ARC Centre of Excellence in Population Ageing Research

Working Paper 2013/11

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22nd March 2013

Abstract

This paper estimates and compares methods of constructing disaggregated house price indices from existing house price models using individual sales data for Sydney. Nine alternative house price models are selected to cover the most frequently used methods in the literature: the mean model, median models (standard and stratified), hedonic models (restricted and unrestricted hedonic), repeat-sales models (age-adjusted and Case-Shiller weighted), and a hybrid of the hedonic and repeat-sales model. The unrestricted hedonic model and the hybrid model have an advantage over the other seven models in that they do not require stratification of the data for estimating disaggregated indices. Both models employ the whole sample to estimate implicit prices of house characteristics that are used to construct disaggregated house price indices. These two models eliminate variability arising from small sample sizes and provide more efficient estimates of house price heterogeneity. In addition, house characteristics that are important drivers of the variability of individual house prices are identified in the two models. Disaggregated indices constructed from these two models provide more accurate comparisons with an aggregate house price index. We quantify the extent to which disaggregated house prices indices have significantly more variability than, and differing trends from, the aggregate index.

Keywords: disaggregated house price index, hedonic models, repeat-sales models, hybrid models

JEL Classifications: C31, C43, G21, R31, R32

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1 Introduction

House price indices are important indicators of average property values and can be constructed at the market-wide level and at more disaggregate levels. Market-wide indices reflect average house price trends and variability. Disaggregated house price indices measure house price trends and risks of properties with specific characteristics.

Banks and insurance companies often base the pricing and risk management of housing-related financial products on country- or city-level house price indices. An example is the valuation of the collateral for mortgage loans (see Clapp and Giaccotto, 1999). However, few providers hold portfolios that are representative of the market and thus pricing and hedging methods based on aggregate house price indices will only cover a limited part of the actual house price risk banks and insurers face. Submarkets within a housing market show very different risk and return profiles and only part of the variability is explained by a market-wide index (see Bourassa et al., 1999; Hanewald and Sherris, 2011). Individual house prices are expected to show even greater variability due to the heterogeneity of individual houses. But due to limited public access to house transactions data, disaggregated house price indices are not available in most previous studies on applications of house price models (Chen et al., 2010; Li et al., 2010). This motivates our study on constructing disaggregated house price indices that can be uses to quantify the house price risk of housing-related financial products including mortgage loans and equity release products.

House price indices can be constructed from different house price models. In general, house price models are based on a decomposition of residential house prices into two parts: the individual house quality measure and the time trend (see Case and Quigley, 1991; Englund et al., 1998; Quigley, 1995). Two types of house price models are identified in the literature: the non-regression-based models and regression-based models (see Hansen, 2009). Non-regression-based models include the mean method and different median methods. The three main types of regression-based methods are: hedonic models, repeat-sales models, and hybrid models of hedonic and repeat-sales.

The indices constructed from different house price models differ substantially in terms of level estimates and precision. The differences are especially large for long estimation and forecast horizons needed for pricing and risk management applications of housing-related financial products that typically have long contract durations. Only few studies compare the different methodologies of index construction, with mixed results (Crone and Voith, 1992; Hansen, 2009; Shimizu and Watanabe, 2010, see Section 2.4 for more details). No study compares different methods for constructing disaggregated indices.

This paper constructs and compares aggregate and more disaggregated house price indices based on a large data set of individual property transactions in Sydney, Australia over the period 1971-2011. Nine alternative models are chosen to reflect a wide range of frequently used methods in the house price literature. The models considered are the mean model, median models (standard and stratified), hedonic models (restricted and unrestricted hedonic), repeat-sales models (age-adjusted repeat-sales and Case-Shiller weighted repeat-sales), and a hybrid of the hedonic and repeat-sales model.

The growth rates in house price indices constructed from the models differ and, although similar in many years, result in marked differences in index levels. The unrestricted hedonic model and the hybrid model provide more precise estimates for finely stratified property portfolios with small sample sizes than the other seven models. These two models are also used to identify house characteristics that are important in driving individual house prices differently from the average price movement. The results show that price indices at portfolio levels are substantially more volatile than the aggregate house price index. This finding confirms that using the aggregate house price index for assessing house price risk in financial products that are based on individual house prices (like equity release products) does not accurately reflect the actual risk.

The structure of the paper is as follows. Section 2 reviews the relevant literature, introducing different models for house price index construction. Section 3 presents detailed methods of constructing aggregate and disaggregated house price indices based on nine selected house price models. Section 4 describes the data used in this study. The estimation results for the nine alternative house price models and comparisons of aggregate and disaggregated house price indices from these models are presented in Section 5. Section

6 concludes.

2 House Price Models

Disaggregated house price indices, as well as the aggregate index, are constructed from existing house price models. As introduced in Section 1, these models are categorised into two major types: non-regression-based and regression-based models.

Of the non-regression-based models, the mean and median models are widely used due to their simplicity, but these two models do not take into account compositional changes or quality changes. Prasad and Richards (2006) propose a stratified median method that is designed to reduce the compositional bias. In this method, median house prices in sub-markets are used to construct cluster-level indices and the weighted average of these stratified median prices is used to produce an aggregate house price index. The mean, the median and the stratified median methods are included in our comparison.

Indices from regression-based house price models are more accurate since these models can control for heterogeneous characteristics of individual houses. In regression-based models, house price indices are constructed from the estimated time trend and implicit prices of house characteristics, by holding the quality measure constant. Depending on which period is chosen as a reference, indices are divided into three types: Laspeyres, Paasche and Fisher indices. The Laspeyres index uses the quality measure in the base year, the Paasche index uses the quality measure in the most recent time, and the Fisher index uses the average quality measures during the observation period. Laspeyres' method is adopted throughout the paper.

Following is an introduction to the three types of regression-based house price models (hedonic, repeat-sales, and hybrid models) and a review of studies that compare alternative house price models.

2.1 Hedonic Models

Hedonic models assume that the price of an individual property is a function of the property's characteristics (see Bourassa et al., 2011; Case et al., 2004; Clapp and Giaccotto, 1998; Goodman, 1978; Knight et al., 1995). The functional form and the selection of relevant explanatory variables are critical to the performance of the model (Bourassa et al., 2010; Goodman and Thibodeau, 1995).

Different functional forms of the relationship between prices and explanatory variables have been proposed. Both linear relationships and the more general Box-Cox transformations (Box and Cox, 1964) have been used in hedonic models. Rosen (1974), Ekeland et al. (2004), Goodman (1978), Halvorsen (1981) and Linneman (1980) find it necessary to use non-linear functions of house prices with respect to characteristics in hedonic models. In non-linear specifications, log-log and log-linear functions of individual house prices with respect to characteristics are employed (see Bourassa et al., 2010, 2011; Case et al., 2004; Clapp and Giaccotto, 1998; Ekeland et al., 2004; Goodman and Thibodeau, 1995).

Based on the specification of the effect of property characteristics on house prices, hedonic models can be divided into restricted and unrestricted hedonic models (see Hansen, 2009; Triplett, 2006). Restricted hedonic models assume that the coefficients of all property characteristics are time-invariant during the observation period. Unrestricted hedonic models allow the implicit prices of house attributes to change over time. Time-varying implicit prices of house characteristics can be allowed for (1) by estimating separate regression equations for each time period (see Knight et al., 1995); (2) by estimating regression equations for adjacent periods; (3) by including the interactions of time dummy variables and house characteristics; or (4) by including continuously time-varying implicit prices of house characteristics as in Auer (2004).

Hedonic models are susceptible to specification errors resulting from misspecification of the functional relationship between house prices and characteristics and the omission of important house attributes (see Bourassa et al., 2011; Case et al., 1991; Quigley, 1995). In addition, hedonic house price models, more than other methods, rely on the availability of data for detailed property characteristics.

A restricted hedonic model and an unrestricted hedonic model are included in our model comparisons. The unrestricted hedonic model employed in this paper includes interactions of time dummy variables and house characteristics to allow for time-varying implicit prices of house characteristics, since this approach is parsimonious and flexible.

2.2 Repeat-Sales Models

The repeat-sales model, initially proposed by Bailey et al. (1963), reduces the specification error potentially present in the hedonic model by differencing the hedonic regression equations for properties that are transacted multiple times (Case, 1986). The standard repeat-sales model regresses log sales price changes of properties that are sold multiple times against time dummy variables.

Implicit prices of property characteristics are assumed to be time-invariant in the standard repeat-sales model (see Bailey et al., 1963; Jansen et al., 2007; Wang and Zorn, 1997). Repeat-sales models employ only houses that are transacted multiple times during the observation period, resulting in possible sample bias (Mark and Goldberg, 1984).

Another underlying assumption of the standard repeat-sales model is that property characteristics do not change over time. But the dwelling age of a property is surely increasing over time. The effect of dwelling age on house prices can be decomposed into two parts: depreciation and vintage effects (see Goodman and Thibodeau, 1995). The depreciation of houses may change over time, whereas the vintage effect, which is related to the year of construction remains constant (see Coulson and McMillen, 2008; McMillen, 2003; Shimizu and Watanabe, 2010). The depreciation effect can be negative when the property value is improved through renovation and maintenance. To account for the depreciation of houses, an age-adjusted repeat-sales model is employed by McMillen (2003) and Shimizu and Watanabe (2010). To capture possible changes of house characteristics due to renovations and maintenance, Shiller (2012) includes changes of characteristics in the repeat-sales regression, Goetzmann and Spiegel (1995) include a constant term in the model, and Clapp and Giaccotto (1998) include assessed property values in the regression. Alternatively, Clapp and Giaccotto (1999) control for possible renovations by removing records of property transactions within short periods of time, since houses that are transacted within short periods of time are more likely to involve renovations. This can also be enforced by limiting the data sample to transactions on properties with unchanging characteristics (Bourassa et al., 2009). The approaches by Clapp and Giaccotto (1999) and Bourassa et al. (2009) "waste" more data and lead to a more serious sample bias. Since no data on time-varying property characteristics or assessed property values is available in our study, we follow Goetzmann and Spiegel (1995)'s approach by including an intercept in the age-adjusted repeat-sales model to account for possible changes in property characteristics.

The standard repeat-sales model also assumes that disturbance terms are uncorrelated over time and across individual properties, and have a constant variance. Case and Shiller (1987) present evidence showing that the variance depends on the time interval between the two sales. Miller and Peng (2006) identify the time-varying volatility for the disturbance term in the standard repeat-sales model. Case and Shiller (1987) propose a weighted repeat-sales model that more accurately measures price changes. The rationale behind the weighted repeat-sales model is that properties with longer interval times between sales should be given less weight due to heteroskedasticity of the disturbance term. To account for this, a three-stage regression is performed in Case and Shiller (1987). In the first stage, the standard repeat sales regression is performed; in the second stage, the squared residuals from the first stage are regressed against the interval times between sales; finally the repeat sales regression is performed after dividing each equation by the square roots of the estimated values from the second stage.

A standard repeat-sales model, an age-adjusted repeat-sales model and a weighted repeat-sales model are included in the model comparison in this paper.

2.3 Hybrid Models

Quigley (1995) presents a hybrid model that combines hedonic and repeat-sales models and uses the data on properties that are sold once or multiple times. Hybrid models overcome the selection bias problems in repeat-sales models and the specification error problems in hedonic models (see Fogarty and Jones, 2011; Jones, 2010; Quigley, 1995). There are different versions of the hybrid model. Case and Quigley (1991) employ three stacked equations: one applied to data on single sales, one applied to repeat sales with unchanged characteristics, and one for repeat sales with changed characteristics. Quigley (1995) and Jones (2010) propose a hybrid model, applying three stacked equations respectively to data on houses with single sales, data on houses with multiple sales except the last sales, and differenced repeat-sales data. A hybrid model, following Quigley (1995) and Jones (2010), is included in the comparison in this paper.

2.4 Model Comparison

Few studies compare the different house price models in terms of goodness of fit, index construction, and predictive power.

