House Price Forecasting using the Multi-level Modelling Method in Sydney

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Abstract
The 'neighbourhood' is an important consideration in housing purchase decisions. Given the households' income constraints, households may have to decide on living in larger and higher-quality housing in lower-priced neighbourhoods or smaller and potentially lower-quality housing in higher-priced neighbourhoods. The households' decisions affect the demand for housing and thus prices. Previous works have predicted housing price as a function of physical variables, such as the number of bedrooms, distance to the central business district from different places, or the investment perspectives. This research develops a house price forecasting model applying multi-level modelling (MLM) methods to incorporate the neighbourhood effects, namely, socio-economic conditions in various locations. Data from the local government areas in Greater Sydney, Australia, has been collected to test the model developed. It was found that the MLM can account for the neighbourhood effects and provide accurate forecasting results.

Keywords: Neighbourhood effects, housing price forecasting, multi-level modelling, Sydney

Introduction
Increases in housing prices impact housing affordability. However, the impacts on specific households may differ because of the various geographic areas' price differences. Housing decision is a complex outcome of cultural, economic, and regulatory environments (Tiwari & Hasegawa, 2000). Durability, heterogeneity, and fixed location are some of the unique characteristics of residential properties (Muth & Goodman, 1989; Galaster, 1996; Tse, 2002). Another feature of housing decisions is the 'neighbourhood effect', which refers to different socio-economic correlations in various locations (Friedman, 1955; Cox, 1969; Miller, 1977), namely, individual households perceive the local neighbourhood differently. Therefore, the neighbourhood is an important consideration in housing purchase decisions. Geyer (2017) stated that given the households' income constraints, families face a choice decision between larger and higher-quality housing in lower-priced neighbourhoods or smaller and potentially lower-quality housing in higher-priced neighbourhoods. The demand and supply of housing in different locations have not behaved uniformly over time. In other words, they demonstrate spatial heterogeneity.

Households' decisions affect the demand for and supply of housing and thus prices. It is crucial to predict housing price performances that involve economic activities, investment, and government decisions on policies. The standard hedonic model (Rosen, 1974) determines house prices as a function of physical variables, such as the number of bedrooms or distance to the central business district (CBD) from different places. Socio-economic status indicators, such as education level, employment status, and household income, play an important role in housing decision-making, the choice of the housing type, and the residential neighbourhood. The standard hedonic model is challenging to incorporate with the neighbourhood effects, namely, the socio-economic conditions in various locations where households live.

Multi-level modelling (MLM) extends the standard hedonic model to incorporate physical characteristics and socio-economic variables to estimate dwelling prices. In addition, differentiation in housing prices in different areas can be caused by a mismatch of housing supply and demand or an imbalance between the geographic amenities, such as water views and the demand for and supply of infrastructures, such as good schools and public transport (Gibbons & Machin, 2008). For these reasons, MLM has been employed to forecast house prices using data from Greater Sydney as an empirical study. The structure of the model includes observations of variables at the local government area (LGA) level, which is nested within the inner, middle, and outer rings of the Greater Sydney Area's regional areas. The assumption was that the purchase decisions of households involve selecting properties according to employment rates, quality of schools, and neighbourhood environment, in addition to other factors that influence demand for housing.

This research aims to include the neighbourhood elements in house price forecasting models for improving forecasting accuracy by applying MLM methods. The main contributions of this research are twofold. First, the neighbourhood elements that affect households' purchase decisions have been incorporated into the forecasting models. Second, an innovative MLM technique has been employed to handle the multilayer relationships in the complex social environment to improve the forecasting accuracy of the model. The following section reviews the literature on demand for housing and house price forecasting models. The model development section describes the methodology and theoretical foundations of MLM and the variables employed for developing the forecasting model. The forecasting results are then discussed and the research is concluded in the last section.

Literature review

Housing purchase decision is complex as it is influenced by households' preferences, income level, and external factors, such as economic and political conditions. The theory of the buyer behaviour model (Howard & Sheth, 1973) advised the main elements affect a purchase decision. The elements include the importance of the purchase, personality variables, social class, culture, time pressure, and financial status. Kotler (2002) developed a buyer behaviour model identifying a 'black box' that affects a buyer's purchase decision. The 'black box' consists of the buyer's characteristics, such as cultural, social, personal, and psychological, and buyer's decision process. A five-step process of buying decision was identified: identify needs, seek information, evaluate alternatives, purchase decisions, and attitudes after purchase (Kotler & Keller, 2005). Hassan et al. (2021) developed a conceptual framework for housing purchase decision-making process consisting of housing purchase intention, housing purchase preferences, and purchase decision. Stanton et al. (1994) established a consumer buying decision process that describes social, psychological, and situational functions, namely, when and where to buy will affect a purchase decision. Further, the 'Overall Model of the Consumer Behaviour' was developed by Neal et al. (2002), who claim 'consumer lifecycle', such as social status, demography, value, culture, and motivation, influence purchase decisions. Kearns and Parkes (2003) analysed the influence of residential perceptions on housing moving behaviour in poor and other areas in London, and suggested that housing is a heterogeneous good differentiator by location, size, and type of neighbourhood among other differentiators. Residential conditions influence the ability and motivation to move at a particular stage at which it occurs in the life cycle, along with socioeconomic status and the availability of options (Lee et al., 1994). Chia et al. (2016) studied the influence of housing attributes on housing purchase intention, and five variables had significant and positive relationships with house purchase intention. These variables were financing, distance, superstition numbers, environment, and house features.

Housing is mainly a consumption good as the determinants of housing demand are driven by 'housing utility' rather than 'financial return on investment'. Households' preferences for specific structural attributes of houses are essential in generating consumption demand (Stamou et al., 2017; Abdulai & Owusu-Ansah, 2011; Kiefer, 2011). The most common structural variables that appear in housing studies include the number of bedrooms and bathrooms, floor area, type of housing (house/unit, single-family/multi-family, attached/detached), number of floors, structural features including the presence of a basement, fireplace, and garage, age of a house, availability and type of heating and cooling systems, structural material used, and quality of finish (or condition). Ioannides and Zabel (2008) developed a model of demand for housing structure, social interactions, and neighbourhood choice using the American Housing Survey with census data and found that individuals prefer to live with others like themselves and the neighbourhood effect influences housing demand. This study also highlights that several locational and neighbourhood attributes are linked to demand generated by consumption preferences (King, 1976; Saiz, 2010; Geyer, 2017). These locational variables are proximity to the CBD (Herath & Maier, 2013) and other amenities, such as green spaces (Herath et al., 2015).

