Extrapolative time-series modelling of house prices: A case study from Sydney, Australia

Abstract

Purpose

House price fluctuations send vital signals to many parts of the economy, and long-term predictions of house prices are of great interest to governments and property developers. Although predictive models based on economic fundamentals are widely used, the common requirement for such studies is that underlying data are stationary. This paper demonstrates the usefulness of alternative filtering methods for forecasting house prices.

Design/methodology/approach

We specifically focus on exponential smoothing with trend adjustment and multiplicative decomposition using median house prices for Sydney from Q3 1994 to Q1 2017. The model performance is evaluated using out-of-sample forecasting techniques and a robustness check against secondary data sources.

Findings

Multiplicative decomposition outperforms exponential smoothing at forecasting accuracy. The superior decomposition model suggests that seasonal and cyclical components provide important additional information for predicting house prices. The forecasts for 2017-2028 suggest that prices will slowly increase, going past 2016 levels by 2020 in the apartment market and by 2022/23 in the detached housing market.

Research implications/Practical implications

We demonstrate that filtering models are simple (univariate models that only require historical house prices), easy to implement (with no condition of stationarity), and used widely in financial trading, sports betting, and other fields where producing accurate forecasts is more important than explaining the drivers of change. The paper puts forward a case for the inclusion of filtering models within the forecasting toolkit as a useful reference point for comparing forecasts from alternative models.

Originality

To the best of the authors' knowledge, this paper undertakes the first systematic comparison of two filtering models for the Sydney housing market.

Keywords: house price, extrapolative modelling, decomposition, exponential smoothing, Sydney

1. Introduction

House price fluctuations send vital signals to many parts of the economy (Stroebel and Vavra, 2019, Cesa-Bianchi et al., 2015, Disney and Gathergood, 2018, Girouard and Blöndal, 2001). Changes in house prices can have far reaching implications for a number of sectors of the economy, including finance, construction, and insurance (Coakley, 1994, Gholipour et al., 2019). From a property development perspective, shifts in house prices indicate the 'right time' to release land for development and when to build or sell (Tideman, 2016). These decisions often involve long term forecasting and planning. In fact, house price forecasting has become imperative for decision-making around releases of new residential land and assessing the infrastructure needs in local areas (Mulley and Tsai, 2016). As such, the long-term prediction of house prices is of interest to a range of stakeholders, including policymakers, property developers, and investors.

Forecasting models are traditionally based on econometric foundations which in turn rely on strict assumptions and the *stationarity* of data (Dufitinema, 2022). *Stationarity* indicates that the statistical properties of a process generating a time series do not change over time. This does not mean the series itself does not change over time; it means the *way* it changes does not change over time. Stationary time-series models are helpful for identifying driving factors. For instance, changes detected in two time-series variables may infer a correlation but both time series must be stationary to make such an inference otherwise the observed correlation may be misleading.

The alternative filtering approach does not require an assumption of stationarity (Cheng et al., 2015), and allows for serial correlation in the data (as usual for most datasets). Extrapolative models, such as filtering models, examine historical movement of house prices and extrapolate these movements into the future, with their primary adjustment being time. These predictions will therefore assume that previous house price patterns will continue into the future. Filtering is commonly used in financial trading, sports betting and other fields where accurate forecasting is more important than explaining the drivers of change (Sargent and Bedford, 2010, Chang et al., 2011).

This paper examines the usefulness of the extrapolative approach – *filtering* methods – for forecasting house prices, an activity that is traditionally undertaken on the assumption of stationary data and using econometric models. As this paper endeavours to demonstrate, since *filtering* methods are the predominant forecasting method in finance, actuaries, and management, they are a worthwhile addition to the toolkit of house price analysts. These methods provide a useful reference point for comparing forecasts from alternative models. We will demonstrate two filtering approaches: (1) exponential smoothing with trend adjustment, and (2) multiplicative decomposition. Method (1) incorporates the trend and random change, whereas method (2) combines the trend, seasonal and cyclical variations, and random change into the filtering models. Median house prices sourced from the New South Wales Department of Family and Community Services (FACS) Rent and Sales Reports for Sydney from Q3 1994 to Q1 2017 are used to calibrate the models. The accuracy measures validated that multiplicative decomposition generated the most accurate forecasts compared to exponential smoothing with trend adjustment. The forecasts for 2017-2028 indicated that house prices in Sydney would slowly increase, going past 2016 levels by 2020 (apartment market) and by 2022/23 (detached housing market). These forecasts move closely with the evidence provided via secondary data sources and the predictions of alternative forecasting models.

Sydney has a dynamic housing market. In the peak of the pandemic in 2021, Sydney house prices soared by 26.7% however recorded a steep annual fall of 11% in 2022 (Burke and Heagney-Bayliss, 2023). These extreme patterns of house prices have been confirmed by The Urban Reform Institute (2022), which ranked Sydney as the world's second most unaffordable housing market. By testing the filtering methods on a market that has high volumes and variability provides stronger evidence on the usefulness of these methods as a forecasting tool. The study period (1994-2017) was chosen due to the availability of a unique dataset widely used in NSW until the late 2010s (NSW Rent and Sales Reports). The forecasts were developed for the period 2017-28 to meet the requirements of a funded research project to develop *long-term* forecasts.

Although long term house price predictions are of great interest to governments and property developers, the most common short-term forecasts typically extend to three years only. Despite the critical need for long term house price forecasts, there are no commonly accepted guidelines or approaches for developing such forecasts. This paper addresses this gap by developing two types of filtering models to extrapolate Sydney house prices for the period 2017-2028 despite that generating eleven-year forecasts is challenging due to the uncertainties associated with longer time intervals.

This paper is structured as follows: Section 2 introduces time-series, univariate, and filtering models and outlines the strengths of the filtering models. Section 3 illustrates the model building process, incorporating exponential smoothing with trend adjustment and multiplicative decomposition methods. Section 4 explains the dataset and variables, followed by model testing and estimation. The real and nominal forecasts developed for 2017-2028 are discussed and ground-truthed in Section 5. The final section concludes the paper with a summary of the key points.

2. Time-series, univariate and filtering models

2.1. Time-series and univariate models

Predictive models based on economic fundamentals are widely used to forecast house prices, with the common requirement that the underlying data are stationary (Dufitinema, 2022). As a prerequisite for such an analysis, stationarity testing must be undertaken before implementing a time-series analysis. A stationary process has the property whereby the mean, variance, and autocorrelation structure do not change over time (Grami, 2016). In other words, a stationary time series has no trend, so it fluctuates around a constant mean using a constant variance. This requirement implies that if the series is stationary, the sample statistics – i.e., the mean, variance, and covariance – are robust descriptors of future behaviour. Multivariate models such as VAR models[i] are examples of stationary time-series models but if the series consistently increases over time, then the sample mean, and variance will increase with the sample size and underestimate the mean and variance in future periods.

Univariate time-series models, also known as extrapolative models, use historical data on only one variable (e.g., house prices) and are extrapolations from past values. These models are thus subject to the assumption that past patterns of change will continue into the future. In other words, univariate time-series models assume that future house prices are a function of previous house prices.

Univariate time-series analysis has a relatively long tradition in house price prediction (Case and Shiller, 1989, Bollerslev et al., 2016, Schindler, 2012). The evidence that supports the *mean reversion* attribute of asset prices and the evidence that refutes the weak-form efficiency (as defined in the *efficient market hypothesis* (EMH)) are justifications for using a univariate prediction. The *mean reversion* indicates that asset prices and historical returns will eventually revert to the long-run average of the entire data series. The mean value of assets can be related to another relevant average such as economic growth or the average return of a particular class of assets. In the literature, Glaeser and Nathanson (2017) suggested house prices display mean reversion at five-year intervals, and Glindro et al. (2011) presented evidence of serial correlation and mean reversion of house prices in nine Asia-Pacific economies.