Crone and Voith (1992) compare five alternative house price models in estimating house price appreciation using data from Montgomery County, PA. They establish the following ranking of the five models (starting with the most accurate): repeat-sales, restricted hedonic, unrestricted hedonic, mean, and median, based on the Mean Squared Prediction Error and Mean Absolute Prediction Error. Crone and Voith (1992) conclude that regression-based parametric models perform better than the two non-parametric methods, which agrees with the findings by Hansen (2009) based on data for Sydney, Melbourne and Brisbane. But Hansen (2009) finds that the hedonic model and the repeat-sales model provide similar house price returns. Shimizu and Watanabe (2010) use Japanese data to compare restricted vs. unrestricted hedonic models and equally-weighted vs. Case-Shiller repeat-sales models (see Case and Shiller, 1989). They conclude that repeat-sales models have delays in showing the turning point in market-wide trends.

Case et al. (1991) compare hedonic, repeat-sales and hybrid models based on a data set on house transactions in Fairfax County, VA. They find that the hybrid model does not have clear efficiency gains over the hedonic or repeat-sales model. Jones (2010) constructs house price index using a hybrid model of hedonic and repeat-sales based on house price data for the city of Mandurah, Western Australia, and compares the hybrid model with the mean, the median, the hedonic and the repeat-sales models. He concludes that the price index constructed from the hybrid model has the narrowest confidence interval and thus is the most accurate, which contradicts with Case et al. (1991)'s conclusion.

These comparative studies show advantages of regression-based over non-regression-based models in constructing an aggregate house price index. The findings with respect to the comparison of repeat-sales and hedonic models are mixed. Crone and Voith (1992) show that the repeat-sales model gives a more accurate index than the two hedonic models, but Shimizu and Watanabe (2010) conclude otherwise.

These previous studies have focused on comparisons of aggregate house price indices. Several studies point out that the average house price index is not accurate in representing house price risk (e.g., Bourassa et al., 1999, 2009; Hanewald and Sherris, 2011). Our study contributes a comparison of disaggregated house price indices.

3 Index Construction Based on Nine House Price Models

This section presents the methods for constructing aggregate (market-wide) and disaggregated house price indices based on nine house price models with different levels of complexity. The models are selected to cover the most frequently used methods in research and industry applications. The nine models are: three non-regression-based models that are straightforward to implement, two hedonic models that require detailed house transactions data and regression analysis, three repeat-sales models that are less data-intensive but subject to possible sample bias, and a hybrid hedonic-repeat-sales model. Disaggregated house price indices provide a more accurate assessment of house price risk than an aggregate house price index. All nine house price models can be used to construct indices at more disaggregated levels, but only the unrestricted hedonic model and the hybrid model can provide accurate indices for finely disaggregated property portfolios.

3.1 Three Non-Regression-Based Models

The mean model computes the average house price for each year, and the mean price index is constructed by deflating these average prices to make the value for the base year equal to 100. The median model computes the median house price for each year, and the median price index can be constructed using the same method as in the mean model. Disaggregated mean and median indices are constructed by calculating the respective index for each property portfolio stratified by the characteristics of interest.

We also consider a stratified median model, which was suggested by Prasad and Richards (2006) as a method for constructing more accurate aggregate indices. Prasad and Richards (2006) compute median house prices in different suburbs and derive the market-wide index by averaging across the suburb-level indices. We extend the method by using other property characteristics as additional classification variables. For example, to construct the index for houses with three bedrooms, the data are first stratified based on the number of bedrooms. The portfolio of houses with three bedrooms is further disaggregated into suburbs. The index is then computed as the equally-weighted average of the median house prices in each suburb. The index is deflated to set the base year's index level to 100.

3.2 Restricted Hedonic and Repeat-Sales Models

3.2.1 A Restricted Hedonic Model

Hedonic models assume that house prices are functions of house characteristics. As indicated in Section 2.1, there are two methods with respect to the assumption on the coefficients of house characteristics in the literature: restricted and unrestricted hedonic models. A restricted hedonic model assumes that the implicit prices of house characteristics are time-invariant. The model estimated in this study is given by:

$$V_{it} = \alpha + T'\beta + X'\gamma + f(Lon_i, Lat_i) + \varepsilon_{it}, \tag{3.1}$$

where V_{it} is the log price of an individual house i at time t, α is the intercept, T is a vector of time dummy variables, β is a vector of coefficients for the time dummy variables, X is a vector of property characteristics, γ is a vector of coefficients for the house characteristics, $f(Lon_i, Lat_i)$ is the function with respect to longitude and latitude, and ε_{it} is the disturbance term.

To account for spatial dependence, a trend surface method is employed by including a function of longitudes and latitudes of individual properties in the regression (see Fik et al., 2003). The function of geographical coordinates is assumed to be linear with respect to both longitude and latitude: $f(Lon_i, Lat_i) = \theta_1 Lon_i + \theta_2 Lat_i$. To disentangle the depreciation and vintage effects of a property's ages, a quartic function of dwelling age and dummy variables indicating the decade the property was built are included in the regression (see Coulson and McMillen, 2008).

3.2.2 A Standard Repeat-Sales Model

Repeat-sales models are derived from hedonic models. To reduce possible misspecification in hedonic models, a random error is introduced to the restricted hedonic regression given in Equation (3.1). The new regression equation is given by:

$$V_{it} = \alpha + T'\beta + X'\gamma + f(Lon_i, Lat_i) + \eta_i + \xi_{it}, \tag{3.2}$$

where η_i is a specification error for each individual house and ξ_{it} is a white noise term. The sum of η_i and ξ_{it} is denoted by ε_{it}. For houses i, k, the assumptions with respect to the error terms are:

$$\begin{aligned}
&E(\xi_{it}) = 0, E(\eta_i) = 0 \ ; \\
&E(\xi_{it}^2) = \sigma_\xi^2, E(\eta_i^2) = \sigma_\eta^2 \ ; \\
&E(\xi_{it}\xi_{js}) = 0 \text{ if } (i-j)^2 + (t-s)^2 \neq 0 \ ; \\
&E(\eta_i\eta_j) = 0 \text{ if } i \neq j; \\
&E(\eta_i\xi_{it}) = 0.
\end{aligned} \tag{3.3}$$

Based on the above assumptions, it can be shown that the variance of ε_{it} is $\sigma_\varepsilon^2 = \sigma_\eta^2 + \sigma_\xi^2$.

For a property j that is transacted multiple times, the differenced log sales prices pairs are expressed as:

$$V_{jt} - V_{js} = D'\beta + \xi_{jt} - \xi_{js}, \tag{3.4}$$

where s and t $(s < t)$ are a pair of consecutive sales of property j, and D is the differenced vector of T. A standard repeat-sales model uses only data on houses with multiple transactions to regress the differenced log sale prices against time dummy variables, as expressed in Equation (3.4).

3.2.3 An Age-Adjusted Repeat-Sales Model

To account for the fact that the dwelling age increases over time, the differenced polynomial function of dwelling ages is included in the regression as suggested by Shimizu and Watanabe (2010). Since the data set used in our study does not record when and to what extent house characteristics are changed, an intercept term is included to capture the effects of possible changes (see Goetzmann and Spiegel, 1995). The regression equation is given by:

$$V_{jt} - V_{js} = \lambda + g(A_t) - g(A_s) + D'\beta + \xi_{jt} - \xi_{js}, \tag{3.5}$$

where λ is the intercept term, and $g(A_t)$ is the polynomial function of dwelling age at time t.

3.2.4 A Weighted Repeat-Sales Model

To account for possible heteroskedasticity of the residuals in the standard repeat-sales model, Case and Shiller (1987) assume that the variance of residuals is dependent on the time intervals between consecutive sales. Equation (3.4) is estimated with additional assumptions on the disturbance term expressed in the following equation:

$$E\left((\xi_{jt} - \xi_{js})^2\right) = \tau_0 + \tau_1(t - s), \tag{3.6}$$

where τ_0 and τ_1 are coefficients that are estimated by regressing the squared residuals from Equation (3.4) against an intercept term and $(t - s)$. The estimated coefficients are denoted by $\hat{\tau}_0$ and $\hat{\tau}_1$. The last step is to run a weighted linear regression of Equation (3.4) with weights equal to $(\hat{\tau}_0 + \hat{\tau}_1(t - s))^{-\frac{1}{2}}$.

3.2.5 Index Construction

In the restricted hedonic and repeat-sales models, the estimated coefficients on the time dummy variables' coefficients, $\hat{\beta}$, are used to construct the aggregate house price index. The index in the base year is set to 100. The index is accumulated with exponential growth rates equal to the differenced values of the $\hat{\beta}$. Disaggregated indices for property portfolios using the restricted hedonic model and repeat-sales models are constructed by estimating the models separately for portfolios of properties with specific characteristics. Both types of models need sufficient number of observations to construct accurate indices.

3.3 Unrestricted Hedonic and Hybrid Models

3.3.1 An Unrestricted Hedonic Model

To capture the possible changes in the implicit prices of house characteristics, interactions of time dummy variables and house characteristics are included. The unrestricted hedonic model is give by:

$$V_{it} = \alpha + T'\beta + X'\gamma + X'\Delta T + f(Lon_i, Lat_i) + \varepsilon_{it}, \tag{3.7}$$

where Δ is a $k \times t$ matrix of coefficients of the interactions between time dummy variables and house characteristics. The remaining notation is the same as in Equation (3.1).

3.3.2 A Hybrid House Price Model

The hybrid model combines the hedonic model and the repeat-sales model. A random error that captures the specification error is introduced to the unrestricted hedonic regression in Equation (3.7), resulting in the following regression equation:

$$V_{it} = \alpha + T'\beta + X'\gamma + X'\Delta T + f(Lon_i, Lat_i) + \eta_i + \xi_{it}. \tag{3.8}$$

Differencing Equation (3.8) for houses with multiple transactions across sales, the equation becomes:

$$V_{it} - V_{is} = D'\beta + X'\Delta D + \xi_{it} - \xi_{is}. \tag{3.9}$$

The hybrid model is estimated using a stack of three equations taking into account the covariance structure. The three equations are: Equation (3.8) for houses with single transactions, Equation (3.8) again for houses with multiple transactions except the last sales, and Equation (3.9) for houses with multiple transactions. With the error assumptions specified in Equation (3.3), the covariance matrix of the hybrid model is:

$$\Sigma = \begin{pmatrix} \sigma_\varepsilon^2 I & 0 & 0 \\ 0 & \sigma_\varepsilon^2 I & -\sigma_\xi^2 I \\ 0 & -\sigma_\xi^2 I & 2\sigma_\xi^2 I \end{pmatrix} \tag{3.10}$$

Two steps are involved in the estimation of the hybrid model. Firs, Equation (3.8) is estimated using all sales to obtain the variance of ε_{it}, denoted by $\hat{\sigma}^2_\varepsilon$ and Equation (3.9) is run on repeat-sales data to estimate the variance of ξ_{it}, denoted by $\hat{\sigma}^2_\xi$. The formula for calculating the estimated variance of ε_{it} is $\hat{\sigma}^2_\varepsilon = \left(\frac{1}{N-M-T-1}\right)\sum_{i=1}^{N}\hat{\varepsilon}^2_{it}$, where N is the total number of observations, M is the number of exogenous variables used, and T is the number of years. Alternatively, $\hat{\sigma}^2_\varepsilon$ is obtained from squaring the value of Root Mean Squared Errors (Root MSE) in the estimation results. Similarly, the estimated variance of ξ_{it} is $\hat{\sigma}^2_\xi = \frac{1}{2}\left(\frac{1}{J-T-2}\right)\sum_{j=1}^{J}(\hat{\xi}_{jt} - \hat{\xi}_{js})^2$, where J is the number of pairs of observations with repeat transactions. The estimated variance $\hat{\sigma}^2_\xi$ is obtained by squaring the value of Root Mean Squared Errors in the estimation results output. The variance of η_i is $\hat{\sigma}^2_\eta = \hat{\sigma}^2_\varepsilon - \hat{\sigma}^2_\xi$. These two estimates are used as inputs in Equation (3.11) to calculate the estimated covariance matrix.