Demographic determinants, such as population, household growth, migration, and household formation, increase the demand for housing. The changes in demographic structure are also considered to influence housing demand as observed in recent research on specific demographic cohorts, particularly the working-age (15–64 years) population (Sunde & Muzindutsi, 2017). Similarly, Eichholtz and Lindenthal (2014) found household age influenced housing demand. However, the significance of the effect of age structure depends on the context. For instance, Green and Lee (2016) indicated that changes in housing demand as a result of changes in the age structure in the US from 1990 to 2014 were unlikely to be significant. The seminal work of Mankiw and Weil (1989) diverted from the traditional approaches. They investigated the impact of baby boomers entering the housing market and found an associated increase in real prices of houses. This could be pertinent to Australia, considering the disproportionate number of baby boomers holding onto second properties. In another interesting piece of research, Hiller and Lerbs (2016) found changes in city size influenced housing demand.

As the key determinants of consumption-demand, income and wealth indicators have been used differently. Composite economic variables representing propensity to consume housing, such as income per head and wealth-to-income ratio (Pains & Westaway, 1997) and debt-to-income ratio (Kim et al., 2017), are also common in the literature. General inflation is typically captured using consumer price indices within these models (e.g. Oestmann & Bennohr, 2015), although some studies have employed specific housing supply-related costs, such as construction costs (Adams & Füss, 2010). Notably, economic variables influencing consumption-driven demand are not limited to national-level indicators. For instance, Agnello and Schuknecht (2011) considered the impact of international liquidity on local housing demand.

The housing market generally reflects the state of the national or regional economy as favourable economic conditions result in employment growth, wage growth, and higher consumer spending (including on housing). Reflecting on this, house price studies have included both macroeconomic variables and individual economic variables. Several housing market analyses have employed aggregate macroeconomic variables, namely, gross domestic product (GDP), interest rate, unemployment rate, and domestic credit availability, within their models (Karantonis & Ge, 2007; Oestmann & Bennohr, 2015). Due to the widely recognised co-movement of housing and stock markets, equity prices and stock market performance have also been incorporated (Mikhed & Zemcik, 2009). Some studies have substituted economic growth, income—more appropriately, disposable income in some studies—or economic activity in the place of gross domestic product (GDP).

Evidence also suggests regulatory factors have influenced housing demand, particularly focusing on the period following the global financial crisis. For instance, Agnello and Schuknecht (2011) found that the deregulation of financial markets in the US had an adverse impact on the housing markets. Moreover, tighter controls from the Australian Prudential Regulation Authority for lending to investors pushed down median dwelling prices in Sydney and Melbourne (KPMG, 2017). Regulatory factors include fiscal policies such as goods and services tax, capital gains tax, acquisition costs, rates, land taxes, tax expenditures, and welfare regulations specific to first home buyers and the aged. The regulatory determinants in the housing market can also be supply-related (Yan et al., 2014), such as national policies and programs that boost housing supply (e.g. the former National Rental Affordability Scheme in Australia). Though this is contested in academic circles, zoning (and rezoning) has also been identified as affecting housing demand and supply, affecting housing prices.

Previous research has also examined the potential relationship between housing consumption (and demand) and national monetary policies. A key monetary policy-related determinant that influences housing purchase decisions of households is interest rates. For instance, Adams and Füss (2010) found a 1% increase in long-term interest rate resulted in a 0.3% decline in house prices. Other research has suggested a monetary policy shock in the form of an increase in central bank total assets was likely to influence house prices in the Organisation for Economic Co-operation and Development countries with a time lag (Rahal, 2016). Similarly, Zhu et al. (2017) demonstrated how a one-time monetary-easing shock could significantly trigger house price booms in the Euro area countries with liberal mortgage markets.

Market conditions can also influence housing consumption. Traditional variables represent market circumstances, such as lending conditions (Nobili & Zollino, 2017), mortgage market structure (Zhu et al., 2017), domestic credit availability, specifically, housing finance credit availability (Cerutti et al., 2017), recurrent holding costs, and emerging new variables such as the ratio of borrowing by residential property investors (KPMG, 2017), foreign direct investment and investment in real estate development (Rahman et al., 2012), and impact housing demand and prices. House prices are also sensitive to indicators such as 'mortgage loans as a share of GDP' (Sunde & Muzindutsi, 2017). Researchers have also recognised several characteristics that impact the prices of the existing housing market, such as housing stock (Abelson et al., 2005), rate of homeownership (Kim et al., 2017), and land supply (Wang & Zhang, 2014). Tai et al. (2017) found evidence that house prices depend on foreign buyers' housing demand, a potentially highly relevant market variable for Sydney.

Several economic, demographic, and market determinants are included in most studies. For instance, a highly relevant Australian study by Abelson et al. (2005) considered several key variables, including real disposable income, the consumer price index, the unemployment rate, real mortgage rates, equity prices, and housing stock.

Many house price forecasting models developed, including the hedonic model (Fletcher et al., 2004), autoregressive models (Jarocinski & Smets, 2008; Gupta & Majumdar, 2012), vector autoregressive model (Algieri, 2013), and error correction model (Shi, et al., 2021) have not fully captured the neighbourhood effects. However, the MLM method, on the other hand, overcomes this weakness by including a simultaneous analysis of neighbourhoods, such as relationships between areas.

Development of MLM housing price forecasting model

MLM is a quantitative statistical method that investigates variations and relationships in and between variables of interest. The MLM has become more popular with software and computing power availability. In estimating the distribution of radon levels in each of the approximately 3,000 US counties, Gelman (2006) adopted MLM and suggested that the model provides more accurate predictions than the no-pooling and complete-pooling regressions, especially when predicting group averages. Feng and Jones (2015) compared multilevel models and artificial neural networks to estimate 2001–2013 house prices in the Greater Bristol area and found that MLM provides a good predictive accuracy with high explanatory power, especially in explaining neighbourhood effects. They applied the same method to study which neighbourhood classification, namely, the postcode and census geography, provides more accurate price predictions for house sales between 2011 and 2014 in London (Feng & Jones, 2016).