Moreover, the EMH defines three forms of asset market efficiency: weak, semi-strong, and strong. The weak form states that it is impossible to predict future movements of asset prices using information from previous prices[ii] because under weak-form efficiency, all current information is already reflected in prices and past information has no relationship with current market prices. Most earlier research testing weak-form efficiency reported evidence supporting market inefficiency (Maier and Herath, 2009). In other words, asset markets are weak-form inefficient and thus past prices can be used to predict future prices, a justification for the use of univariate models of house prices.

2.2. Filtering models: A type of univariate models

Filtering models are univariate time-series models that do not assume stationarity, and like other univariate models, it is an extrapolative forecasting method that assumes that the patterns that existed in the past will continue into the future. Filtering methods assume that those patterns are regular and can be measured by decomposing[iii] a time series down into its component parts: trend, seasonal, cyclical, and random components:

i. a *trend* detects either a general upward or downward direction in data values over a period of time
ii. a *seasonal* component measures the variation in a time series representing intra-year fluctuations, such as daily, weekly, monthly or quarterly changes (known as ‘calendar effects’)
iii. a *cyclical* variation refers to regular or periodic fluctuations around the trend, revealing a succession of phases of expansion and contraction
iv. a *random* change incorporates the irregular movements in data values. The variability of these movements cannot be determined.

Due to the different components of a time series, namely Trend (T), Seasonal (S), Cyclical (C), and Random (R), various time-series forecasting methods may capture one or more components of a time series. Table 1 summarises the commonly used forecasting methods and the time-series components they capture. Note that these forecasting methods are primarily twofold in their function: averaging (moving average, weighted moving average, and centred moving average) and filtering (exponential smoothing, seasonal indexing, regression, exponential smoothing with trend, and decomposition). Averaging is more common in the econometric approach, whereas filtering is more common in the finance and management disciplines.

If all variations in a time series are due to random variations, with no trend or seasonal or cyclical components, some type of averaging or smoothing model would be appropriate (Render et al., 2012). However, if the data are more sophisticated and represent other components, a different method should be considered (see Table 1).

Table 1: Univariate time-series methods overview

Time-series component	**Forecasting method**
Random	Moving average Weighted moving average Exponential smoothing
Seasonal	Seasonal indexing (deseasonalisation)
Trend and seasonal	Regression
Trend and random	Exponential smoothing with trend
Seasonal with trend	Centred moving average (CMA)
Trend, cyclical, seasonal and random	Decomposition

Source: Render et al. (2012)

2.3. Strengths and adaptability of filtering models

If the focus is on forecasting house prices rather than identifying the driving factors, techniques that involve filtering methods are generally useful. These models are: (a) simple (univariate models that only require historical house prices); (2) easy to implement (with no condition of stationarity); and (3) those used in financial trading, sports betting, and other fields where producing accurate forecasts is more important than explaining the drivers of change.

In the area of sports betting, for example, Clarke (1993) and Sargent and Bedford (2010) published two Australian filtering applications using exponential smoothing to forecast the results of Australian rules football matches. The latter study achieved improved forecasts by supplementing exponential smoothing, whereas the forecasts developed in the former study performed at the level of expert tipsters.

In the financial trading area, the filtering model developed by Yu (2002) to forecast stock volatility in the New Zealand stock market was one of the best-performing models among the competing models compared in that study. Chang et al. (2011) looked at a decision system for stock trading signal detection and used a filtering model to identify the best stock turning points (trading signals) based on historical data. Through a series of experiments, that research showed far better results than other benchmark models. Anatolyev and Gospodinov (2010) analysed the predictability of excess stock returns using a filtering approach and found that an empirical analysis of US stock return data showed statistically and economically significant forecasting gains by the decomposition model over the conventional predictive regression.

3. Development of the model

We use two sophisticated yet well-established methods to comprehensively predict house prices in the long run: exponential smoothing with trend adjustment and multiplicative decomposition. Based on Table 1, the former method incorporates trend and random change, whereas the latter method incorporates trend, seasonal and cyclical variations, and random change into the filtering model.

3.1. The setting: Australian and Sydney housing markets

Much of Australia's wealth is dependent on property investments. Australia is the world's 12th largest economy with a GDP of A$2.5 trillion (The Australian Trade and Investment Commission, 2023). Australia's housing stock, valued at A$9.7 trillion in 2022 (Australian Bureau of Statistics, 2022), is worth four times the size of its gross domestic product. This represents more than the combined market value of all companies listed on the Australian Securities Exchange, the retirement savings pool (i.e., superannuation), and total commercial real estate assets (Mehra, 2022). Also, the housing sector has strong links to the finance, construction, and insurance sectors, and generates spillovers to other parts of the economy, including household consumption and employment. As cited in recent media commentaries, the study of Australian house prices is important also due to concerns about the crippling household debt-to-income ratio in that country, which is at one of the highest levels (119.8%) (CEIC DATA, 2023). This is in the back of skyrocketing house prices and a deepening housing affordability crisis over the past few decades.

Sydney is home to some of Australia's most expensive houses. Sydney's housing market has certain distinct characteristics however it also responds to national events and macroeconomic policies. As a result, Sydney's house prices show city-specific patterns at times but move closely with house prices in other Australian cities at other times. Therefore, house price changes across major cities may vary by direction and/or dimension of such changes, and forecasts developed in this study may not be transferable to other Australian cities.

Broadly, there are two housing categories in Australia – the Torrens (nonstrata) and Strata title houses. A vast majority of traditional detached homes and some attached dwellings such as duplexes are included in the former. The latter includes all other attached dwellings such as townhouses, apartments, and flats. In Torrens title dwellings, the purchaser owns both the land and building – i.e., freehold. The Strata title dwellings allow for individual ownership of a lot and shared ownership of common property (e.g., gardens, lifts, and driveways). For Strata dwellings, all lot owners are members of the owner's corporation, which is responsible for the maintenance of common property, and managing the finances and insurances of the scheme. As these are two different asset classes with different ownership structures, there is a considerable difference between the prices of non-strata (primarily, detached houses) and strata (mainly, apartments) dwellings in Australia. This paper thus develops separate forecasts for detached houses and apartments.

3.2. Exponential smoothing with trend adjustment

The first filtering model considered, exponential smoothing, tends to be more robust with non-stationary time series (Salles et al., 2019). The basic exponential smoothing model forecasts random variations of a variable but it should be extended with a trend adjustment if a trend is present. This involves developing an exponential smoothing forecast and then adjusting it for trend, as follows:

1. Compute smoothed forecast (F_{t+1})

$$F_{t+1} = FIT_t + \alpha(Y_t - FIT_t)$$

2. Update the trend (T_{t+1})

$$T_{t+1} = T_t + \beta(F_{t+1} - FIT_t)$$

3. Calculate trend-adjusted exponential smoothing forecast (FIT_{t+1})

$$FIT_{t+1} = F_{t+1} + T_{t+1}$$

Where *F* is the smoothed forecast, *FIT* is the forecast including trend, *Y* is the observed value, and T is the smoothed trend. α and β are smoothing constants, both with values between 0 and 1.