The second step is to perform a general linear regression on the stacked three equations taking into account the estimated covariance structure. The squared residuals are also regressed against relevant exogenous variables to assess the fluctuations around the expected price. A Cholesky decomposition of Σ^{-1} is needed to obtain the linear transformation matrix P, where $PP^T = \Sigma^{-1}$. It is not feasible to calculate the Cholesky decomposition due to the large volume of data. The method that utilises the diagonal blockwise matrices in the covariance matrix is adopted (see Fogarty and Jones, 2011). It can be shown that:

$$P^T = (\Sigma^{-1/2})^T = \begin{pmatrix} \frac{1}{\sigma_\varepsilon}I & 0 & 0 \\ 0 & \sqrt{\frac{2}{2\sigma^2_\varepsilon - \sigma^2_\xi}}I & -\frac{1}{\sqrt{4\sigma^2_\varepsilon - 2\sigma^2_\xi}}I \\ 0 & 0 & \frac{1}{\sqrt{2}\sigma_\xi}I \end{pmatrix} \tag{3.11}$$

The stack of three regression equations are run on the data after being left multiplied by P^T.

3.3.3 Index Construction

The method of constructing indices in the unrestricted hedonic model and in the hybrid model is the same, since the two models share the same specification on the functional form and explanatory variables and only differ in the assumptions on the disturbance term.

The aggregate house price index at time s is computed as follows:

$$HPI_s = 100 \exp(\beta_s + \sum_i^K \delta_{is} X_i^0), \tag{3.12}$$

where β_s is the estimated coefficient of the s^{th} time dummy variable, X_i^0 denotes the variables' average values in the base year, and δ_{is} is the corresponding estimated coefficients of the interactions between the s^{th} time dummy variable and the characteristics variables. K is the number of characteristics that are interacted with time dummy variables in the regression.

The index for a disaggregated portfolio of properties with specific characteristics X_i^ρ is constructed in a similar way:

$$HPI_s^\rho = 100 \exp(\beta_s + \sum_i^K \delta_{is} X_i^\rho). \tag{3.13}$$

The unrestricted hedonic model and the hybrid model have three main advantages for constructing disaggregated house price indices: (1) only one regression is needed rather than separate regressions for each stratified portfolio; (2) the constructed house price indices at a portfolio level can be easily linked to the aggregate house price index; and (3) estimation for finely disaggregated portfolios is accurate compared to the other seven models that require a sufficient number of observations in finely disaggregated portfolios.

Combining Equations (3.13) and (3.12), we can link the price index for properties with certain characteristics to the aggregate house price index as follows:

$$HPI_s^\rho = HPI_s \exp\left(\sum_i^K \delta_{is} (X_i^\rho - X_i^0)\right). \tag{3.14}$$

4 Data

Two data sets were provided by the Sydney-based company, Residex Pty Ltd. One set contains data on the characteristics of individual residential properties together with the latest transaction prices and dates. The other set data set contains transaction prices and dates of houses with repeated sales. We combine the two data sets to use both house characteristics and repeat sales information.

4.1 Property Characteristics Data

There are 815,929 observations on individual house sales prices as well as detailed characteristics from 1951 to 2011 and across the 258 postcode areas of Sydney, Australia. This data set only includes data on the sales prices and characteristics at the last sales. Recorded characteristics include: building year, land area, number of bedrooms, number of bathrooms, number of garages, geographical location[1] (given by latitude and longitude of the house), and date of the sale.

The distance to the CBD (Central Business District), dwelling age and a dummy variable indicating the decade in which a property was built are calculated based on given information. Distance to CBD is calculated as the distance of a property to the Sydney General Post Office (GPO) at No.1 Martin Place, using the great-circle method[2], which takes into account the curvature of the earth. The dwelling age at the date of sale is calculated as the difference between the sale year and the building year. There are observations where the building year is more recent than the sales year. This is possible when houses are pre-sold before they are built. In these cases, the dwelling age is set to zero. Dummy variables are created that indicate the decade in which the house was built: before 1960, from 1960 to 1969, 1970 to 1979, $\cdots$, and 2009 to 2011.

[1]The majority of the geographical coordinates are recorded at the street level (92% of the observations).

[2]The SAS code for calculating the great-circle distances (in kilometres) is: Dcbd = 6373 * ARCOS (sin((90 - lat) * constant('pi') / 180) * sin((90 + 33.868167) * constant('pi') / 180) * cos((lon - 151.207632) * constant('pi') / 180) + cos((90 - lat) * constant('pi') / 180) * cos((90 + 33.868167) * constant('pi') / 180)).

4.2 Repeat-Sales Data

A separate data set is available that contains 2,620,941 observations of repeated sale prices and contract dates (which proxies sales dates) of properties with multiple sales. Since records on characteristics are absent in the repeat-sales data, changes in characteristics due to renovations cannot be identified. There are in total 824,704 pairs of transactions on 462,873 properties with the first sale year ranging from 1969 to 2010 and the later sale year ranging from 1969 to 2011.

4.3 Merged Data

The property characteristics data and the repeat-sales data are merged by the unique property identity number. The merged data set comprises 2,169,715 observations. After applying the following filtration, there are 1,553,120 valid observations left:

1. Any observation that has incomplete entries is removed (520,219 observations).

2. Any house with the number of bedroom, bathroom, or garages being -1 is removed[3](48,625 observations).

3. Any observation with a sale date earlier than 1971 is removed because data before 1971 is sparse and discontinuous (17,388 observations).

4. Any observation with the sales price less than the 0.5% quantile or greater than 99.5% quantile in each year is removed (two-sided 99% winsorisation for each year's data).

5. Any observation with a total land area of less than 82 m^2 (the 0.5% quantile) or greater than $14,856$ m^2 (the 99.5% quantile) is removed (two-sided 99% winsorisation).

After the filtration, there are 314,862 observations on properties with single sales, and 1,238,258 observations on properties with multiple sales. For observations on prop-

[3]In the raw data, the value of -1 for the number of bedrooms, bathrooms or garages implies a missing or abnormal value.

erties with multiple transactions, there are 799,474 pairs of consecutive sales on 438,784 properties.

A statistical summary of the merged data after filtration is presented in Table 1.

Table 1: Summary of Variables

Variable	**Mean**	**Std Dev**	**Minimum**	**Maximum**
Sales Price	327,228.41	366,931.59	1,400	10,000,000
Sales Year	1996	9.2719	1971	2011
Building Year	1988	8.8124	1910	2012
Age (years)	7.7015	9.4768	0	100
Area (m^2)	655.5367	573.9229	82	14,856
No of Bedrooms	3.3625	0.8276	1	9
No of Bathrooms	1.6071	0.7241	1	9
Garages	1.4500	0.8275	0	9
Latitude	-33.8090	0.1746	-34.3253	-33.1306
Longitude	151.0404	0.2179	149.7395	151.5908
Distance to CBD (km)	26.8038	18.6130	0.1105	135.6240
Number of Observations				1,553,120

Houses with repeated sales are classified according to how many times they are transacted during 1971 and 2011. The maximum number of sales for each property is 16, with only one property falling in this group. The numbers of properties across the frequency of transactions are plotted in Figure 1, and the average years between consecutive sales are plotted in Figure 2.

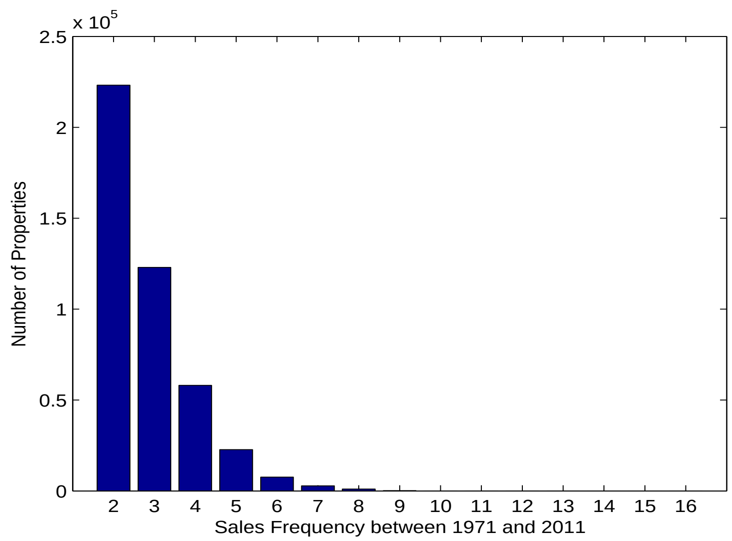

Figure 1: Number of Properties for Different Sale Frequencies

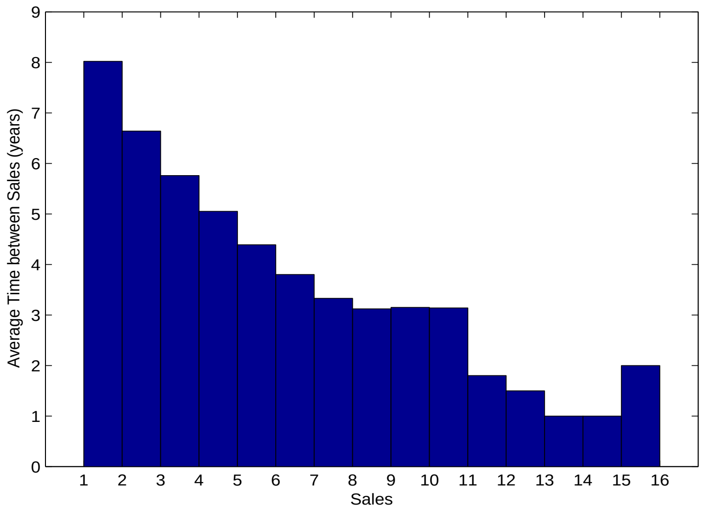

Figure 2: Average Time between Consecutive Sales

5 Estimation of House Price Models and Indices

The first part of this section presents the estimation results of the six alternative regression-based house price models. Indices are directly constructed from non-regression-based models, so estimation results are not involved. The second part compares aggregate indices that are constructed from the nine models. The disaggregated house price indices are compared in the third part. All analyses are based on the merged data set.

5.1 Estimation Results of Regression-Based Models

The restricted hedonic model is given by Equation (3.1). Explanatory variables included in the equation are: the number of bedrooms, the number of bathrooms, the number of garages, a quartic function of the dwelling age, building decade dummy variables, the log of land area[4], the distance to CBD, postcode dummy variables, and time dummy variables. The estimated coefficients for most of these explanatory variables are significant at the 1% level. The estimation results are presented in Appendix A.

The standard repeat-sales model is given in Equation (3.4). The coefficients of all time dummy variables are significant at the 1% level. The estimation results are presented in Appendix B.

[4]The scatter plot of log sales price against the log areas shows a linear relation.

The age-adjusted repeat-sales model is estimated by running Equation (3.5). The coefficients of all explanatory variables are significant at the 1% level. The results are given in Appendix B.

The Case-Shiller weighted repeat-sales model is estimated using the three regression equations described in Section 3.2.4. In the second regression of the squared residuals against sales intervals, Equation (3.6), the explanatory power is close to zero and the coefficient of the sales interval is not significant (the p-value is 0.1965). This suggests that the disturbance term in the standard repeat-sales model does not show significant heteroskedasticity. Therefore, using the Case-Shiller weighted repeat-sales model does not improve the estimation in the standard repeat-sales model. The estimation results are given in Appendix B.

The unrestricted hedonic model is given by Equation (3.7). In addition to the explanatory variables included in the restricted hedonic model, the interactions of time dummy variables with five characteristics variables (the number of bedrooms, the number of bathrooms, the number of garages, the log of land area and the distance to CBD) are also included. The coefficients for most property characteristics and the interaction terms are significant at the 1% level. The estimation results are presented in Appendix C.