In many cases, the observational data collected with a hierarchical or clustered structure can frequently be found in housing research. For example, a house is in a suburb nested within a local government area (LGA). Consequently, the data reflect a hierarchical structure with at least two levels: the microlevel of housing transactions and the macrolevel of LGAs. Given the hierarchical nature of the data, a conventional regression model may produce biased estimates, higher standard errors, and may lead to more spurious significance (Goldstein, 1995). Multilevel models recognise the existence of such data hierarchies by allowing for residual components at each level in the hierarchy, namely, data are organised at more than one level and are nested. MLM can develop macrolevel regression models with intercepts and regression weights across macrounits (LGA) as outcomes and other macrolevel variables as covariates (Chou et al., 1998). It can handle many independent variables, estimates group effects simultaneously with the effects of macrolevel, and does not require the sphericity assumption for valid inferences (Quene & van den Bergh, 2004).

The changes in housing prices are driven by the physical characteristics of housing and the surrounding environments, such as neighbourhood and economic conditions. In this study, growth curve models under the MLM framework were used as they can estimate the main determinants of property prices and forecast long-term trends of housing prices for different geographical areas. The growth curve models refer to *statistical methods that allow for the estimation of inter-individual variability in intra-individual patterns of change over time* (Bollen & Curran, 2006; Preacher et al., 2008). Growth curve models can incorporate a time trend in the fixed part of the model while allowing the trend to vary across areas. In this case, the quarterly property transaction data or observations of variables at Level 1 were nested within an LGA at Level 2, forming a two-level structure. The LGAs were in turn nested within larger regions (e.g. Sydney metropolitan area and the remaining metro regions, forming a hierarchical structure (see Figure 1)).

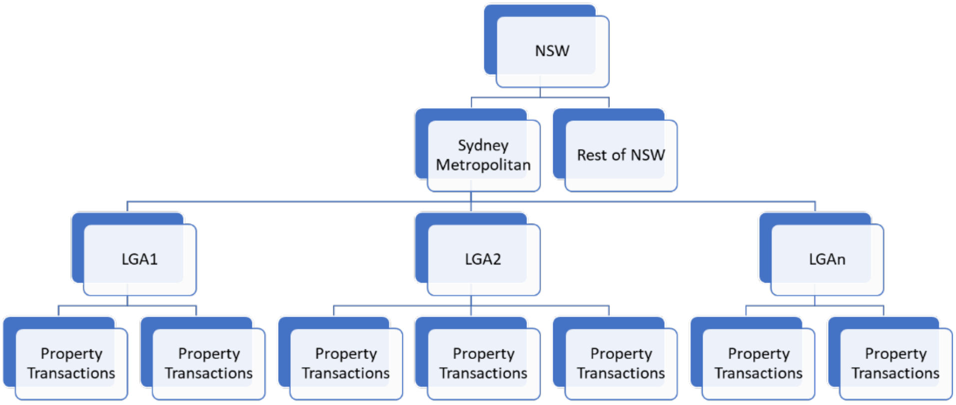


Figure 1: MLM structure used for the forecasting

Using this technique, the heterogeneous house price growth trajectories in the LGAs were analysed by allowing the random intercepts and slopes of growth to vary randomly between the LGAs around an average mean trajectory. In other words, it explicitly models the differential price growth trajectories of LGAs over time. Using this framework, a parsimonious representation[1] of the average price trajectory for Sydney and the extent of LGA variations compared to the average trend for Sydney can be provided.

A two-level growth curve model with *T* time points and *N* LGAs with random intercepts and linear slopes with no covariates other than time is specified as follows:

$$y_{ti} = \beta_{0i} + \beta_{1i} time_{ti} + \beta_{2i} x_{ti} + e_{0ti} + e_{1ti} \quad (1)$$

$$\beta_{0i} = \beta_0 + u_{0i} \quad (2)$$

$$\beta_{1i} = \beta_1 + u_{1i} \quad (3)$$

Here, the response variable y_{ti} is the logarithm of real price of LGAs *i* (*i* = 1, ..., *N*) in year *t* (*t* = 1, ..., T). $time_t$ is the coding of the time variable, the quarter of measurement in LGA *i*. x_{ti} represents the quarterly demographic, social, macroeconomic variables, housing characteristics, and supply variable in LGA *i*. The parameters, β_{0i} and β_{1i} are random intercepts and slopes. They are respectively specified as an overall average intercept and slope across all LGAs plus the LGA-specific random term u_{0i} and u_{1i}. The latter represents the price differential of LGA *i* from the Sydney-wide average trend and the growth rate compared to the average growth.

A key result of such a modelling method is the LGA latent random terms, $\boldsymbol{u_{0i}}$ and $\boldsymbol{u_{1i}}$, which describes the unique trajectory of LGA *i*. A positive value for $\boldsymbol{u_{0i}}$ represents a relatively expensive LGA at the start of the study period; a negative value indicates a relatively inexpensive area. A positive value for $\boldsymbol{u_{1i}}$ indicates an LGA that has grown much faster over time in terms of its pricing level, while a negative value indicates an LGA has become relatively low-priced compared with the Sydney-wide overall trend.

Study of the geographic LGAs

[1] A parsimonious representation of dwelling price changes is a mathematical model parametrised with several parameters. Such models are useful for analysis, interpolation, filtering, feature extraction, and data compression.

The focus of this study was on the Greater Sydney Areas (GSA). The ‘Areas’ variable was included in the model as a category variable having a fixed effect on house price. LGAs were also considered in the model but they were modelled as having random effects and were included as Level-2 units. Figure 2 depicts the LGAs of GSA.

Many LGA boundaries changed in 2016 and many previous LGAs were merged into larger LGAs. For data consistency and forecasting in this study, the most recent (i.e., 2016)[2] LGA classifications were used and any merged LGAs were applied to the prior period by merging the data according to the 2016 LGA boundaries.