The level of the forecast is adjusted by multiplying the first smoothing constant α by the most recent forecast error and adding it to the previous forecast (step 1 above). The trend is adjusted by multiplying the second smoothing constant β by the most recent error or excess amount in the trend (step 2 above). A higher value gives more weight to recent observations and thus responds much faster to changes in the patterns. Adding these two – the smoothed forecast and the trend – generates the trend-adjusted exponential smoothing forecast (step 3 above). This process requires that F_t and T_t must be given or estimated. MS Excel Solver, an optimisation tool that can maximise or minimise a value given a set of constraints, is used to generate the optimal values of α and β that minimises the error.

3.3. Multiplicative decomposition

The intuition behind the application of decomposition models to forecasting is appealing. Disaggregating the various components in the time series (i.e., trend, cyclical component, seasonal factor, and random change) and predicting each component individually is viewed as a process of identifying the separate parts of the overall change that are driven by a strong and persistent element, thus separating them from any 'noise' and inconsistent variability. These processes are then also easier to extrapolate due to their more deterministic nature. It should therefore be possible to obtain more accurate forecasts for the individual components than for the overall process. This becomes important in the case of time series with high levels of noise (Theodosiou, 2011).

The decomposition model predicts that house prices are made up of three components – trend, cyclical and seasonal variations – and error:

$$X_t = f(T_t, C_t, S_t, E_t)$$

T_t = trend component at time period t

C_t = cyclical component at time period t

S_t = seasonal component at time period t

E_t = error component at time period t

The error is defined as the difference between the combined effect of three components of the data series – trend, cyclical and seasonal components – and the actual data. The components have clear meanings, so models decomposing a given time series into these components are very transparent (Novák et al., 2010). This model assumes that the entirety of time-variant determinants of house prices are captured by variations in the trend, as well as the cyclical component, seasonal factors, and random components.

The decomposition model has either an additive or multiplicative functional form. For a given pattern function of the four variables, trend, seasonality, cyclical variation and randomness, the *multiplicative* model assumes a mathematical representation of the following form:

$$X_t = T_t * C_t * S_t * E_t$$

The multiplicative decomposition model is implemented using five simple steps: first, the cumulative moving average (CMA), in which the number of terms is equal to the length of the seasonality (e.g., monthly or quarterly), is computed. A CMA of this length contains no seasonal effect and little or no randomness. The data is then deseasonalised by dividing each number by its seasonal index[iv]. This deseasonalised data is used to find the equation of a trend line, which can then be used to forecast the trend for future periods. Finally, the trend line forecast is multiplied by the appropriate seasonal index to generate the adjusted forecast.

Decomposition is a useful forecasting technique in certain contexts. For example, Liang (2011) found it superior to ARIMA[v] and neural network model prediction techniques in assessing the reliability of repairable systems in companies.

3.4. Measures of forecasting accuracy

The forecasting accuracy of the two methods described above is assessed using average error (Bias), mean absolute deviation (MAD), mean squared error (MSE), mean absolute percent error (MAPE) and root mean square error (RMSE). These methods compare forecasted values with actual values to assess accuracy (i.e., forecast error = actual value – forecast value). In each of the below formulae, *n* is the number of forecasts.

Bias (average error) indicates if the forecast is too high/low and by how much:

$$\text{Bias} = \frac{\sum error}{n}$$

MAD (mean absolute deviation) expresses accuracy in the same units as the data, which helps conceptualise the amount of error:

$$\text{MAD} = \frac{\sum |forecast\ error|}{n}$$

MSE (mean squared error) corresponds to the average of the squared errors:

$$\text{MSE} = \frac{\sum (error)^2}{n}$$

MAPE (mean absolute percent error) measures the accuracy as a percentage (i.e., relative error %) and is scale-independent:

$$\text{MAPE} = \frac{\sum |\frac{error}{actual}|}{n} 100\%$$

RMSE (root mean square error) measures the average magnitude of the error:

$$\text{RMSE} = \sqrt{\frac{\sum (error)^2}{n}}$$

4. Model testing and estimation

4.1. Dataset and variables

Median house prices for the Sydney Metro Area were obtained from the New South Wales Department of Family and Community Services (FACS) Rent and Sales Reports. The median values were reported for (i) all dwellings, (ii) detached houses (non-strata), and (iii) apartments (strata). Quarterly data covered the period from September 1994 to March 2017, a total of 91 quarters.

An analysis of house prices over time means they must be adjusted for inflation. This is typically accomplished by deflating house prices using the CPI (Robstad, 2017, Cesa-Bianchi et al., 2015, Dettling and Kearney, 2014, Knoll et al., 2017). In the Australian context, 'All groups CPI (Australia)[vi]' is most commonly used. However, the ABS advises: 'Capital city indexes used by the CPI are based on the 2011 Australian Statistical Geography Standard (ASGS) Greater Capital City Statistical Areas. The capital city indexes measure individual price movements over time in each city, and they do not measure differences in retail price levels between cities (Australian Bureau of

Statistics, 2018). Considering this, the data has been deflated in this study using CPI All Groups (Sydney) to generate real house prices (ibid).

4.2. Out-of-sample forecasting performance

The exponential smoothing with trend adjustment and multiplicative decomposition models were estimated (see sections 3.1 and 3.2). Model performance was evaluated using out-of-sample forecasting techniques. In the literature, there are two alternative methods for selecting the length of the training dataset:

1. Use 80% of the dataset to train data and the remaining 20% to test model accuracy (80/20 rule) – e.g., Plakandaras et al. (2015), Gupta and Walia (2021)
2. Keep the length of test data the same as the length of the forecasting period – e.g., Li et al. (2020), Pierdzioch et al. (2015)

Firstly, following the 80/20 rule, the total dataset span of 91 quarters was split into training (73 quarters) and testing (18 quarters) datasets. Accordingly, data from Q3 1994 to Q3 2012 (the training data) was used to fit the model and data from Q4 2012 to Q1 2017 (the test data) was used to test the model. Note that the second-period test data were never used during the model development, so these forecasting models were always tested on untouched, out-of-sample data.

Secondly, by following the criteria to keep the length of the test data the same as the forecasting period, 59 quarters (from Q3 1994 to Q1 2009) (training data) were used to fit the model and 32 quarters (from Q2 2009 to Q1 2017) (test data) to test the model.

Table 2(a) - Measures of forecasting accuracy: 80/20 rule

	Bias	MAD	MSE	MAPE	RMSE
Method 1: Exponential smoothing with trend adjustment					
Detached Houses (non-strata)	164.74	164.74	36093.84	19.09%	47320.80
Apartments (strata)	102.09	102.09	12886.38	14.78%	15355.90
Method 2: Multiplicative decomposition					
Detached Houses (non-strata)	54.16	77.99	8431.29	9.14%	11780.54
Apartments (strata)	42.85	50.51	3144.69	7.35%	3793.19

Source: Authors

Table 2(b) - Measures of forecasting accuracy (length of test data = length of forecasting period)

	Bias	MAD	MSE	MAPE	RMSE
Method 1: Exponential smoothing with trend adjustment					
Detached Houses (non-strata)	274.59	274.59	91290.57	35.50%	119022.21
Apartments (strata)	184.92	184.92	41222.83	28.77%	51824.80
Method 2: Multiplicative decomposition					
Detached Houses (non-strata)	-53.20	75.75	7674.55	11.16%	11074.13
Apartments (strata)	-5.88	41.48	2059.73	6.92%	2813.80

Source: Authors

As evident from the above analysis, each forecasting method yielded differing forecast values, so it was imperative to choose the most feasible approach to converge to a realistic forecast. Along with forecast determination, several error detection parameters that offered a great deal of assistance in the decision-making process were evaluated simultaneously. From the above table(s), it is deduced that multiplicative decomposition offered the least forecast error across all five error parameters of Bias, MAD, MSE, MAPE and RMSE, and outperformed exponential smoothing with trend adjustment.

