, V. S. (2003). Do Housing Submarkets Really Matter? *Journal of Housing Economics*, **12**(1), 12–28.

Bourassa, S. C., Haurin, D. R., Haurin, J. L., Hoesli, M., and Sun, J. (2009). House Price Changes and Idiosyncratic Risk: The Impact of Property Characteristics. *Real Estate Economics*, **37**(2), 259–278.

Bourassa, S. C., Cantoni, E., and Hoesli, M. (2010). Predicting House Prices with Spatial Dependence: A Comparison of Alternative Methods. *Journal of Real Estate Research*, **32**(2), 139–160.

Caplin, A., Goetzmann, W. N., Hangen, E., Nalebuff, B., Prentice, E., Rodkin, J., Spiegel, M. I., and Skinner, T. (2003). Home Equity Insurance: A Pilot Project. Yale ICF Working Paper No. 03-12, Yale International Center for Finance.

Case, B., Clapp, J., Dubin, R., and Rodriguez, M. (2004). Modeling Spatial and Temporal House Price Patterns: A Comparison of Four Models. *The Journal of Real Estate Finance and Economics*, **29**(2), 167–191.

Case, K. E., Shiller, R. J., and Weiss, A. N. (1996). Mortgage Default Risk and Real Estate Prices: The Use of Index-Based Futures and Options in Real Estate. *Journal of Housing Research*, **7**(2), 243–258.

Chang, C.-C., Huang, W.-Y., and Shyu, S.-D. (2010). Pricing Mortgage Insurance with Asymmetric Jump Risk and Default Risk: Evidence in the U.S. Housing Market. *The Journal of Real Estate Finance and Economics*, (Forthcoming).

Chen, H., Cox, S., and Wang, S. (2010a). Is the Home Equity Conversion Mortgage in the United States sustainable? Evidence from pricing mortgage insurance premiums and non-recourse provisions using the conditional Esscher transform. *Insurance: Mathematics and Economics*, **46**(2), 371–384.

Chen, M.-C., Chang, C.-C., Lin, S.-K., and Shyu, S.-D. (2010b). Estimation of Housing Price Jump Risks and Their Impact on the Valuation of Mortgage Insurance Contracts. *Journal of Risk and Insurance*, **77**(2), 399–422.

Chernih, A. and Sherris, M. (2004). Geoadditive hedonic pricing models. Technical report, University of New South Wales.

Costello, G. (2001). Seasonal Influences in Australian Housing Markets. *Pacific Rim Property Research Journal*, **7**(1), 47–55.

Davidoff, T. (2009). Housing, Health, and Annuities. *Journal of Risk and Insurance*, **76**(1), 31–52.

Englund, P. (2010). Trading on Home Price Risk: Index Derivatives and Home Equity Insurance. In S. J. Smith and B. A. Searle, editors, *The Blackwell Companion to the Economics of Housing: The Housing Wealth of Nations*, pages 499–511. Wiley-Blackwell.

Frees, E. W. (2004). *Longitudinal and Panel Data: Analysis and Applications in the Social Sciences*. New York: Cambridge University Press.

Hansen, J. (2009). Australian House Prices: A Comparison of Hedonic and Repeat-Sales Measures. *Economic Record*, **85**(269), 132–145.

Harrington, S. E. (2009). The Financial Crisis, Systemic Risk, and the Future of Insurance Regulation. *Journal of Risk and Insurance*, **76**(4), 785–819.

Hatzvi, E. and Otto, G. (2008). Prices, Rents and Rational Speculative Bubbles in the Sydney Housing Market. *Economic Record*, **84**(267), 405–420.

Knight, E. and Cottet, R. (2011). Australian Residential Housing Market & Hedonic Construction of House Price Indices for Metropolitan Sydney. OME Working Paper No: 02/2011, The University of Sydney, Australia.

Li, J. S.-H., Hardy, M. R., and Tan, K. S. (2010). On Pricing and Hedging the No-Negative-Equity Guarantee in Equity Release Mechanisms. *Journal of Risk and Insurance*, **77**(2), 499–522.

Malpezzi, S. (2002). Hedonic Pricing Models and House Price Indexes: A Select Review. In K. Gibb and A. O'Sullivan, editors, *Housing Economics and Public Policy: Essays in Honour of Duncan Maclennan*, pages 67–89. Oxford: Blackwell Publishing.

Mian, A. and Sufi, A. (2009). The Consequences of Mortgage Credit Expansion: Evidence from the U.S. Mortgage Default Crisis. *The Quarterly Journal of Economics*, **124**(4), 1449–1496.

Otto, G. (2007). The Growth of House Prices in Australian Capital Cities: What do Economic Fundamentals Explain? *The Australian Economic Review*, **40**(3), 225–238.

Páez, A. (2009). Recent Research in Spatial Real Estate Hedonic Analysis. *Journal of Geographical Systems*, **11**(4), 311–316.

Rossini, P. A. (2000). Estimating the Seasonal Effects of Residential Property Markets - A Case Study of Adelaide. The proceedings of the Pacific-Rim Real Estate Society Conference, Sydney.

Rossini, P. A. (2002). Calculating stratified residential property price indices to test for differences in trend, seasonality and cycle. Technical report. The proceedings of the Pacific-Rim Real Estate Society Conference, Christchurch, New Zealand.

Shiller, R. J. and Weiss, A. N. (1999). Home Equity Insurance. *The Journal of Real Estate Finance and Economics*, **19**(1), 21–47.

Sirmans, S. G., Macpherson, D. A., and Zietz, E. N. (2005). The Composition of Hedonic Pricing Models. *Journal of Real Estate Literature*, **13**(1), 1–44.

Sommervoll, D. E. and Wood, G. (2011). Home Equity Insurance. *Journal of Financial Economic Policy*, **3**(1), 66–85.

Street, A. (2011). A House or a Home? Finding Value in Australian Residential Property. Technical report. Presented to the Institute of Actuaries of Australia Biennial Convention.

Sun, D. and Sherris, M. (2010). Risk Based Capital and Pricing for Reverse Mortgages Revisited. UNSW Australian School of Business Research Paper No. 2010ACTL04, University of New South Wales, Australia.

Wang, L., Valdez, E. A., and Piggott, J. (2008). Securitization of Longevity Risk in Reverse Mortgages. *North American Actuarial Journal*, **12**(4), 345–371.