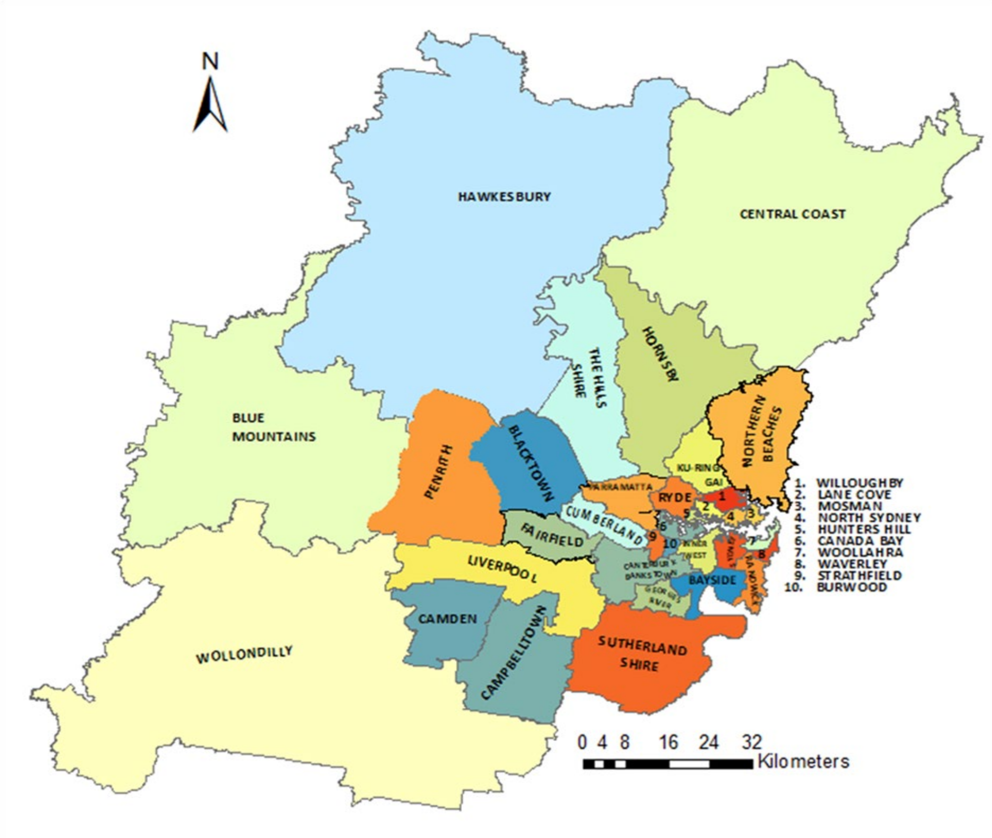


Figure 2. LGAs of Greater Sydney *(Source: YY Feng, 2020)*

Data and empirical estimates

This forecasting collected the secondary data for developing models. The dependent variable uses a logarithm of real property prices. The data were sourced from the NSW Department of Housing from Q1 of 1992 to Q2 of 2018. Quarterly median house prices for detached housing by LGA were obtained. The nominal prices were adjusted to real prices using logarithm transformation. Five types of data, including demand and supply variables, were collected to develop the forecasting models in this study: social, and demographic variables, macroeconomic variables, housing characteristics, supply of houses, and temporal trends as depicted in Table 1.

[2] The key population data of 2021 census data will be released in June 2022 and the location variables and employment data will be released in October 2022. Thus, 2016 census data is the most updated data used (https://www.abs.gov.au/census/2021-census-data-release-plans/2021-census-product-release-guide).

The social and demographic variables were sourced from three Australian censuses, 2006, 2011, and 2016. The variables included country of birth, the percentage of families with children, education level, median income, the unemployment rate for over 18-year-olds, the percentage of the Indigenous population, English proficiency, marital status, median mortgage repayment, median rent payment, and the mean age of residents.

The housing variables included the percentage of semi-detached houses, the percentage of social housing, the average number of bedrooms, the percentage of each housing type, the percentage of housing in rental tenure, the percentage of housing that was owner-occupied (with or without a mortgage), and the percentage of detached housing. All the variables were collected from the ABS censuses.

The macroeconomic variables included GDP, mortgage interest rate, lending rate changes, and the historical Consumer Price Index (CPI). The GDP and CPI variables were sourced from the Australian Bureau of Statistics (ABS) and the lending rate data from the Reserve Bank of Australia. The supply factor was incorporated into the model using ABS data on the total number of housing approvals. The number of housing approvals had a 3-year lag effect.

Table 1: Variables used to develop price models

Variables			Measurement	Source
Dependent variable		Property prices	Logarithm & real	NSW Department of Housing Q1 1992 - Q2 2018
Independent variables	Social and Demographic variables	Population	Changes	Australian census, 2006, 2011 & 2016
		Country of birth	Changes	
		Family with children	Percentage	
		Asian population	Changes	
		Unemployed rate over 18-year old	Percentage	
		Indigenous population	Percentage	
		People who do not speak English	Changes	
		People with a bachelor degree	Changes	
		Median income	Changes, real	
		Age of residents	Mean	
		Median mortgage repayment	Changes	
		Median rent payment	Changes	
		People renting	Percentage	
	Housing/dwelling characteristics variables	Owner-occupiers	Percentage	
		Bedrooms	Number	
		Rental housing	Percentage	
		Social housing	Percentage	
		Semi-detached housing	Percentage	
		Detached housing	Percentage	
	Macroeconomic variables	GDP	Changes, real	ABS
		CPI	Percentage	
		Mortgage variable lending interest rate	Percentage	RBA
		Lending rate	Changes	
	Supply factor	House approvals	Total number	ABS
		Unit approvals	Total number	
	Temporal variables	Time period	Year	

The 'Temporal variables' was included as a predictor through a 5th order polynomial to capture the underlying time trend in house price changes. Temporal trends in each LGA were modelled as the lowest level (Level 1) in the multilevel structure to capture the temporal trajectories within the LGAs. The effects of the 2nd and 3rd order terms were also modelled as having random effects allowing different areas to have different temporal price growth trajectories over time. The temporal change in the above macro- and micro-demographic variables were captured by using the time-varying variables for each LGA.

The correlation between house prices some time apart was captured using a lag of two quarters. The length of the lag was tested and a two-quarter lag was shown to be the most appropriate.