Once the forecasting accuracy of each method was assessed, the total dataset was used to forecast eight (8) years (32 quarters) into the future. Given that the dataset covered to Q1 2017, the forecasts were initially developed to Q1 2025. The forecasts were subsequently extended to Q4 2028 to provide a longer forecast duration.

5. Forecasts from Q2 2017 to Q4 2028

5.1. Forecasts of real house prices

Only the forecasts based on multiplicative decomposition are reported because the accuracy tests indicate they were superior to those of exponential smoothing with trend adjustment. The price correction in 2016/17 was pronounced for both types of dwellings (see Figure 1). They started from a lower base, suggesting that prices should have been lower from 2017. Based on previous patterns, there were indications that prices would slowly increase for both types of dwellings. The forecasts also showed that prices of detached houses will move past 2016 levels in 2022 or 2023, and the prices of apartments will move past 2016 levels in 2020. Price forecasts of detached houses are relatively more volatile than apartments.

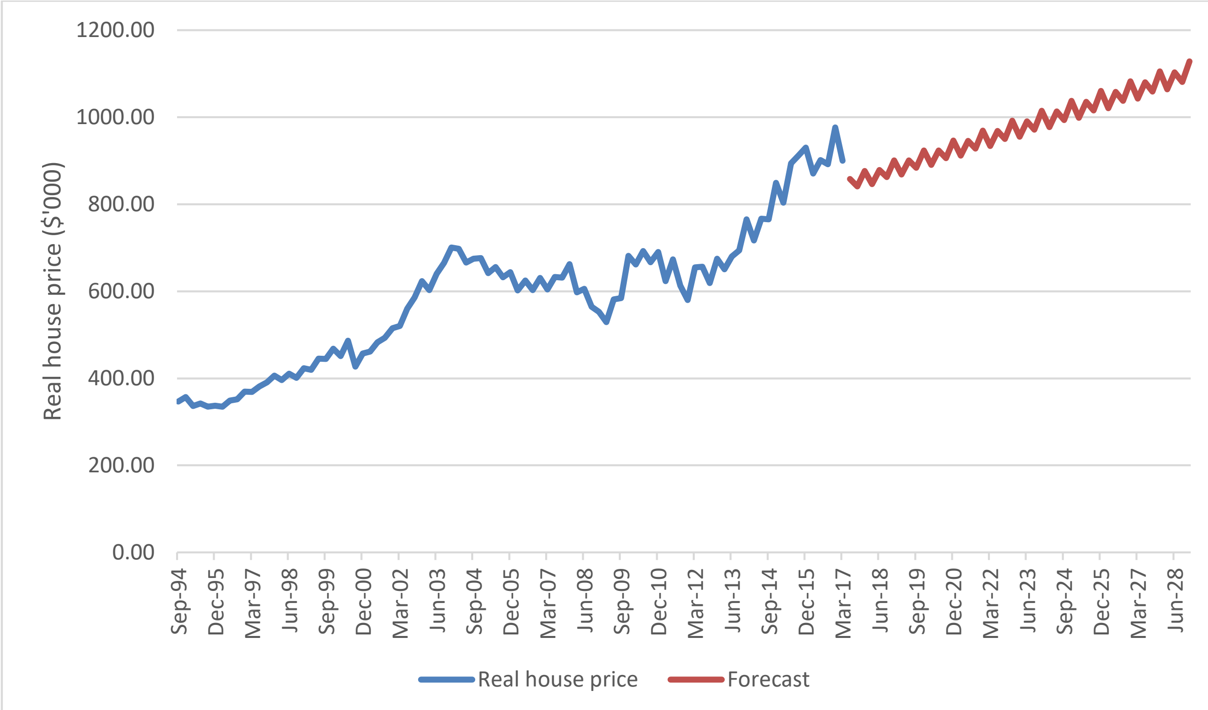

Figure 1(a) – Forecasts of Sydney detached house prices using Multiplicative Decomposition, real prices, 2017-2028

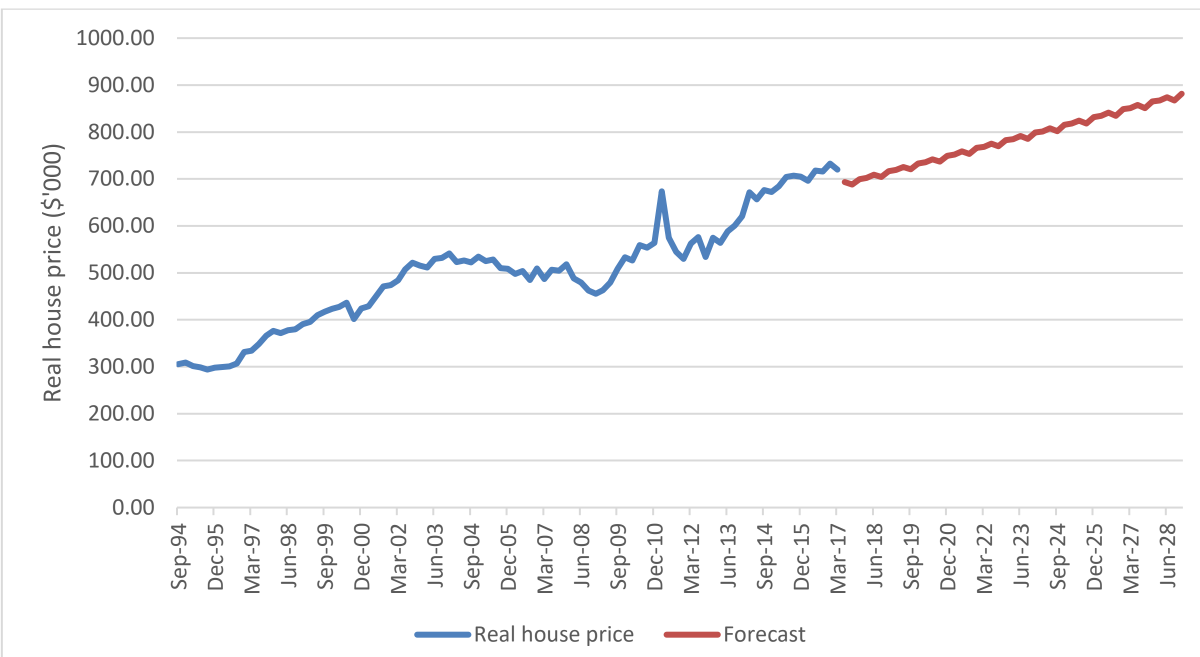

Figure 1(b) – Forecasts of Sydney apartment prices using Multiplicative Decomposition, real prices, 2017-2028.

5.2. Forecasts of nominal house prices

The real house price forecasts above control for inflation to understand the fundamental and accurate movements of house prices over time. In contrast, nominal house price forecasts trace the current market prices that are needed to understand actual prices at any given time. Therefore, the same All Groups CPI (Sydney) was used to convert real house price forecasts back to nominal values. However, the challenge here was that only short-term CPI forecasts were available from secondary sources, so two simple long-term projections of CPI values were developed as a solution by assuming linear and exponential patterns of evolution into the next 11 years. The predictive accuracies of the two assumed patterns were similar, with R^2 values ranging from 0.986 for the linear trend line to 0.995 for the exponential trend line. Due to the slightly higher predictive performance of the exponential trend line (see Figure 2), the real forecasts were converted to nominal values by assuming exponential growth in the CPI.