The hybrid model is estimated using the three stacked equations described in Section 3.3.2. The estimated coefficients of most explanatory variables and the interaction variables are significant at the 1% level. The results are presented in Appendix D.

The goodness of fit of these six regression-based models is compared based on the adjusted R^2. The coefficient of variation (CV) is used to assess how close the model's predictions are to the actual values. The F-test is used to test whether the coefficients of all explanatory variables are zero. The results are presented in Table 2. The hybrid model has the highest adjusted R^2 and F values. The higher R^2 value in the hybrid model is partially due to the larger variability of the dependent variable as a result of combining hedonic and repeat-sales equations. The coefficient of variation is very low in the two hedonic models and in the hybrid model, but much higher in the three repeat-sales models.

Table 2: Evaluation of Regression-Based Models

Regression-Based Models	**Adj** R^2	**CV**	F **Value**	$Pr > F$
Restricted Hedonic	0.8770	2.6758	35,151	<.0001
Unrestricted Hedonic	0.8813	2.6291	22,380	<.0001
Standard Repeat-Sales	0.7057	80.9689	48,231	<.0001
Age-Adj Repeat-Sales	0.4698	80.6765	17,398	<.0001
Weighted Repeat-Sales	0.7040	113.5345	47,848	<.0001
Hybrid	0.9979	3.7651	1,741,453	<.0001

The age effects from the two hedonic models, age-adjusted repeat-sales models and the hybrid model show similar patterns (age effects are not captured in the standard and weighted repeat-sales models). The two components of the age effect (depreciation and vintage effects) in the restricted hedonic models are shown in Figures 3 and 4. House values depreciate slowly in the first 40-60 years and start to decrease dramatically after 70 years. The vintage effect captures the market's preference for houses that are built in a certain time period due to their special building styles or materials. Figure 4 suggests that houses built between 1960 and 1980 are the most favoured in the Sydney market.

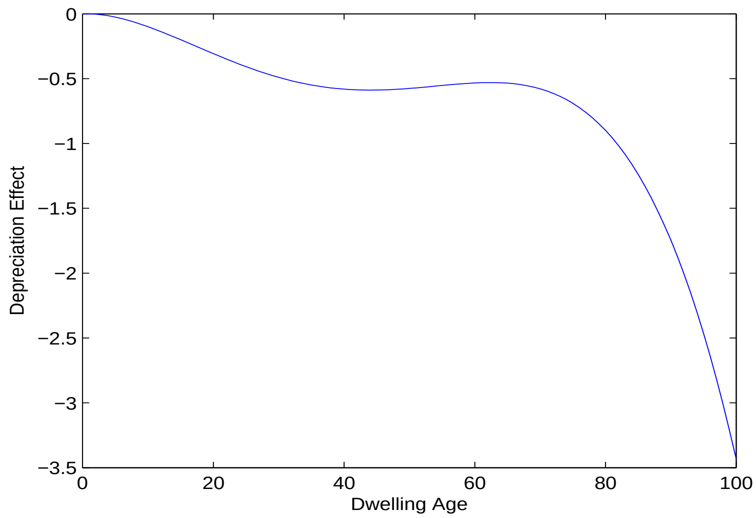

Figure 3: Depreciation Effect

The relation between the residuals and other variables is analysed by regressing residuals from the six regression-based models against the respective explanatory variables in the different models. None of the explanatory variables' coefficients are significant and the R^2 is close to zero in all these models, which shows that residuals are not correlated

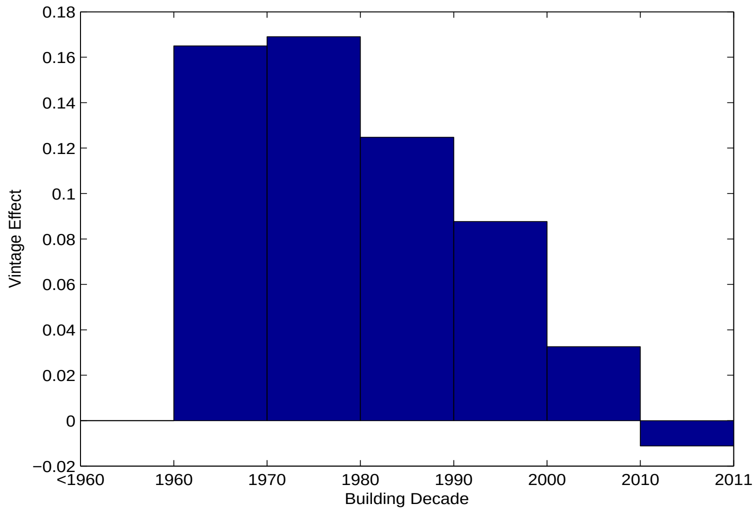

Figure 4: Vintage Effect

with the explanatory variables and that the models capture the main structure of the data. A statistical analysis of the standardised residuals of the six regression-based models is presented in Table 3. The residuals of the two hedonic models have closer to zero skewness and much lower kurtosis than those from the three repeat-sales models. It can be seen from the table that the errors in the hybrid model are less skewed than the other models' errors, which shows the better fit of the hybrid model.

Table 3: Statistical Summary of Standardised Residuals

Model	**Median**	**Std Error Mean**	**Skewness**	**Kurtosis**	**Min**	**Max**
Restricted Hedonic	0.0492	0.0008	-0.0867	8.5268	-9.5035	14.7448
Unrestricted Hedonic	0.0587	0.0008	-0.1245	9.0046	-9.4533	14.9249
Standard Repeat-Sales	-0.0860	0.0011	1.1377	70.5629	-30.9801	32.3383
Age-Adj Repeat-Sales	-0.1043	0.0011	1.2389	69.8273	-30.6149	31.4477
Weighted Repeat-Sales	-0.0860	0.0011	1.1376	70.5585	-30.9794	32.3380
Hybrid	-0.0358	0.0007	0.1809	9.2952	-14.4372	27.8646

The squared residuals are also regressed against property characteristics in the two hedonic models and the hybrid model (the other models do not involve property characteristics). Although the R^2 is very low compared to the regression of log sales prices, many variables' coefficients are statistically significant. For example, in the three models, the impact of the number of bathrooms on house price variability is higher than the impact of the number of bedrooms and the number of garages. This implies that the number of bathrooms rather than the number of bedrooms or garages is a more important factor in affecting the volatility of individual house prices. To conclude, the prices of residential properties with fewer bedrooms, bathrooms or garages, with a smaller land area, built a longer time longer ago and located closer to the CBD show less volatility.

5.2 Aggregate House Price Indices

Aggregate (city-level) indices are constructed from the nine estimated house price models described in Section 3. The indices are compared with city-level indices for Sydney provided by Residex [5] and by the Australian Bureau of Statistics (ABS)[6]. The Residex index is provided on a monthly basis, the ABS index has a quarterly frequency. Index values for 30 June are used to compare these indices with the annual indices constructed in this paper. All indices are deflated to 1986 as the base year, since the ABS index starts in 1986. Figure 5 compares the index levels and Figure 6 compares the index growth rates.

The growth rates of the aggregate house price indices estimated from these models differ and, although similar in many years, result in a large difference in index levels for the period considered. ABS is using a stratified median method for constructing the house price index, but the resulting index is dramatically lower than the stratified median index we estimated using Residex data. A possible explanation is that different data sets are employed. ABS uses data from the State/Territory Land Titles Office and the Valuers-General Office.

Residex uses a hybrid method of repeat-sales and median models. It can be seen from Figure 5 that the Residex index is between the standard repeat-sales index and the median index in most time periods.

The indices constructed from the nine alternative models in this paper result in higher index levels over the sample period than the ABS index. The Residex index is very close to the mean index and the median index, but generally lower than the indices derived from regression-based models. The three non-regression-based indices result in lower index

[5] Data on the Residex index was provided by Residex Pty Ltd. in March 2012. Due to the possible revision in the index construction method adopted by Residex, the index is subject to changes.

[6] Data on the ABS index was obtained from http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/6416.0Sep%202011?OpenDocument

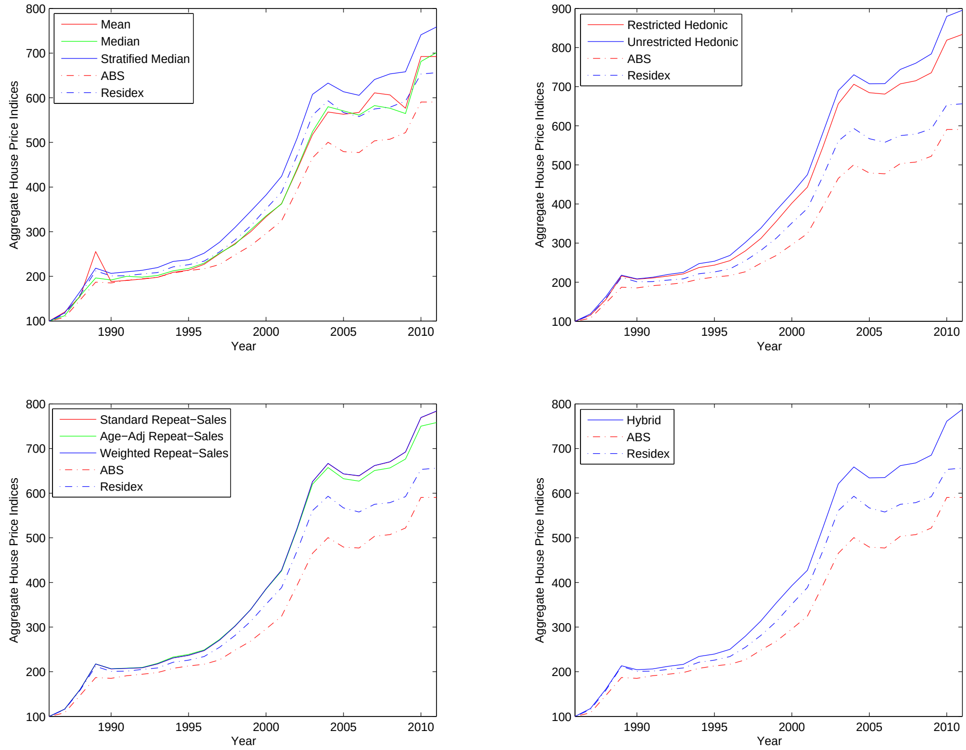

Figure 5: Aggregate Index Levels

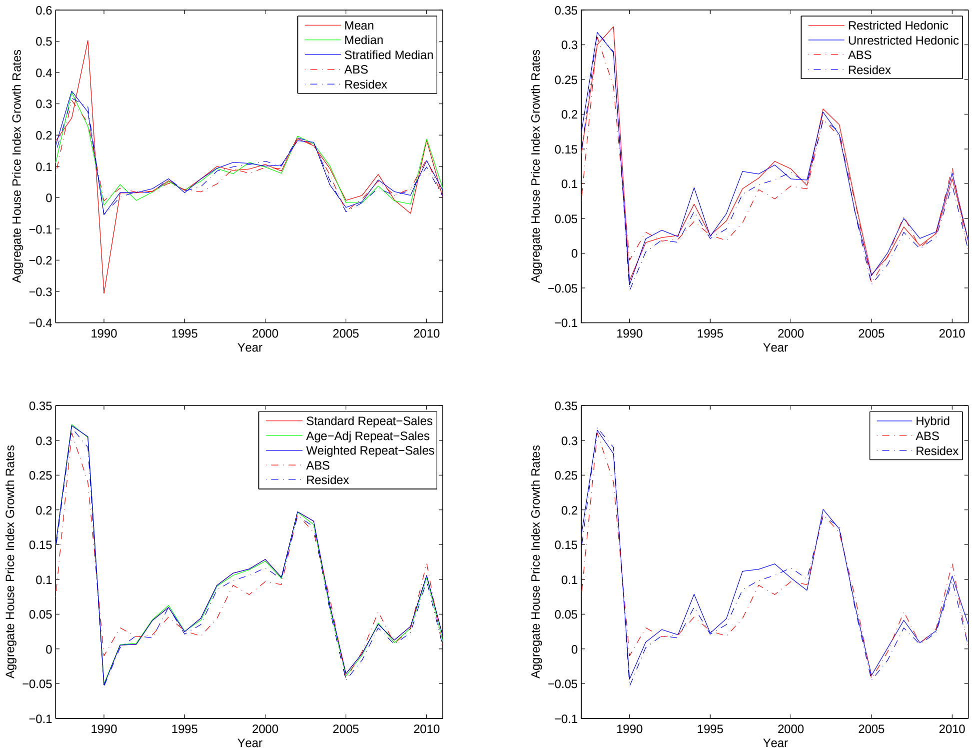

Figure 6: Aggregate Index Growth Rates

levels than the regression-based indices. The reason is that non-regression-based models do not capture the compositional changes in the property market, while regression-based models take into account the composition of houses with heterogeneous characteristics.