Assumptions and modelling preparation

The following assumptions were made to produce the price forecast for the GSA. Demographic information prior to the 2006 census and post-2016 was interpolated by assuming linear changes during the 10-year period. The changes in individual LGAs were then applied to other years to derive the demographic information about the relevant areas for each period. For the other variables, namely, the macroeconomic factors such as the CPI, lending rates, GDP, and building approvals, the averages for the previous 10 years were used for the *ex-ante* forecast. The model was limited by the accuracy of the forecasting for the independent variables, which need to be improved further. Thus, the demographic characteristics need to be updated every 5 years and the other variables should be updated every quarter.

The average (or median) trend for Sydney's house/flat markets was derived by applying the following two stages:

Stage 1: Model development and specification

The first step is to convert the LGA median prices to the real prices for detached houses and strata units/flats) by Sydney CPI for all LGAs. The second step is to update the models to include any new data sources that catch dynamic changes using MLwiN software to run the model.

Some strategies were employed to improve prediction accuracy. Different scenarios were added as predictors and different combinations of the scenarios were applied via trial and error as the 1-year average/median may not capture the long-term trend while the 20-year average/median may no longer be accurate. Thus, the average of the previous 10 years was included as a predictor for modelling purposes.

In relation to 'Temporal variables', namely, time periods (in quarters, expressed in numerical form), $time_{ti}$ was applied for each LGA in equation (1) and their validity was test using historical data. Once the model was established, the forecasted variable in X_{ti} was used to estimate the value of $time_{ti}$ for each LGA into the future. In addition, the model had a random effect on both the linear and quadratic forms.

Stage 2: Forecasting method

The model was developed by applying the training period (in-sample data) and then verified (out-of-sample testing) to test the accuracy of the forecast. Figure 3 illustrates the foresting method. In this study, the housing data from Q1 1992 to Q4 2016 were used to learn the price change behaviours that were affected by determinants such as changes in housing demand and supply variables. The performance of the model developed was tested for its forecasting accuracy by using data from Q1 2017 to Q2 2018. Multiple regression analysis is applied in the forecasting. Once the model was confirmed as statistically significant according to the development and testing periods, it could be used for ex-ante forecasting from Q3 2018 to Q4 2029. *R*, *R-square*, *RMSE*, and *MAPE* were used to measure the model performance. The model with statistical significance was applied to the forecasting.

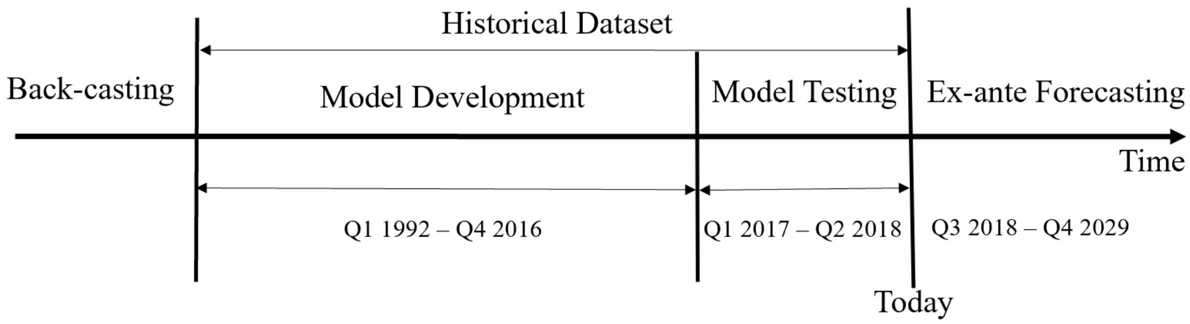


Figure 3: Forecasting method *(Source: XJ Ge, 2020)*

Model results and forecasting performance

Two models (one for detached houses and one for units) were developed as the market behaviour and main determinants of the prices of detached houses and units/flats are different. Table 2 shows the statistically significant results (95% significance) of the forecasting models for both types of dwellings.

Table 2: Sydney detached houses and flats/units price forecasting model results

Measurement	**Houses**		**Flat**	
Log real price scale	In sample	Out-of-sample	In sample	Out-of-sample
R	0.9928533	0.9817481	0.9441569	0.9958382
R-square	0.9857576	0.9638293	0.8914323	0.9916938
MSE	0.0081884	0.0099276	0.0193519	0.0191685
RMSE	0.0904898	0.0996374	0.1391111	0.1384503
Nominal price scale				
MAPE(%)	5.85%	7.07%	12.13%	12.54%

The overall forecasting model of houses performs better than the flats. The mean square error (MSE) of both in-sample and out-of-sample tests was less than 1% in real terms, but 1.9% for flats. In nominal terms, the mean absolute percentage error (MAPE) for houses and flats was in the range 5.85%–7.07 % and 12.13%–12.54% respectively.

The multilevel models address the characteristics of multidimensional, unique, and heterogeneous housing markets. In other words, no two properties are exactly identical, and they are physically and geographically different. As such, their values/prices are different. When this method is used, data in the model can be organised at more than one level, namely, individual houses are nested in the local council, which is nested in the LGA. The forecast of the LGA level price trends for houses is depicted in Figure 4. Each of the blue trend lines shows the in-sample house price prediction at the LGA level. However, as expected with neighbourhood differences, the prices in different LGAs perform differently.