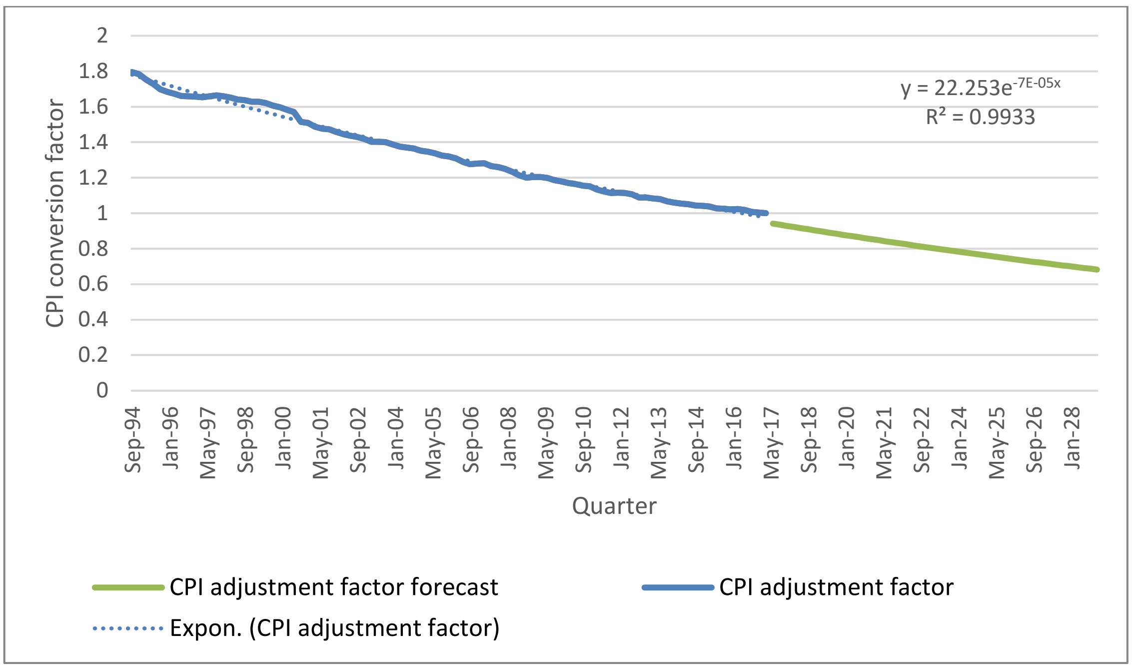

Figure 2 – All Group CPI (Sydney): Forecasts assuming exponential growth. Source: Author's work based on Australian Bureau of Statistics (2018).

As Figure 3 shows, the price correction in 2016/17 was pronounced for detached houses and less so for apartments. The forecasts for detached houses started from a lower base, which suggests that prices should have been lower from 2016. In other words, the prices of detached houses stagnated from 2016-2018 but started to increase soon after. Moreover, as with real price forecasts, there are indications that prices will slowly increase for both types of dwellings. Price forecasts of detached houses were also more volatile than apartments. The forecasted real and nominal prices for detached houses and apartments are presented in Appendix 1.

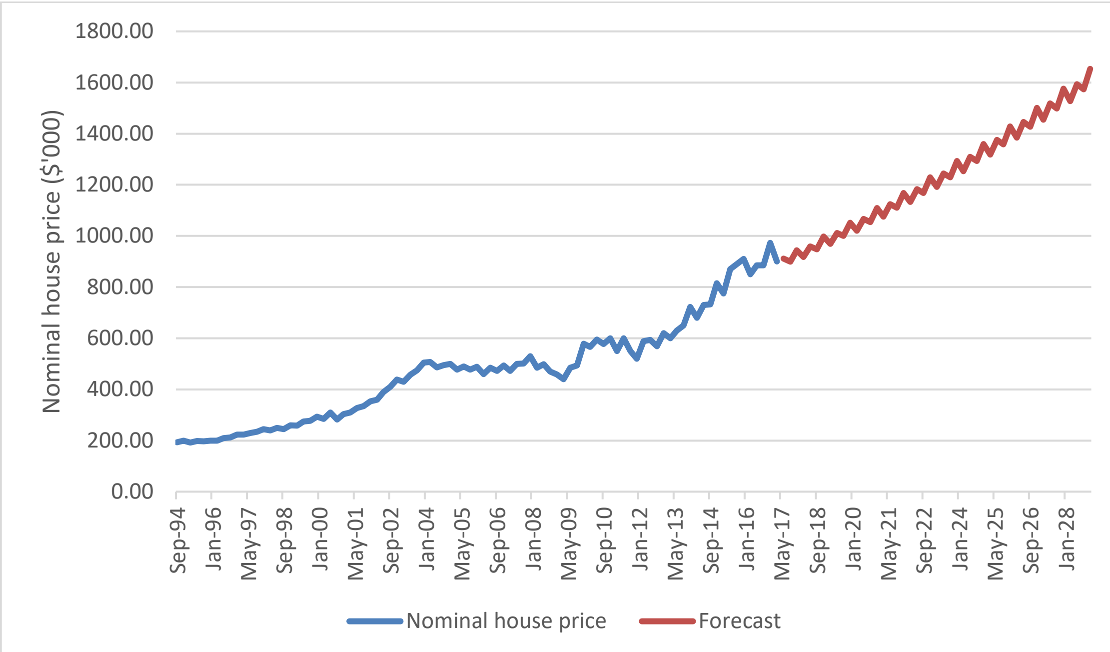

Figure 3(a) – Forecasts of Sydney detached house prices using Multiplicative Decomposition, nominal prices, 2017-2028