Of the three non-regression-based models, the stratified median model produces a higher index level than the mean and median models, since the stratified median model controls for the compositional changes to a certain extent. Both the two hedonic indices have significantly higher levels than the ABS and Residex indices. The unrestricted hedonic index results in a slightly higher level than the restricted hedonic index, suggesting that the pure price changes are underestimated when the coefficients of house characteristics are restricted to be constant over time. As discussed in Section 5.1, heteroskedasticity is not obvious in our data, and as a result, the weighted repeat-sales model has little improvement over the standard repeat-sales model. The age-adjusted repeat-sales index results in a slightly lower level than the other two repeat-sales indices, implying that the depreciation effect is smaller than the effect of possible renovations and maintenance. The hybrid index results in a higher level than ABS and Residex indices, but the level is lower than the levels of the two hedonic indices. The hybrid model produces an index that is very similar to the standard repeat-sales index. This finding implies that the specification errors in hedonic models are more serious than the sample bias problem in repeat-sales models.

The summary statistics of the growth rates and index levels for the nine house price models and the ABS and Residex indices are presented in Table 4. The index derived from the unrestricted hedonic model has the highest average growth rate, whereas the ABS index has the lowest.

5.3 Disaggregated House Price Indices: Illustration

Price indices and growth rates are calculated for property portfolios that are disaggregated by the number of bedrooms, the number of bathrooms, the number of garages, the distance to CBD (inner, middle and outer rings), and the land area (small, medium and large). These five variables are selected to show the impact of building structure, land size and location on house price trend and volatility. Houses are disaggregated into

Table 4: Statistic Summaries of Aggregate House Price Indices

House Price Indices (1986 - 2011)

Model	**Mean**	**Std Dev**	**Min**	**Max**
Mean	361.67	192.43	100	692.40
Median	358.62	190.72	100	701.18
Stratified Median	397.46	212.82	100	758.66
Restricted Hedonic	425.21	244.62	100	833.80
Unrestricted Hedonic	447.79	261.02	100	895.58
Standard Repeat-Sales	405.59	226.03	100	783.58
Age-Adj Repeat-Sales	401.18	219.27	100	758.24
Weighted Repeat-Sales	405.75	226.18	100	784.07
Hybrid	406.09	223.49	100	787.74
ABS	320.82	157.90	100	590.50
Residex	364.50	186.63	100	656.09

House Price Growth Rates (1987 - 2011)

Model	**Mean**	**Std Dev**	**Min**	**Max**
Mean	0.0336	0.0601	-0.1327	0.2181
Median	0.0338	0.0391	-0.0105	0.1461
Stratified Median	0.0352	0.0403	-0.0237	0.1480
Restricted Hedonic	0.0368	0.0404	-0.0171	0.1416
Unrestricted Hedonic	0.0381	0.0393	-0.0198	0.1380
Std Repeat-Sales	0.0358	0.0409	-0.0225	0.1395
Age-Adj Repeat-Sales	0.0352	0.0409	-0.0219	0.1403
Weighted Repeat-Sales	0.0358	0.0409	-0.0225	0.1395
Hybrid	0.0359	0.0390	-0.0190	0.1367
ABS	0.0308	0.0360	-0.0187	0.1350
Residex	0.0327	0.0405	-0.0234	0.1382

four groups according to the quartiles of their distance to the CBD: inner ring ($\leq 10km$, first quartile), middle ring ($10km$ - $20km$, second quartile) outer ring ($20km$ - $50km$, third quartile) and outskirt ($\geq 50km$, fourth quartile). Land area is used to disaggregate houses into three stratifications: small ($\leq 400m^2$), medium ($400m^2$ - $800m^2$) and large ($\geq 800m^2$).

For illustration purposes, price indices of houses with three bedrooms, two bathrooms, one garage, located in Sydney's middle ring and with a medium land area (denoted as portfolio ρ) are constructed from the nine alternative house price models, using the methods described in Section 3. The results are presented in Figure 7. Only a few houses within portfolio ρ are sold in some years, which would result in inaccurate price indices for the portfolio using non-regression-based, repeat-sales and restricted hedonic models. The unrestricted hedonic model and the hybrid model are not subject to this problem, since disaggregated indices are constructed from the coefficients that are estimated based on the whole data set. The constructed indices for portfolio ρ from the unrestricted hedonic model and the hybrid model are compared with the corresponding aggregate house price indices from the two models in Figure 8. Based on either the unrestricted hedonic or hybrid index, the portfolio ρ accumulates faster than the aggregate house price movement after 1990. The results suggest that houses in the portfolio ρ have characteristics that are more valued in recent years.

A statistics summary of the price indices for Portfolio ρ is presented in Table 5. The growth rates of the hybrid house price index show the lowest coefficient of variation, which suggests that the volatility arising from the small number of observations can be eliminated in the hybrid model. But the coefficient of variation for the unrestricted hedonic index growth rates is not significantly lower than that of other indices' growth rates. A possible reason is that the implicit prices estimated from the unrestricted hedonic model are very volatile (see Figure 9).

5.4 Disaggregated House Price Indices: Identifying Factors

The unrestricted hedonic model and the hybrid model can be used to select the most important factor that makes house prices at disaggregated levels different from the aggregate price. Correlation coefficients are calculated between estimated implicit prices of house characteristics and the aggregate time trend. Houses with characteristics that have lower correlations with the aggregate trend show more different price variability from the aggregate movement, since the variability cannot be captured by the aggregate time trend if they are not highly correlated. Calculated correlation coefficients and their $p-$values are presented in Table 6. Total land area is the factor that has the lowest correlation coefficient of implicit prices with the aggregate time trend in both the two models.

The implicit prices of house characteristics are presented in Figure 9. It can be seen from the unrestricted hedonic model and the hybrid model that the implicit price for an additional bathroom has been steadily increasing over time. In the unrestricted hedonic

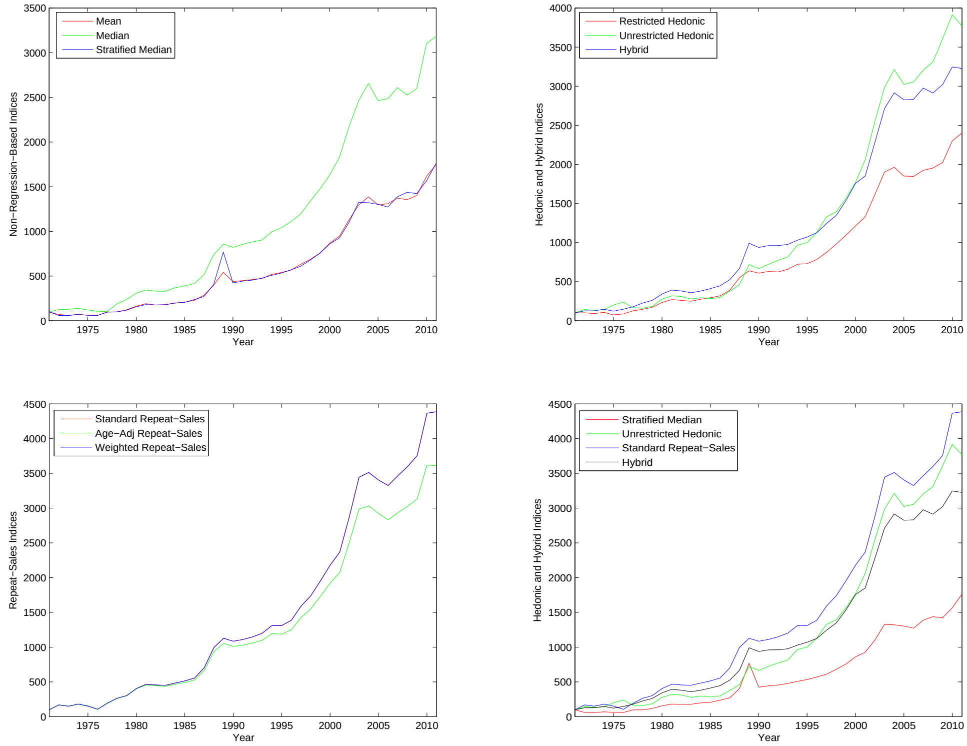

Figure 7: Comparison of Disaggregated Indices

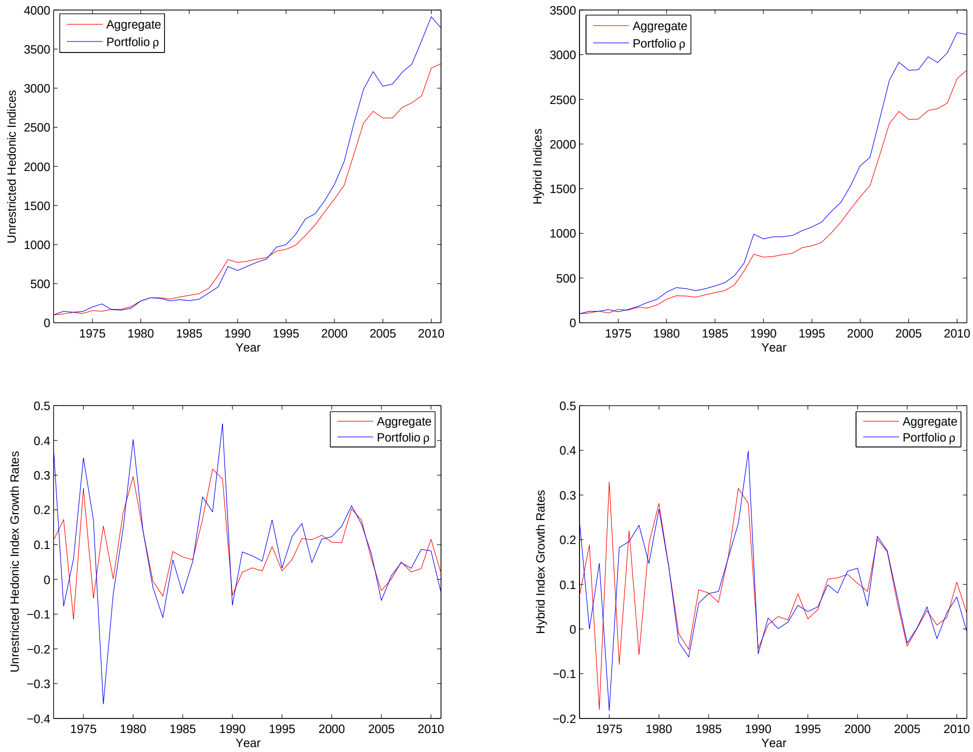

Figure 8: Aggregate and Disaggregated Indices

Table 5: Statistic Summaries of Disaggregated House Price Indices

House Price Indices (1971 - 2011)

Model	**Mean**	**Std Dev**	**Min**	**Max**	**CV**
Mean	599.35	514.09	59.87	1748.21	0.86
Median	1126.39	975.78	100.00	3182.75	0.87
Stratified Median	601.26	515.50	58.81	1764.39	0.86
Restricted Hedonic	841.98	732.09	74.53	2401.22	0.87
Unrestricted Hedonic	1266.15	1254.28	100.00	3914.94	0.99
Std Repeat-Sales	1519.49	1349.12	100.00	4385.91	0.89
Age-Adj Repeat-Sales	1332.51	1122.18	100.00	3619.62	0.84
Weighted Repeat-Sales	1519.40	1349.19	100.00	4387.73	0.89
Hybrid	1221.46	1068.96	100.00	3246.31	0.88

House Price Growth Rates (1972 - 2011)

Model	**Mean**	**Std Dev**	**Min**	**Max**	**CV**
Mean	0.0311	0.0647	-0.1522	0.2117	2.08
Median	0.0376	0.0576	-0.0617	0.2636	1.53
Stratified Median	0.0312	0.0886	-0.2575	0.2790	2.84
Restricted Hedonic	0.0345	0.0548	-0.1610	0.1610	1.59
Unrestricted Hedonic	0.0394	0.0644	-0.1558	0.1943	1.64
Std Repeat-Sales	0.0411	0.0725	-0.1545	0.2597	1.77
Age-Adj Repeat-Sales	0.0389	0.0727	-0.1671	0.2565	1.87
Weighted Repeat-Sales	0.0411	0.0723	-0.1551	0.2601	1.76
Hybrid	0.0377	0.0475	-0.0794	0.1729	1.26

model, the implicit price of the total land size increased up to the year 1988 and since then has been steadily declining, whereas the hybrid model suggests an increasing trend of the implicit prices of the total land size. The other three characteristics show more stable implicit prices over time under both models. The correlation coefficient between the number of bedrooms and the number of bathrooms is significantly negative in both models (see Table 6), which reflects the fact that people's preference has been switching from more bedrooms to bathrooms (see Knight and Cottet, 2011).