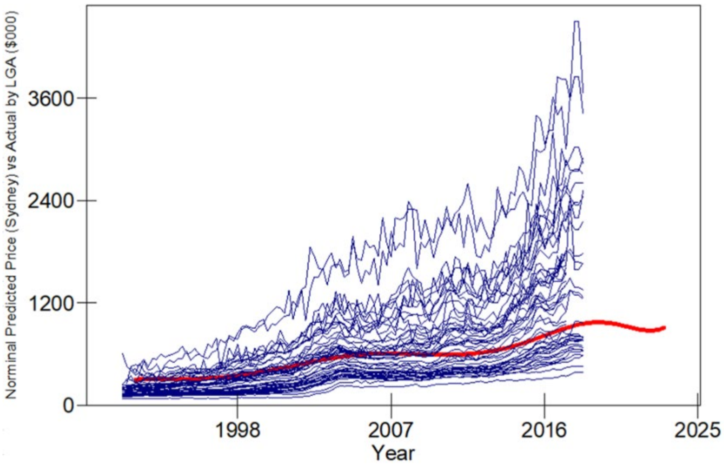
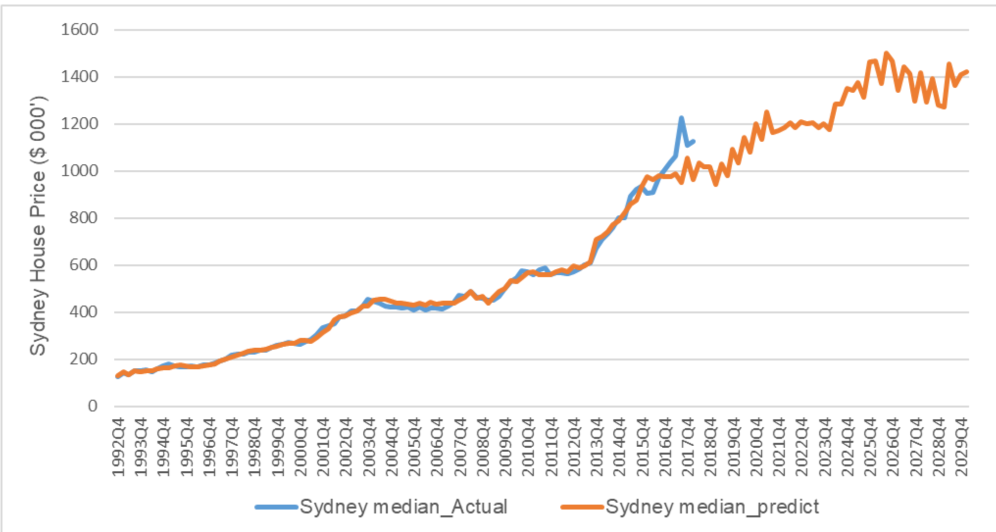


Figure 4: House price forecasting trends for Sydney LGAs

The price models for Greater Sydney are developed by averaging the price trends at the LGA level. Figure 5 shows the forecasting performance of houses and flats/units. Based on the results of the models developed, the prices of detached houses in Sydney are expected to show an upward trend for 10 years from Q2 2019 to Q4 2029 with slight corrections, given that government policy changes are not large. It is suggested that the prices of both houses and flats/units will increase in the long term. However, the in-sample and out-of-sample models fit better for houses than flats/units in Sydney. The upward house prices have indicated a cyclic trend, whereas the flats/units' prices show a steady upward trend.



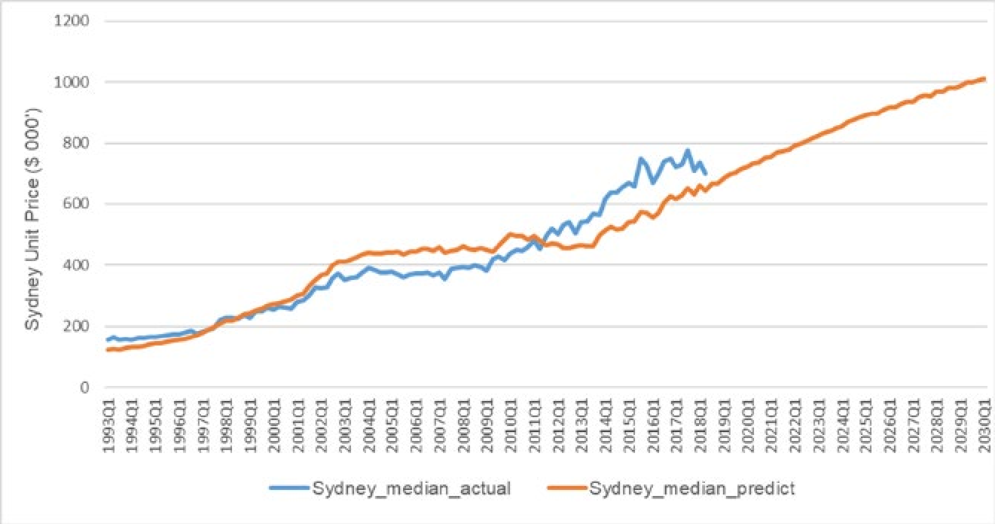


Figure 5: Price forecasting trends for houses and flats/units in Sydney

The changes in demography have altered detached house prices. As shown in Table 3, the changes in house prices are negatively related to the changes in the mean age and total population. Negative effects were found in the changes in Asian and African populations. Therefore, increasing the total number of households leads to rising house prices. The results also show a greater fluctuation in house prices in areas with an increasing non-English speaking population. The greater the change in education (bachelor's degree) of the population, the less the impact on the house prices.

The changes in real income have not shown a statistically significant result. However, the greater the percentage change in population unemployment, the lesser the change in house prices. The mortgage repayment and lending rates have further contributed to the changes in house prices. The performance of the rental market and prices of the previous period have also affected house price fluctuations.

In terms of supply factors, the changes in property prices have been affected by the changes in building approval. The changes in building approval have shown statistical significance in the price forecasting models. The results indicate that property prices could increase approximately 3.4–3.7% if the building approval is reduced.

For the flats/units, mortgage repayment, lending rate, and population unemployment are the main price determinants. Rent tenure, building approvals, and semi-detached building type are also the attributes of flats'/units' prices. The demographic factors have not shown a significant impact on the prices.

Model accuracy and limitations

MLM forecasts differential growth trajectories between different locations through the specification of the hierarchical structure. In this case, an LGA nested within a region. It can also capture the perceived 'status' value of an area through random effects specification. Another benefit of MLM is that it extends the hedonic pricing model and explicitly models spatial heterogeneity. While the multilevel models can handle many independent variables and take neighbourhood effects into consideration, this strength also brings a weakness, where the model is limited by the accuracy of its forecasting of independent variables, thus assumptions are required for the forecasted independent variables. To address this limitation, the models were tested and developed by using the forecasting results presented by some organisations and experts for the GSR. For example, lending rates were estimated from the Sydney property cycle, and economic patterns and building approval assumptions were based on ABS Building Approvals reports. These showed a sharp (32.8%) decline over the 12 months to November 2018. Peteh (2019) indicates that 'the private sector dwellings excluding houses had a significant 53.9% decline, i.e., the pipeline for multi-dwelling and unit construction is likely to dry up as developments reach completion.'