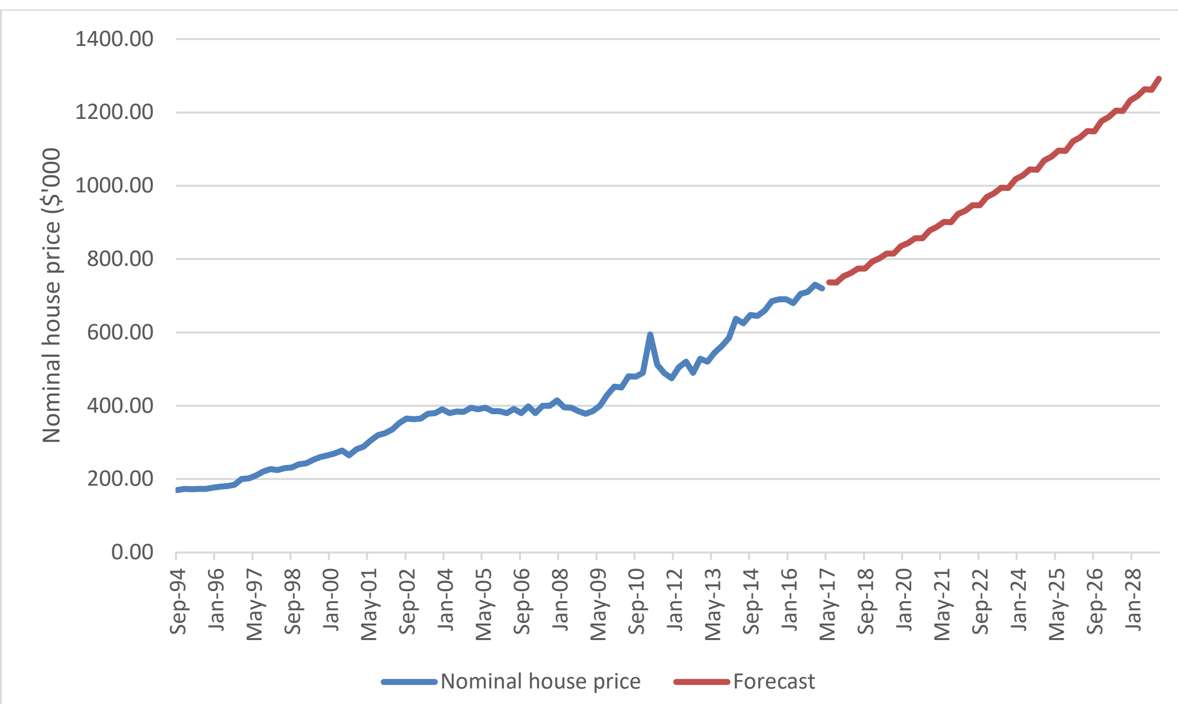

Figure 3(b) – Forecasts of Sydney apartment prices using Multiplicative Decomposition, nominal values, 2017-2028

5.3. Ground-truthing using actual data and previous studies

The forecasts were developed using a unique dataset widely used in NSW until the late 2010s (NSW Rent and Sales Reports), however this source no longer publishes timeseries data. Since several quarters have passed beyond the period covered in the original dataset, and to further interrogate the validity of these forecasts, we compare the forecasts for 2017-2022 and actual prices available via an alternative data source (i.e., ABS). While actual median prices are volatile compared to forecast values, they fluctuate closely around forecast values. For instance, the actual median price for detached houses observed a market correction and reverted to the nominal price forecast by Q3 of 2022 (see Figure 4(a). In the apartment market, actual median price and real price forecast moved closely together throughout – see Figure 4(b). The divergence of nominal forecast away from the actual median in this market seems to be due to the forecast error of the CPI.

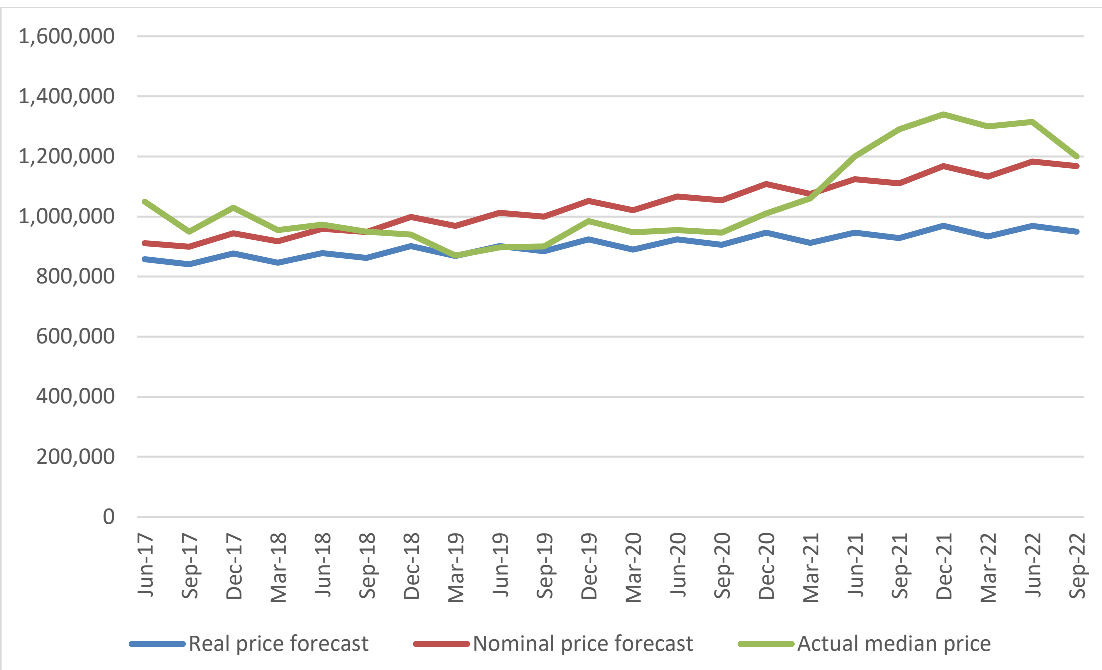

Figure 4(a) – Forecasts of Sydney detached house prices versus actual median price, 2017-2022. Notes: Actual median prices are for ‘established house transfers’ (Cat. no. 6432.0 Total Value of Dwellings, ABS 2022).

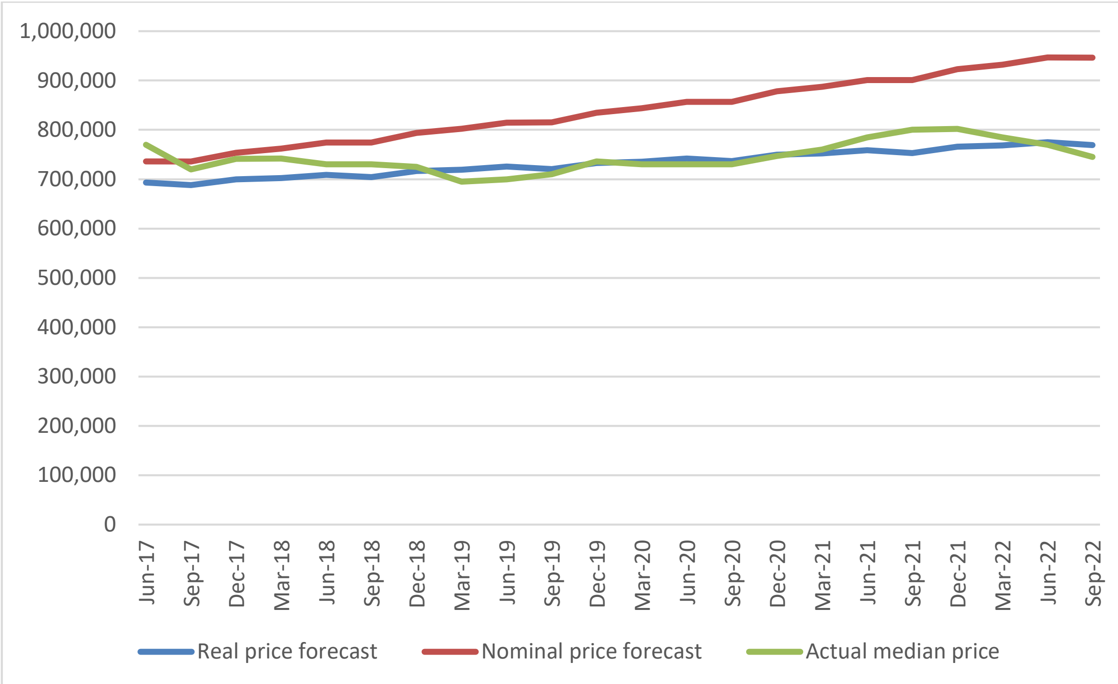

Figure 4(b) – Forecasts of Sydney apartment prices versus actual median price, 2017-2022. Notes: Actual median prices are for 'attached dwelling transfers' (Cat. no. 6432.0 Total Value of Dwellings, ABS 2022).