To conclude, the total land area is the most important factor that drives the variability of individual house prices from the average price movement. In addition, the distance to CBD is a proxy for the geographical location, having a large impact on the house price variability. The implicit prices of these two characteristics are used to construct disaggregated house price indices based on the unrestricted hedonic model and the hybrid

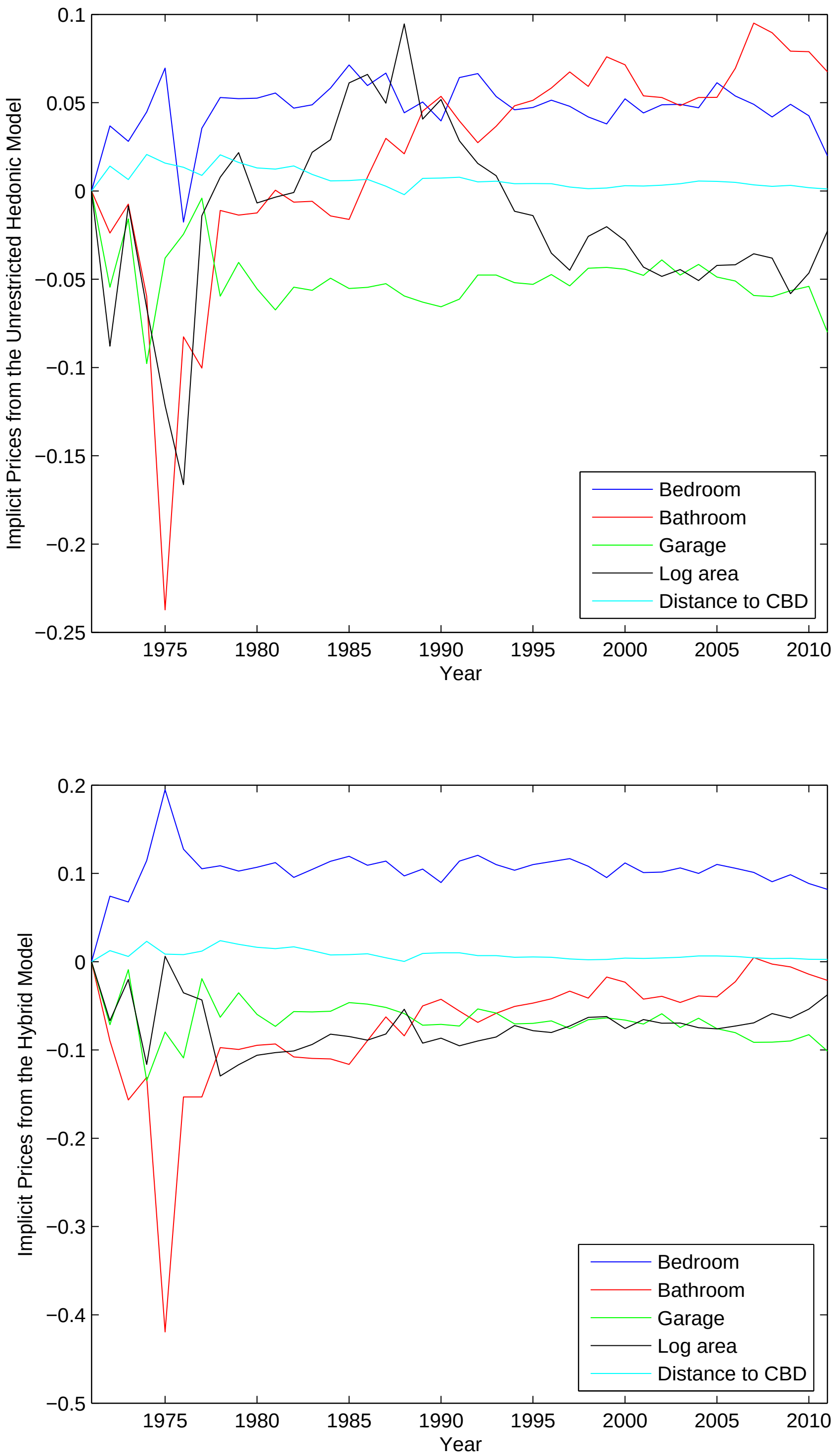

Figure 9: Implicit Prices of House Characteristics

Table 6: Correlation Coefficients of Implicit Price Growth Rates

	Aggregate	**Bedroom**	**Bathroom**	**Garage**	**Log area**	**DCBD**
Unrestricted hedonic model						
Aggregate	-	-0.22	-0.32**	0.08	-0.81***	0.04
Bedroom	-0.22	-	-0.57***	-0.13	0.12	0.27*
Bathroom	-0.32**	-0.57***	-	-0.21	0.11	0.08
Garage	0.08	-0.13	-0.21	-	0.29*	-0.78***
Log area	-0.81***	0.12	0.11	0.29*	-	-0.49***
DCBD	0.04	0.27*	0.08	-0.78***	-0.49***	-
Hybrid model						
Aggregate	-	0.11	0.02	-0.22	-0.30*	0.32**
Bedroom	0.11	-	-0.73***	-0.25	0.03	0.13
Bathroom	0.02	-0.73***	-	-0.33**	-0.60***	0.34**
Garage	-0.22	-0.25	-0.33**	-	0.71***	-0.65***
Log area	-0.30*	0.03	-0.60***	0.71***	-	-0.92***
DCBD	0.32**	0.13	0.34**	-0.65***	-0.92***	-

Note: ***,** and * indicate significance at the 1%, 5% and 10% level, respectively.

model.

Using the land area, stratified indices for small, medium and large houses are also constructed. Results are presented in Figure 10. The values of large houses are more volatile than other houses but the total growth rate over this period for large houses is the lowest. Small houses show the greatest accumulation over this period, slightly higher than medium houses. This indicates that small and medium houses are more valued in recent years.

Based on the distance to CBD, disaggregated house price indices for houses in inner ring, middle ring, outer ring, and outskirt are constructed using the unrestricted hedonic model and the hybrid model. Results are presented in Figure 11. Houses in the outskirt show faster accumulation in values and more volatility. A possible reason is that more people prefer to live in the outskirt for a quiet and quality life style. The result agrees with the findings by Hatzvi and Otto (2008) who conclude that house prices in the outer ring of Sydney are influenced by a speculative bubble.

Table 7 presents a statistics summary of disaggregated house price index growth rates that are calculated from the unrestricted hedonic model and the hybrid model. It can be seen that prices of large-sized houses are more volatile than medium- and small-sized

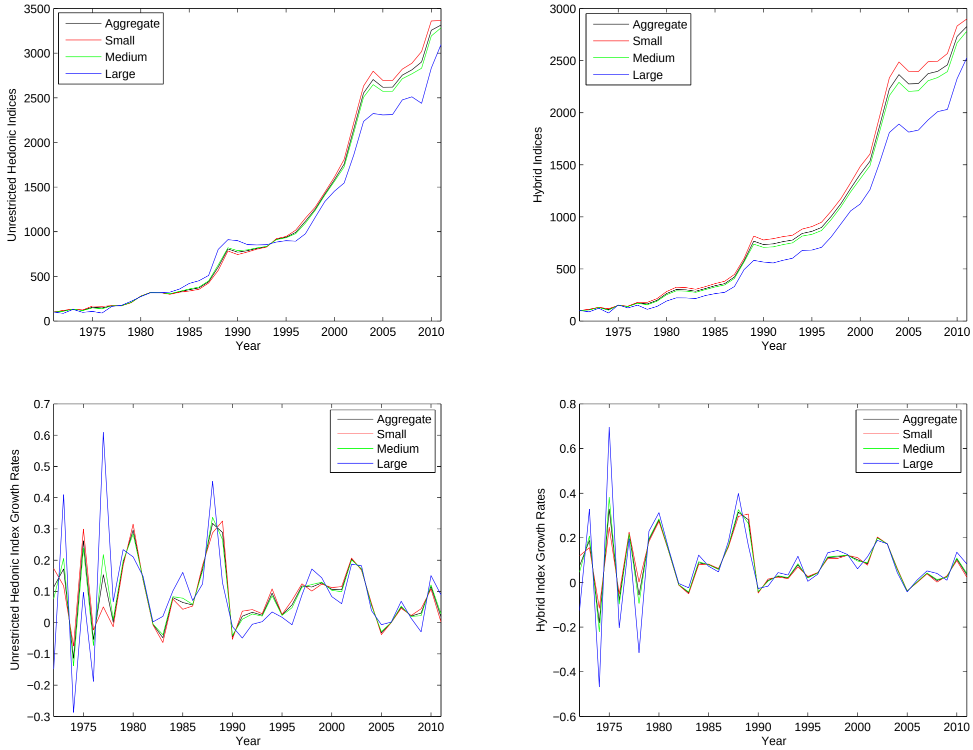

Figure 10: Disaggregated Indices by the Land Area

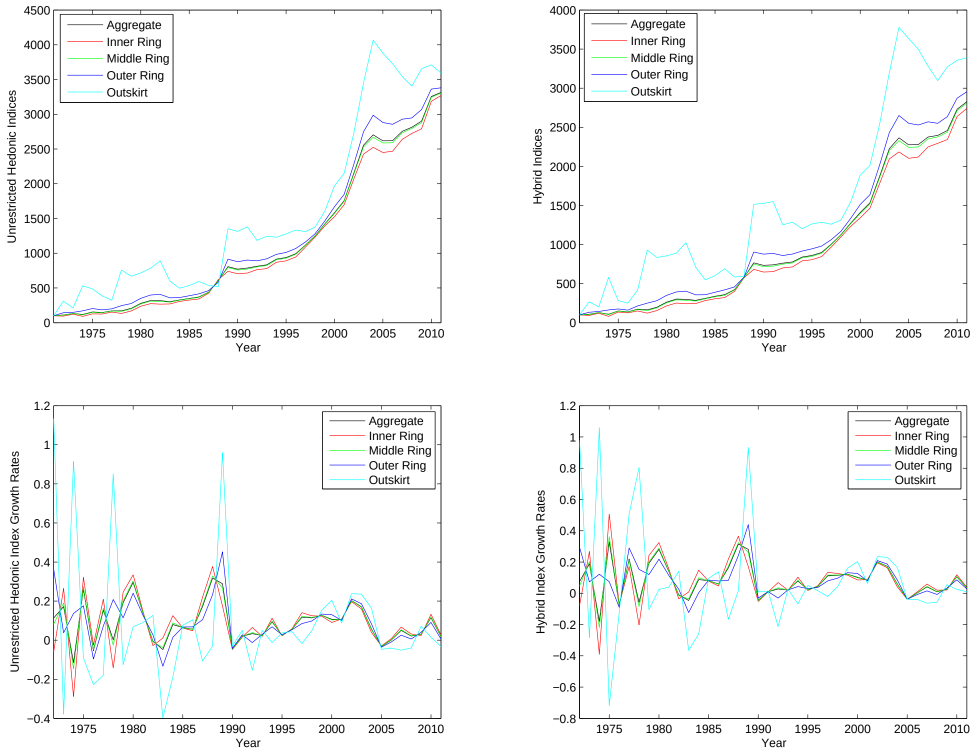

Figure 11: Disaggregated Indices by the Distance to CBD

houses, and that prices of houses located in the outskirt are more volatile than houses in the inner, middle and outer rings.