Demographic information prior to the 2006 census and post-2016 census was interpolated by assuming linear changes during the 10-year period. The increase/decrease change rates in individual LGAs were then applied to other years to derive the demographic information about the relevant areas for each period. Another limitation was that some councils were recently merged. Thus, the LGA 2016 data collected was not consistent with the previous census data areas. As a result, the accuracy of the forecasting could be affected as the forecasting results of houses or units in Sydney were the average median prices of all LGAs. However, it is not detrimental as it is the same pool of property that was merged into larger geographical areas.

The strategies used to improve the prediction accuracy include the following: 1) only cubic polynomial was used to keep the model simple; 2) as the random effect was specified using a time variable and CPI change may have different effects on different areas, the coefficient for CPI was allowed to vary between areas. The results were compared and proved to produce better predictive accuracy; 3) although it is hypothesised that different areas may respond to lending rates differently, the model could not converge if the coefficients were allowed to vary between LGAs.

Table 3: Main determinants of Sydney detached houses and flats'/units' price

Independent Variables	Detached Houses					Flats or Units				
	Coefficient	S.E.	z-ratio	p-value	Sig.	Coefficient	S.E.	z-ratio	p-value	Sig.
cons	4.215	0.508	8.296	0	*	4.069	0.561	7.255	0	*
Inner Ring	-0.041	0.022	-1.892	0.059		0.023	0.051	0.451	0.652	
Middle Ring	-0.11	0.018	-6.133	0	*	-0.07	0.045	-1.556	0.12	
change in asia population	-0.156	0.036	-4.374	0	*	-0.074	0.085	-0.872	0.383	
change in african population	-0.558	0.038	-14.663	0	*	-0.067	0.08	-0.831	0.406	
change_population unemployed	1.143	0.21	5.439	0	*	0.038	0.287	0.132	0.895	
change_english_skills	0.467	0.038	12.203	0	*	0.022	0.056	0.394	0.694	
change_semi detached	0.183	0.04	4.543	0	*	-0.026	0.051	-0.515	0.606	
change_detached	1.026	0.17	6.022	0	*	-0.551	0.273	-2.019	0.044	
change_total number of household	1.089	0.359	3.035	0.002	*	0.136	0.674	0.202	0.84	
change_total population	-1.204	0.309	-3.898	0	*	-0.579	0.623	-0.929	0.353	
change_rental property %	0.129	0.024	5.456	0	*	-0.006	0.036	-0.166	0.868	
change_owned property %	0.06	0.043	1.396	0.163		-0.065	0.062	-1.048	0.294	
change in mean age of population	-6.24	0.638	-9.783	0	*	-3.678	1.033	-3.561	0	*
change in % of bachelor degree	-0.157	0.046	-3.42	0.001	*	0.063	0.113	0.562	0.574	
change in % of family with dependants	-0.134	0.107	-1.25	0.211		-0.027	0.183	-0.148	0.883	
change in average no of bedroom	0.515	0.614	0.838	0.402		2.372	0.873	2.717	0.007	
change_real income	0.394	0.323	1.219	0.223		-1.395	0.578	-2.416	0.016	
change_real rent	-0.529	0.13	-4.083	0	*	-0.033	0.223	-0.148	0.883	
change_real mortgage repayment	-2.168	0.227	-9.543	0	*	-2.108	0.461	-4.567	0	*
change_building approval	-0.037	0.008	-4.699	0	*	-0.034	0.008	-4.272	0	*
change_lending_rate	0.287	0.03	9.704	0	*	0.279	0.03	9.356	0	*
change_real GDP	0.214	0.153	1.399	0.162		0.226	0.154	1.465	0.143	
% of Asian population	0.193	0.062	3.104	0.002	*	-0.076	0.068	-1.131	0.258	
% of population unemployed	-0.267	0.107	-2.482	0.013		0.464	0.163	2.847	0.004	*
English skills	1.503	0.16	9.412	0	*	-0.482	0.294	-1.639	0.101	
semi detached	0.828	0.094	8.76	0	*	0.34	0.115	2.966	0.003	*
detached	0.184	0.041	4.485	0	*	0.065	0.066	0.986	0.324	
rent_tenure	-0.085	0.054	-1.59	0.112		0.185	0.075	2.447	0.014	
mean_age	-0.013	0.003	-4.543	0	*	-0.018	0.003	-5.486	0	*
bachelor	0.052	0.057	0.9	0.368		0.224	0.067	3.343	0.001	*
bedroom	-0.166	0.025	-6.513	0	*	-0.06	0.031	-1.934	0.053	
log_realwklyrent	0.025	0.006	4.094	0	*	0.04	0.01	3.883	0	*
log_realmthlymortgage	0.043	0.008	5.175	0	*	0.007	0.017	0.432	0.666	
log_totalappv	0.082	0.019	4.358	0	*	0.077	0.019	4.023	0	*
log_totalhouse	0.004	0.01	0.364	0.716		-0.054	0.015	-3.639	0	*
lag_price	0.595	0.013	46.222	0	*	0.624	0.013	48.707	0	*
Time^1	0.037	0.009	4.004	0	*	0.034	0.009	3.808	0	*
Time^2	0	0	-0.998	0.318		0	0	-1.387	0.166	
Time^3	0	0	-4.497	0	*	0	0	-4.117	0	*
CPI	-0.105	0.009	-11.384	0	*	-0.096	0.009	-10.1	0	*
Lending Rate	-0.026	0.002	-12.096	0	*	-0.027	0.002	-12.02	0	*
Real GDP	-7.914	0.643	-12.313	0	*	0	0	9.753	0	*
Building_approval	0	0	2.577	0.01		0	0	2.481	0.013	
change in building approval	0.052	0.008	6.474	0		0.051	0.008	6.256	0	*
log_real_gdp-gm						-7.238	0.66	-10.97	0	*
owned						0.117	0.039	2.975	0.003	*
change_aboriginal						0.093	0.046	2.021	0.043	
aboriginal						-0.154	0.222	-0.692	0.489	
no of dependant						-0.098	0.091	-1.082	0.279	

To verify the model accuracy, residual analysis by paired *t*-test was conducted for the developed forecasting models. The test results for the house and flat/unit models can be found in Table 4. As forecasting accuracy relies on the accuracy of many independent variables, any changes in demand and supply variables, such as government immigration policies, land supply policies, and global economic conditions, may alter the model's performance. Thus, it is recommended that the developed models be used by trained professionals and experts.