Two Sydney-based studies using different approaches provide comparative forecasts covering a similar forecast horizon. Building on investment theory, Shi et al. (2021) forecasted Sydney house prices over the period 2019-29 using an error-correction model. This research provided evidence that house prices were cointegrated with rents, interest rates, population growth, unemployment, migration, construction activities, and bank lending in the long run. The forecasts suggested that Sydney house prices will continue to increase with no significant decline in the foreseeable future. Ge et al. (2022) considered neighbourhood effects, including socio-economic conditions, within a multi-level model (MLM) in developing house price forecasts for Sydney. The forecasts developed for the period 2018-2029 indicated prices of both houses and flats/units will increase in the long term, the former also indicating a cyclic pattern. Generally, the forecasts of both these studies are consistent with those developed in the present study, suggesting an upward price moment in the next decade for both houses and apartments.

6. Conclusion

House price fluctuations send vital signals to many parts of the economy, and long-term predictions of house prices are of great interest to policymakers and property developers. The most common economic forecasts assume that underlying data are stationary, an assumption that is difficult to adhere to in many circumstances. This paper presents filtering models as an alternative approach to forecasting long-term house prices and puts forward a case for their inclusion within the forecasting toolkit. This is justified by the wide use of filtering models in financial trading and sports betting, among others. Filtering models represent a useful baseline scenario for comparing forecasts from alternative models. The widespread application of filtering models improves our understanding of different forecast outcomes.

This paper focused specifically on exponential smoothing with trend adjustment and multiplicative decomposition using median house prices obtained from the NSW FACS Rent and Sales Reports for Sydney from Q3 1994 to Q1 2017. The accuracy measures indicated that multiplicative decomposition outperformed exponential smoothing in forecasting accuracy. The superior decomposition model suggests that seasonal and cyclical components provide important additional information for predicting house prices. The forecasts for 2017-2028 accurately detected the house price correction from 2016-18 (nominal prices) and from 2016-20 (real prices), indicating that prices will slowly increase until 2028. A limitation of using median house prices is that the analysis may be impacted by the weaknesses of using aggregate data – e.g., the loss of information due to ignoring variations in individual data points.

An important constraint of filtering models is that they cannot explain the impact of economic shocks such as COVID-19 on house prices. Filtering models assume house prices are made up of different components (e.g., trend, cyclical, seasonal and random variations) as evidenced in past prices. Therefore, the predictions of filtering models are based on the assumption that previous house price patterns will continue into the future. As such, filtering models are less informative if there are significant shocks to the economy.

However, filtering models are useful as a pragmatic and relatively simple approach to house price forecasting, and since they are univariate time-series models, only house price data are required to develop the forecasts. This is an advantage compared to multivariate time-series analyses requiring multiple data sources and additional statistical processes (e.g., stationary tests). The relative simplicity of the methods also means that it is easy to understand, and to interpret and adapt within organisations. This paper exemplifies the usefulness of filtering methods for forecasting house prices, but the predicted house prices should be viewed as scenarios of possible futures rather than a definitive set of expected values.

[i] This model predicts multiple time-series variables and captures the linear interdependencies among them.

[ii] The semi-strong form states that prices reflect all publicly available information, including past price information, public financial information and other relevant information that influence asset prices. The strong form states that even non-public information is included in the asset values.

[iii] In mathematics and modelling, decomposition means expressing a number or function as a combination of simpler components.

[iv] Seasonal index is a measure of how a particular season compares on average to the mean of the cycle

[v] ARIMA stands for autoregressive integrated moving average model, a generalisation of an autoregressive moving average model.

[vi] 'All groups CPI' is the most common consumer price index used in Australia. It measures movements in indexes from one period to another and considers the weighted average of eight capital cities. See cat. No 6401.0 - Consumer Price Index, Australia (ABS, 2018).

References

ANATOLYEV, S. & GOSPODINOV, N. 2010. Modeling Financial Return Dynamics via Decomposition. *Journal of Business & Economic Statistics,* 28**,** 232-245.

AUSTRALIAN BUREAU OF STATISTICS 2018. Consumer Price Index (Cat. no 6401). Canberra.

AUSTRALIAN BUREAU OF STATISTICS. 2022. *Total Value of Dwellings: Dec-quarter-2022* [Online]. ABS. Available: https://www.abs.gov.au/statistics/economy/price-indexes-and-inflation/total-value-dwellings/latest-release [Accessed 3 March 2023].

BOLLERSLEV, T., PATTON, A. J. & WANG, W. 2016. Daily House Price Indices: Construction, Modeling, and Longer-run Predictions. *Journal of Applied Econometrics,* 31**,** 1005-1025.

BURKE, K. & HEAGNEY-BAYLISS, M. 2023. Sydney house prices post steepest annual fall on record. *The Sydney Morning Herald*, 25.01.2023.

CASE, K. E. & SHILLER, R. J. 1989. The Efficiency of the Market for Single-Family Homes. *The American Economic Review,* 79**,** 125-137.

CEIC DATA. 2023. *Australia Household Debt: % of GDP* [Online]. Available: https://www.ceicdata.com/en/indicator/australia/household-debt--of-nominal-gdp [Accessed 3 March 2023].

CESA-BIANCHI, A., CESPEDES, L. F. & REBUCC, A. 2015. Global Liquidity, House Prices, and the Macroeconomy: Evidence from Advanced and Emerging Economies. *Journal ofMoney, Credit and Banking,,* 47.

CHANG, P.-C., LIAO, T. W., LIN, J.-J. & FAN, C.-Y. 2011. A dynamic threshold decision system for stock trading signal detection. *Applied Soft Computing,* 11**,** 3998-4010.

CHENG, C., SA-NGASOONGSONG, A., BEYCA, O., LE, T., YANG, H., KONG, Z. & BUKKAPATNAM, S. T. S. 2015. Time series forecasting for nonlinear and non-stationary processes: a review and comparative study. *IIE Transactions,* 47**,** 1053-1071.

CLARKE, S. R. 1993. Computer Forecasting of Australian Rules Football for a Daily Newspaper. *The Journal of the Operational Research Society,* 44**,** 753-759.

COAKLEY, J. 1994. The Integration of Property and Financial Markets. *Environment and Planning A: Economy and Space,* 26**,** 697-713.

DETTLING, L. J. & KEARNEY, M. S. 2014. House prices and birth rates: The impact of the real estate market on the decision to have a baby. *Journal of Public Economics,* 110**,** 82-100.

DISNEY, R. & GATHERGOOD, J. 2018. House Prices, Wealth Effects and Labour Supply. *Economica,* 85**,** 449-478.

DUFITINEMA, J. 2022. Forecasting the Finnish house price returns and volatility: a comparison of time series models. *International Journal of Housing Markets and Analysis,* 15**,** 165-187.

GE, X. J., MANGIONI, V., SHI, S. & HERATH, S. 2022. House price forecasting using the multi-level modelling method in Sydney. *International Journal of Housing Markets and Analysis,* ahead-of-print.

GHOLIPOUR, H. F., LEAN, H. H., TAJADDINI, R. & PHAM, A. K. 2019. Foreign investment in Australian residential properties. *International Journal of Housing Markets and Analysis,* 12**,** 166-180.

GIROUARD, N. & BLÖNDAL, S. 2001. House Prices and Economic Activity.

GLAESER, E. L. & NATHANSON, C. G. 2017. An extrapolative model of house price dynamics. *Journal of Financial Economics,* 126**,** 147-170.

GLINDRO, E. T., SUBHANIJ, T., SZETO, J. & ZHU, H. 2011. Determinants of House Prices in Nine Asia-Pacific Economies. *International Journal of Central Banking,* 7.

GRAMI, A. 2016. Chapter 4 - Probability, Random Variables, and Random Processes. *In:* GRAMI, A. (ed.) *Introduction to Digital Communications.* Boston: Academic Press.