Table 7: Statistic Summaries of Disaggregated House Price Index Growth Rates Based on the Unrestricted Hedonic and Hybrid Models

The Unrestricted Hedonic Model

Houses	**Mean**	**Std Dev**	**Min**	**Max**
Small Area	0.0879	0.1018	-0.0748	0.3251
Medium Area	0.0873	0.1028	-0.1384	0.3366
Large Area	0.0858	0.1581	-0.2870	0.6087
Inner Ring	0.0872	0.1284	-0.2881	0.3766
Middle Ring	0.0875	0.1037	-0.1466	0.3287
Outer Ring	0.0880	0.1118	-0.1332	0.4519
Outskirt	0.0895	0.3286	-0.3969	1.1344
Aggregate	0.0875	0.1003	-0.1139	0.3177

The Hybrid Model

Houses	**Mean**	**Std Dev**	**Min**	**Max**
Small Area	0.0842	0.1003	-0.1152	0.3068
Medium Area	0.0832	0.1192	-0.2208	0.3809
Large Area	0.0807	0.1859	-0.4678	0.6951
Inner Ring	0.0828	0.1509	-0.3899	0.5068
Middle Ring	0.0834	0.1167	-0.2195	0.3625
Outer Ring	0.0847	0.1090	-0.1235	0.4397
Outskirt	0.0881	0.3482	-0.7193	1.0587
Aggregate	0.0835	0.1109	-0.1802	0.3293

6 Conclusion

This paper compares nine alternative house price models in constructing city-level and disaggregated house price indices. Based on the determination coefficient R^2, the hybrid model has the best goodness of fit. Judging from the coefficient of variation of these models, predictions from the unrestricted hedonic model and the hybrid model are the closest to the actual values.

Indices constructed from the mean and median models underestimate house price changes since compositional changes are not captured. The stratified median model controls for compositional changes, but still underestimates house price changes compared with regression-based models. The standard and weighted repeat-sales indices are very similar, indicating that repeat-sales house prices in Sydney do not have obvious heteroskedasticity, which agrees with the conclusion by Shimizu and Watanabe (2010) in Japanese context. The results from restricted and unrestricted hedonic models show that house price changes are underestimated if the coefficients of house characteristics are restricted to be constant over time in hedonic models. ABS adopts a stratified median method but uses different data, so the stratified index constructed using our data is significantly different from the ABS index. Residex employs a combined method of repeat-sales and median models. The index provided by Residex is, for most of the time, between the standard repeat-sales index and the median index that are constructed in this paper.

Disaggregated house price indices constructed from the nine alternative house price models are compared. When portfolios are disaggregated to a very fine level, only the unrestricted hedonic model and the hybrid model can produce accurate indices. The other seven models have problems in the number of samples and their fluctuations are largely due to insufficient observations. The unrestricted hedonic model and the hybrid model are used to identify house characteristics that are important in driving individual house prices differently from the aggregate house price trend. The results indicate that the total land size is the most important factors that represent house structures. The distance to CBD is a proxy variable for the geographical location which is also an important factor. These two house characteristics should be taken into account when constructing disaggregated house price indices. Comparison of disaggregated house price indices with the aggregate index shows that individual house prices have significantly different trend and volatilities than the aggregate house price index.

The results in this paper provide the building blocks for several applications. For example, equity release products are based on individual house prices rather than the average house price movement. Quantifying individual house price risk provides better insights into designing reliable products and helps the lender to better manage the risk they undertake. Based on the unrestricted and hybrid models in this paper, the aggregate house price index and portfolio indices can be projected using time series analysis and individual house prices can be linked to the projected aggregate index. Another application is index-based hedging. Hedging methods based on aggregate house price indices cover only a limited part of house price risk. The disaggregated house price indices developed in this paper allow us to investigate the risk of heterogeneous portfolios at a more disaggregated level.

Acknowledgement

The authors acknowledge the financial support of ARC Linkage Grant Project LP0883398 Managing Risk with Insurance and Superannuation as Individuals Age with industry partners PwC and APRA and the ARC Centre of Excellence in Population Ageing Research (CEPAR). Adam Wenqiang Shao also acknowledges the financial support from Australian School of Business and China Scholarship Council. Data provision by Residex Pty Ltd is kindly acknowledged. John Edwards and Dan Liebke from Residex provided valuable technical support and suggestions.

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A Estimation Results of the Restricted Hedonic Model

Parameter	Estimate	Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
Intercept	-148.9411***	Postcode2030	0.1590***	Postcode2122	-0.5761***	Postcode2220	-0.6983***
Bedrooms	0.0769***	Postcode2031	-0.2900***	Postcode2125	-0.5545***	Postcode2221	-0.4524***
Bathrooms	0.0906***	Postcode2032	-0.4748***	Postcode2126	-0.6622***	Postcode2222	-0.6855***
Garages	0.0569***	Postcode2033	-0.2478***	Postcode2127	-0.5342***	Postcode2223	-0.5997***
Age/100	0.1413***	Postcode2034	-0.2754***	Postcode2128	-0.9052***	Postcode2224	-0.4991***
$Age^2/1,000$	-1.4915***	Postcode2035	-0.4535***	Postcode2130	-0.5771***	Postcode2225	-0.7273***
$Age^3/10,000$	3.7982***	Postcode2036	-0.6644***	Postcode2131	-0.6189***	Postcode2226	-0.7785***
$Age^4/100,000$	-2.6642***	Postcode2037	-0.3788***	Postcode2132	-0.6077***	Postcode2227	-0.7305***
Built60s	0.1650***	Postcode2038	-0.4867***	Postcode2133	-0.7341***	Postcode2228	-0.7175***
Built70s	0.1690***	Postcode2039	-0.4573***	Postcode2134	-0.4334***	Postcode2229	-0.6112***
Built80s	0.1248***	Postcode2040	-0.5809***	Postcode2135	-0.2443***	Postcode2230	-0.5716***
Built90s	0.0877***	Postcode2041	-0.2282***	Postcode2136	-0.6883***	Postcode2231	-1.0974***
Built00s	0.0326*	Postcode2042	-0.6022***	Postcode2137	-0.4865***	Postcode2232	-0.7522***
Built09-11	-0.0111	Postcode2043	-0.6679***	Postcode2138	-0.5696***	Postcode2233	-0.8074***
Log area	0.1511***	Postcode2044	-0.8551***	Postcode2140	-0.6058***	Postcode2234	-0.7695***
DCBD	0.0009*	Postcode2045	-0.3821***	Postcode2141	-0.9184***	Postcode2250	-1.2479***
$DCBD^2$	-0.0001***	Postcode2046	-0.4217***	Postcode2142	-0.9915***	Postcode2251	-1.1746***
Longitude	0.9786***	Postcode2047	-0.3081***	Postcode2143	-0.9452***	Postcode2256	-1.1537***
Latitude	-0.3055***	Postcode2048	-0.5831***	Postcode2144	-0.9407***	Postcode2257	-1.1652***
Year1972	0.1695***	Postcode2049	-0.6084***	Postcode2145	-0.8343***	Postcode2258	-1.2945***
Year1973	0.2864***	Postcode2050	-0.5732***	Postcode2146	-0.9375***	Postcode2259	-1.3783***
Year1974	0.1562***	Postcode2060	-0.0651**	Postcode2147	-0.9570***	Postcode2260	-1.0485***
Year1975	0.3783***	Postcode2061	0.1481***	Postcode2148	-1.0012***	Postcode2261	-1.3049***
Year1976	0.3247***	Postcode2062	-0.2137***	Postcode2150	-0.7725***	Postcode2262	-1.4600***
Year1977	0.5188***	Postcode2063	-0.1022***	Postcode2151	-0.6912***	Postcode2263	-1.4082***
Year1978	0.5473***	Postcode2064	-0.2670***	Postcode2152	-0.8064***	Postcode2555	-1.5809***
Year1979	0.7558***	Postcode2065	-0.2818***	Postcode2153	-0.7009***	Postcode2556	-0.8169***
Year1980	1.0449***	Postcode2066	-0.3008***	Postcode2154	-0.5995***	Postcode2557	-0.7492***
Year1981	1.1823***	Postcode2067	-0.3544***	Postcode2155	-0.7577***	Postcode2558	-1.1592***
Year1982	1.1823***	Postcode2068	-0.3116***	Postcode2156	-0.6340***	Postcode2559	-1.3400***
Year1983	1.1372***	Postcode2069	-0.2096***	Postcode2157	-0.7062***	Postcode2560	-1.1005***
Year1984	1.2138***	Postcode2070	-0.2452***	Postcode2158	-0.6540***	Postcode2563	-0.6265***
Year1985	1.2932***	Postcode2071	-0.1692***	Postcode2159	-0.7829***	Postcode2564	-1.1603***
Year1986	1.3494***	Postcode2072	-0.2625***	Postcode2160	-0.9209***	Postcode2565	-0.9997***
Year1987	1.4926***	Postcode2073	-0.3439***	Postcode2161	-1.0040***	Postcode2566	-1.1188***
Year1988	1.7928***	Postcode2074	-0.4108***	Postcode2162	-0.9680***	Postcode2567	-1.0448***
Year1989	2.1188***	Postcode2075	-0.3930***	Postcode2163	-1.1051***	Postcode2568	-0.9477***
Year1990	2.0795***	Postcode2076	-0.4588***	Postcode2164	-0.9751***	Postcode2569	-1.0558***
Year1991	2.0949***	Postcode2077	-0.7692***	Postcode2165	-1.0120***	Postcode2570	-0.7975***
Year1992	2.1175***	Postcode2079	-0.8973***	Postcode2166	-1.0230***	Postcode2571	-0.9059***
Year1993	2.1430***	Postcode2080	-0.8938***	Postcode2167	-0.9865***	Postcode2572	-0.8631***
Year1994	2.2137***	Postcode2081	-0.8789***	Postcode2168	-1.0697***	Postcode2573	-0.9319***
Year1995	2.2393***	Postcode2082	-0.8605***	Postcode2170	-0.9572***	Postcode2574	-0.9983***
Year1996	2.2857***	Postcode2083	-0.8601***	Postcode2171	-0.8520***	Postcode2745	-0.8014***
Year1997	2.3786***	Postcode2084	-0.5336***	Postcode2172	-0.7906***	Postcode2747	-0.8751***
Year1998	2.4867***	Postcode2085	-0.5892***	Postcode2173	-0.9798***	Postcode2748	-0.7546***
Year1999	2.6190***	Postcode2086	-0.6653***	Postcode2174	-0.6573***	Postcode2749	-0.8717***
Year2000	2.7405***	Postcode2087	-0.6206***	Postcode2175	-0.6056***	Postcode2750	-0.6946***
Year2001	2.8379***	Postcode2088	0.0541**	Postcode2176	-0.8936***	Postcode2752	-0.8593***
Year2002	3.0457***	Postcode2089	-0.0937***	Postcode2177	-0.9917***	Postcode2753	-0.7438***
Year2003	3.2307***	Postcode2090	-0.0502*	Postcode2178	-0.6943***	Postcode2754	-0.6294***
Year2004	3.3042***	Postcode2092	-0.3257***	Postcode2179	-0.8014***	Postcode2756	-0.9110***
Year2005	3.2734***	Postcode2093	-0.4012***	Postcode2190	-0.9191***	Postcode2757	-0.6129***
Year2006	3.2680***	Postcode2094	-0.3667***	Postcode2191	-0.7947***	Postcode2758	-0.5730***
Year2007	3.3058***	Postcode2095	-0.2867***	Postcode2192	-0.8538***	Postcode2759	-0.9177***
Year2008	3.3168***	Postcode2096	-0.5405***	Postcode2193	-0.7432***	Postcode2760	-1.0130***
Year2009	3.3452***	Postcode2097	-0.5629***	Postcode2194	-0.8287***	Postcode2761	-1.0512***
Year2010	3.4526***	Postcode2099	-0.6704***	Postcode2195	-0.9655***	Postcode2762	-0.9497***
Year2011	3.4703***	Postcode2100	-0.6748***	Postcode2196	-0.8989***	Postcode2763	-0.9609***
Postcode2007	-0.4195***	Postcode2101	-0.6647***	Postcode2197	-0.8835***	Postcode2765	-0.9330***
Postcode2008	-0.5113***	Postcode2102	-0.6698***	Postcode2198	-0.7810***	Postcode2766	-1.0203***
Postcode2009	-0.4012***	Postcode2103	-0.5995***	Postcode2199	-0.9264***	Postcode2767	-1.0440***
Postcode2010	-0.2437***	Postcode2104	-0.4195***	Postcode2200	-0.8809***	Postcode2768	-0.9593***
Postcode2011	-0.0146	Postcode2105	-0.4944***	Postcode2203	-0.7140***	Postcode2769	-0.8358***
Postcode2015	-0.6408***	Postcode2106	-0.5381***	Postcode2204	-0.7659***	Postcode2770	-1.1717***
Postcode2016	-0.5786***	Postcode2107	-0.5424***	Postcode2205	-0.8313***	Postcode2773	-0.4590***
Postcode2017	-0.6784***	Postcode2108	-0.2021***	Postcode2206	-0.6948***	Postcode2774	-0.5810***
Postcode2018	-0.6060***	Postcode2110	-0.0886***	Postcode2207	-0.7505***	Postcode2775	-1.2816***
Postcode2019	-0.7360***	Postcode2111	-0.4792***	Postcode2208	-0.6926***	Postcode2776	-0.5858***
Postcode2020	-0.7226***	Postcode2112	-0.6545***	Postcode2209	-0.7285***	Postcode2777	-0.6192***
Postcode2021	-0.0016	Postcode2113	-0.6829***	Postcode2210	-0.7080***	Postcode2778	-0.6276***
Postcode2022	-0.2528***	Postcode2114	-0.6583***	Postcode2211	-0.8443***	Postcode2779	-0.6235***
Postcode2023	0.2676***	Postcode2115	-0.8445***	Postcode2212	-0.8770***	Postcode2780	-0.2766***
Postcode2024	-0.2088***	Postcode2116	-0.8634***	Postcode2213	-0.7968***	Postcode2782	-0.3248***
Postcode2025	0.1265***	Postcode2117	-0.7636***	Postcode2214	-0.7540***	Postcode2783	-0.5646***
Postcode2026	-0.2789***	Postcode2118	-0.6445***	Postcode2216	-0.7225***	Postcode2784	-0.5759***
Postcode2027	0.1984***	Postcode2119	-0.4421***	Postcode2217	-0.6208***	Postcode2785	-0.2540***
Postcode2028	0.2331***	Postcode2120	-0.6383***	Postcode2218	-0.7404***	Postcode2786	-0.3255***
Postcode2029	0.0121	Postcode2121	-0.5670***	Postcode2219	-0.5411***	Postcode2787	0.1427***