Table 4: Model verification

<table>
<tr><th>t-test (house)</th><th>t-test (flat)</th></tr>
<tr><td>
in-sample
Paired t test

Variable | Obs Mean Std. err. Std. dev. [95% conf. interval]
---------+--
yhat | 3,110 6.47102 .0114026 .6358955 6.448662 6.493377
log_re~p | 3,110 6.469015 .0111338 .6209001 6.447185 6.490845
---------+--
diff | 3,110 .0020048 .0016225 .0904822 -.0011765 .0051861
----
mean(diff) = mean(yhat - log_realp) t = 1.2356
H0: mean(diff) = 0 Degrees of freedom = 3109

Ha: mean(diff) < 0 Ha: mean(diff) != 0 Ha: mean(diff) > 0
Pr(T < t) = 0.8917 Pr(|T| > |t|) = 0.2167 Pr(T > t) = 0.1083

out-of-sample
Paired t test

Variable | Obs Mean Std. err. Std. dev. [95% conf. interval]
---------+--
yhat | 126 7.133921 .0510901 .5734845 7.032808 7.235035
log_re~p | 126 7.185738 .0523176 .5872631 7.082195 7.289281
---------+--
diff | 126 -.0518169 .0076119 .0854434 -.0668818 -.036752
----
mean(diff) = mean(yhat - log_realp) t = -6.8073
H0: mean(diff) = 0 Degrees of freedom = 125

Ha: mean(diff) < 0 Ha: mean(diff) != 0 Ha: mean(diff) > 0
Pr(T < t) = 0.0000 Pr(|T| > |t|) = 0.0000 Pr(T > t) = 1.0000
</td><td>
in-sample
Paired t test

Variable | Obs Mean Std. err. Std. dev. [95% conf. interval]
---------+--
yhat | 3,236 6.38799 .01121 .6376919 6.36601 6.409969
logrealp | 3,236 6.496863 .01116 .6348456 6.474982 6.518745
---------+--
diff | 3,236 -.1088736 .0015275 .0868909 -.1118685 -.1058788
----
mean(diff) = mean(yhat - logrealp) t = -71.2776
H0: mean(diff) = 0 Degrees of freedom = 3235

Ha: mean(diff) < 0 Ha: mean(diff) != 0 Ha: mean(diff) > 0
Pr(T < t) = 0.0000 Pr(|T| > |t|) = 0.0000 Pr(T > t) = 1.0000

out-of-sample
Paired t test

Variable | Obs Mean Std. err. Std. dev. [95% conf. interval]
---------+--
yhat | 126 6.99051 .053398 .5993908 6.884829 7.096191
logrealp | 126 7.185476 .0523122 .587203 7.081944 7.289009
---------+--
diff | 126 -.1949663 .0080216 .0900421 -.210842 -.1790906
----
mean(diff) = mean(yhat - logrealp) t = -24.3052
H0: mean(diff) = 0 Degrees of freedom = 125
</td></tr>
</table>

Discussion and conclusion

This research developed and defined the utility of MLM for detached houses and flats/units in Sydney. The models have assumed that house prices perform differently in every geographical location due to spatial heterogeneity. Thus, the structure of the model includes variables at the LGA levels nested within the regional areas in the Sydney region. LGAs' future prices of properties have been forecasted and an upward price trend in both detached houses and flats/units in Sydney has been predicted. These models add to the existing literature by articulating predictability by reference to local attributes of the property including neighbourhood factors. The findings suggest that the level of education, ethnicity, age group, and English skills are the important factors in a housing purchase decision.

The estimated determinants coincide with the literature (Abelson et al., 2005) that economic, demographic, and market condition factors have contributed greatly to the changes in dwelling prices. The changes in population and households' age affect the demand for housing that support the findings of Sunde and Muzindutsi (2017) and Eichholtz and Lindenthal (2014), respectively. The estimated results have supported Nobili and Zollino (2017), Karantonis and Ge (2007), and Oestmann and Bennohr (2015) that the lending conditions have impacted on housing demand and prices. Compared to Adams and Füss (2010) that 1% increase in long-term interest rate resulted in a 0.3% decline in house prices, the lending rate has contributed significantly to Sydney property prices in which a 1% increase in the lending rate led to a 2.6% decline in house prices. Different from the literature (Stamou et al., 2012; Abdulai & Owusu-Ansah, 2011; Kiefer, 2011), the consumer preferences for specific structural attributes of houses, such as the number of bedrooms, have not been found statistically significant for the detached houses and flats/units.

However, the unique contribution from this research includes the neighbourhood factor as one of the elements in housing purchase decisions. A residential neighbourhood reflects a place that is surrounded by the types of housing and a group of people who live there. By applying the MLM methods, it was found that the proportion of ethnic groups, education background, and English-speaking levels contribute to the demand for detached houses. This characteristic may be one of the attributes of price differentiation for LGAs. These findings concise with the purchase decision theories (Kotler, 2002; Stanton et al., 1994; Lee et al., 1994; Neal et al., 2002; Kearns & Parkes, 2003; Chia et al., 2016) that consumers' purchase decisions are affected by cultural, social, personal, and psychological factors, financial status, and buyer's decision process. However, the neighbourhood factor was not revealed to be statistically significant in the flats/units where prices are cheaper relative to detached houses. A household may have an intention to buy a detached house in a good location. The preference may come from financial status, housing location, and housing characteristics. The purchase decision can be altered by the changed health and safety environment. Considering the COVID-19 pandemic lock-down measurement, as households can work from home post the COVID-19 pandemic, many households may prefer to purchase detached houses if financially allowed. Further research is required to study the implications of neighbourhood effects on housing demand.

Price forecasting models are crucial for governments monitoring housing markets which are one of the important indicators contributing to the performance of the overall economy and finance sectors. Government can also formulate informed decisions on urban planning for land supply and infrastructure development, provide guidelines on constructing different types of housing, and devise strategies for addressing the housing affordability issues. Understanding the future price trend is important for property developers who can make decisions on land purchase and development strategies. Equity fund investors can also benefit from the model results in valuing long term investment decisions. Given the research significance, further research on overcoming the limitations of applying the MLM techniques may be required.

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