GUPTA, N. & WALIA, R. S. Predictive Soft Modeling of Turning Parameters Using Artificial

Neural Network. *In:* AGRAWAL, R., JAIN, J. K., YADAV, V. S., MANUPATI, V. K. & VARELA, L., eds. Recent Advances in Smart Manufacturing and Materials, 2021// 2021 Singapore. Springer Singapore, 189-196.

KNOLL, K., SCHULARICK, M. & STEGER, T. 2017. No Price Like Home: Global House Prices, 1870–2012. *American Economic Review,* 107**,** 331-353.

LI, X., KANG, Y. & LI, F. 2020. Forecasting with time series imaging. *Expert Systems with Applications,* 160**,** 113680.

LIANG, Y. H. 2011. Analyzing and forecasting the reliability for repairable systems using the time series decomposition method. *International Journal of Quality & Reliability Management,* 28**,** 317-327.

MAIER, G. & HERATH, S. 2009. Real Estate Market Efficiency: A Survey of Literature. *SRE - Discussion Papers* [Online].

MEHRA, P. 2022. *Australia's huge housing market keeps central bank on knife edge* [Online]. Available: https://asia.nikkei.com/Economy/Australia-s-huge-housing-market-keeps-central-bank-on-knife-edge [Accessed 3 March 2023].

MULLEY, C. & TSAI, C.-H. P. 2016. When and how much does new transport infrastructure add to property values? Evidence from the bus rapid transit system in Sydney, Australia. *Transport Policy,* 51**,** 15-23.

NOVÁK, V., ŠTĚPNIČKA, M., DVOŘÁK, A., PERFILIEVA, I., PAVLISKA, V. & VAVŘÍČKOVÁ, L. 2010. Analysis of seasonal time series using fuzzy approach. *International Journal of General Systems,* 39**,** 305-328.

PIERDZIOCH, C., RISSE, M. & ROHLOFF, S. 2015. A real-time quantile-regression approach to forecasting gold returns under asymmetric loss. *Resources Policy,* 45**,** 299-306.

PLAKANDARAS, V., GUPTA, R., GOGAS, P. & PAPADIMITRIOU, T. 2015. Forecasting the U.S. real house price index. *Economic Modelling,* 45**,** 259-267.

RENDER, B., RALPH M. STAIR, J. & HANNA, M. E. 2012. *Quantitative Analysis for Management,* New Jersey, Pearson.

ROBSTAD, Ø. 2017. House prices, credit and the effect of monetary policy in Norway: evidence from structural VAR models. *Empirical Economics,* 54**,** 461-483.

SALLES, R., BELLOZE, K., PORTO, F., GONZALEZ, P. H. & OGASAWARA, E. 2019. Nonstationary time series transformation methods: An experimental review. *Knowledge-Based Systems,* 164**,** 274-291.

SARGENT, J. & BEDFORD, A. 2010. Improving Australian Football League player performance forecasts using optimized nonlinear smoothing. *International Journal of Forecasting,* 26**,** 489-497.

SCHINDLER, F. 2012. Persistence and Predictability in UK House Price Movements. *The Journal of Real Estate Finance and Economics,* 48**,** 132-163.

SHI, S., MANGIONI, V., GE, X. J., HERATH, S., RABHI, F. & OUYSSE, R. 2021. House Price Forecasting from Investment Perspectives. *Land,* 10**,** 1009.

STROEBEL, J. & VAVRA, J. 2019. House Prices, Local Demand, and Retail Prices. *Journal of Political Economy,* 127**,** 1391-1436.

THE AUSTRALIAN TRADE AND INVESTMENT COMMISSION. 2023. *A resilient economy that outperforms in global rankings* [Online]. Available: https://www.austrade.gov.au/benchmark-report/resilient-economy [Accessed 3 March 2023].

THE URBAN REFORM INSTITUTE 2022. Demographia International Housing Affordability: 2022 Edition.

THEODOSIOU, M. 2011. Forecasting monthly and quarterly time series using STL decomposition. *International Journal of Forecasting,* 27**,** 1178-1195.

TIDEMAN, T. N. 2016. Taxing land is better than neutral: land taxes, land speculation, and the timing of development. *Land-Value Taxation.* Routledge.

YU, J. 2002. Forecasting volatility in the New Zealand stock market. *Applied Financial Economics,* 12**,** 193-202.

Appendix 1 - Sydney house price forecasts for the next 11 years (2017-2028): Apartments and detached dwellings

Quarter	Apartments		Detached houses	
	Real price	Nominal price	Real price	Nominal price
Jun-17	693,141	736,124	857,878	911,077
Sep-17	688,097	735,901	841,007	899,434
Dec-17	699,553	753,408	876,678	944,169
Mar-18	702,338	761,721	846,033	917,565
Jun-18	708,985	774,332	878,627	959,610
Sep-18	704,182	774,489	862,251	948,339
Dec-18	716,559	793,637	901,074	998,000
Mar-19	719,088	802,033	868,316	968,473
Jun-19	725,501	814,870	901,100	1,012,100
Sep-19	720,487	814,922	884,153	1,000,041
Dec-19	733,032	834,936	923,750	1,052,167
Mar-20	735,540	843,678	890,092	1,020,952
Jun-20	742,006	857,073	923,546	1,066,765
Sep-20	736,784	857,020	906,040	1,053,896
Dec-20	749,521	877,960	946,480	1,108,669
Mar-21	751,993	887,042	911,857	1,075,615
Jun-21	758,511	901,016	945,991	1,123,719
Sep-21	753,083	900,852	927,926	1,110,003
Dec-21	766,010	922,752	969,208	1,167,529
Mar-22	768,445	932,188	933,622	1,132,562
Jun-22	775,016	946,764	968,437	1,183,047
Sep-22	769,381	946,482	949,813	1,168,447
Dec-22	782,499	969,381	991,936	1,228,838
Mar-23	784,898	979,183	955,388	1,191,875
Jun-23	791,522	994,383	990,882	1,244,839
Sep-23	785,679	993,977	971,700	1,229,315
Dec-23	798,988	1,017,914	1,014,664	1,292,687
Mar-24	801,350	1,028,096	977,154	1,253,644
Jun-24	808,027	1,043,944	1,013,328	1,309,186
Sep-24	801,977	1,043,406	993,587	1,292,698
Dec-24	815,476	1,068,422	1,037,392	1,359,172
Mar-25	817,802	1,078,996	998,919	1,317,959
Jun-25	824,532	1,095,517	1,035,773	1,376,183
Sep-25	818,275	1,094,841	1,015,473	1,358,689

Dec-25	831,965	1,120,977	1,060,120	1,428,390
Mar-26	834,255	1,131,959	1,020,685	1,384,916
Jun-26	841,037	1,149,177	1,058,219	1,445,930
Sep-26	834,573	1,148,355	1,037,360	1,427,386
Dec-26	848,454	1,175,655	1,082,848	1,500,443
Mar-27	850,707	1,187,059	1,042,451	1,454,613
Jun-27	857,543	1,205,002	1,080,665	1,518,529
Sep-27	850,871	1,204,026	1,059,247	1,498,889
Dec-27	864,942	1,232,535	1,105,576	1,575,436
Mar-28	867,160	1,244,375	1,064,216	1,527,152
Jun-28	874,048	1,263,070	1,103,110	1,594,084
Sep-28	867,169	1,261,933	1,081,134	1,573,301
Dec-28	881,431	1,291,697	1,128,304	1,653,478