Note: ***,** and * indicate significance at the 1%, 5% and 10% level, respectively.

B Estimation Results of Repeat-Sales Models

Parameter	Standard	Age-Adjusted	Weighted
Intercept	--	0.0650***	--
(Sales Interval)^2/100	--	-0.0430***	--
(Sales Interval)^3/10,000	--	0.1174***	--
(Sales Interval)^4/1,000,000	--	-0.1060***	--
Year1972	0.3005***	0.3153***	0.2986***
Year1973	0.3675***	0.3568***	0.3663***
Year1974	0.4247***	0.4126***	0.4244***
Year1975	0.4132***	0.3677***	0.4131***
Year1976	0.4348***	0.3738***	0.4348***
Year1977	0.5978***	0.5376***	0.5977***
Year1978	0.7359***	0.7647***	0.7355***
Year1979	0.9164***	0.9419***	0.9159***
Year1980	1.2151***	1.2396***	1.2148***
Year1981	1.3690***	1.3864***	1.3688***
Year1982	1.3690***	1.3830***	1.3687***
Year1983	1.3404***	1.3505***	1.3402***
Year1984	1.4164***	1.4246***	1.4162***
Year1985	1.4927***	1.4978***	1.4926***
Year1986	1.5536***	1.5569***	1.5535***
Year1987	1.7033***	1.7065***	1.7033***
Year1988	2.0245***	2.0295***	2.0246***
Year1989	2.3299***	2.3338***	2.3299***
Year1990	2.2781***	2.2834***	2.2781***
Year1991	2.2835***	2.2894***	2.2835***
Year1992	2.2899***	2.2974***	2.2900***
Year1993	2.3308***	2.3395***	2.3309***
Year1994	2.3904***	2.4021***	2.3905***
Year1995	2.4152***	2.4274***	2.4153***
Year1996	2.4592***	2.4688***	2.4594***
Year1997	2.5506***	2.5590***	2.5507***
Year1998	2.6595***	2.6647***	2.6596***
Year1999	2.7745***	2.7786***	2.7746***
Year2000	2.9032***	2.9048***	2.9035***
Year2001	3.0062***	3.0061***	3.0064***
Year2002	3.2035***	3.2029***	3.2038***
Year2003	3.3873***	3.3817***	3.3876***
Year2004	3.4505***	3.4402***	3.4508***
Year2005	3.4147***	3.4014***	3.4151***
Year2006	3.4079***	3.3926***	3.4083***
Year2007	3.4433***	3.4299***	3.4436***
Year2008	3.4559***	3.4388***	3.4562***
Year2009	3.4882***	3.4686***	3.4886***
Year2010	3.5938***	3.5719***	3.5942***
Year2011	3.6123***	3.5828***	3.6128***

Regression of residuals from the standard repeat-sales model against the interval time between sales

Parameter	Estimate
Intercept	0.2589***
Sales Interval	0.0006

Note: ***,** and * indicate significance at the 1%, 5% and 10% level, respectively.

C Estimation Results of the Unrestricted Hedonic Model

Parameter	Estimate	Parameter	Estimate	Parameter	Estimate	Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
Intercept	-142.0819***	Postcode2037	-0.3816***	Postcode2140	-0.6311***	Postcode2260	-0.9850***	Bedrooms*Year2000	-0.0141***	Garages*Year2006	0.0041***
Bedrooms	0.0280*	Postcode2038	-0.4978***	Postcode2141	-0.9464***	Postcode2261	-1.2321***	Bedrooms*Year2001	0.0088***	Garages*Year2007	0.0473***
Bathrooms	0.0458**	Postcode2039	-0.4651***	Postcode2142	-1.0185***	Postcode2262	-1.3819***	Bedrooms*Year2002	0.0529***	Garages*Year2008	0.0513***
Garages	0.1106***	Postcode2040	-0.5969***	Postcode2143	-0.9752***	Postcode2263	-1.3346***	Bedrooms*Year2003	-0.0111***	Garages*Year2009	-0.0529***
Age/100	0.1447***	Postcode2041	-0.2378***	Postcode2144	-0.9685***	Postcode2555	-1.6002***	Bedrooms*Year2004	-0.0596***	Garages*Year2010	-0.0139***
$Age^2/1,000$	-1.4888***	Postcode2042	-0.6123***	Postcode2145	-0.8672***	Postcode2556	-0.8712***	Bedrooms*Year2005	0.0078***	Garages*Year2011	0.0042***
$Age^3/10,000$	3.8189***	Postcode2043	-0.6787***	Postcode2146	-0.9680***	Postcode2557	-0.8534***	Bedrooms*Year2006	0.0205***	Logarea*Year1972	0.0514***
$Age^4/100,000$	-2.7094***	Postcode2044	-0.8706***	Postcode2147	-0.9867***	Postcode2558	-1.2055***	Bedrooms*Year2007	0.0523***	Logarea*Year1973	0.0583
Built60s	0.1522***	Postcode2045	-0.4042***	Postcode2148	-1.0371***	Postcode2559	-1.3869***	Bedrooms*Year2008	-0.0136**	Logarea*Year1974	-0.0473***
Built70s	0.1557***	Postcode2046	-0.4435***	Postcode2150	-0.7967***	Postcode2560	-1.1688***	Bedrooms*Year2009	-0.0405***	Logarea*Year1975	-0.0352***
Built80s	0.1155***	Postcode2047	-0.3277***	Postcode2151	-0.7160***	Postcode2563	-0.6181***	Bedrooms*Year2010	0.0217**	Logarea*Year1976	0.0041***
Built90s	0.0797***	Postcode2048	-0.5932***	Postcode2152	-0.8327***	Postcode2564	-1.2114***	Bedrooms*Year2011	0.0161	Logarea*Year1977	0.0479
Built00s	0.0259	Postcode2049	-0.6228***	Postcode2153	-0.7282***	Postcode2565	-1.0587***	Bathrooms*Year1972	0.0526	Logarea*Year1978	0.0674
Built09-11	-0.0109	Postcode2050	-0.5861***	Postcode2154	-0.6234***	Postcode2566	-1.1735***	Bathrooms*Year1973	-0.0124	Logarea*Year1979	-0.0537
Log area	0.1614***	Postcode2060	-0.0798***	Postcode2155	-0.7724***	Postcode2567	-1.0839***	Bathrooms*Year1974	-0.0554**	Logarea*Year1980	-0.0449
DCBD	-0.0054***	Postcode2061	0.1291***	Postcode2156	-0.6573***	Postcode2568	-0.9853***	Bathrooms*Year1975	-0.0068***	Logarea*Year1981	0.0022
$DCBD^2$	-2.88E-05***	Postcode2062	-0.2323***	Postcode2157	-0.7325***	Postcode2569	-1.0602***	Bathrooms*Year1976	0.0130***	Logarea*Year1982	0.0420
Longitude	0.9136***	Postcode2063	-0.1194***	Postcode2158	-0.6748***	Postcode2570	-0.8714***	Bathrooms*Year1977	0.0554***	Logarea*Year1983	0.0592
Latitude	-0.3995***	Postcode2064	-0.2795***	Postcode2159	-0.8047***	Postcode2571	-0.9545***	Bathrooms*Year1978	0.0004	Logarea*Year1984	-0.0438*
Year1972	0.3955***	Postcode2065	-0.2998***	Postcode2160	-0.9525***	Postcode2572	-0.9056***	Bathrooms*Year1979	-0.0674	Logarea*Year1985	-0.0257***
Year1973	0.1657	Postcode2066	-0.3242***	Postcode2161	-1.0364***	Postcode2573	-0.9779***	Bathrooms*Year1980	-0.0035	Logarea*Year1986	0.0013***
Year1974	0.3102**	Postcode2067	-0.3697***	Postcode2162	-1.0021***	Postcode2574	-1.0548***	Bathrooms*Year1981	0.0124	Logarea*Year1987	0.0379***
Year1975	1.1060***	Postcode2068	-0.3581***	Postcode2163	-1.1429***	Postcode2745	-0.8203***	Bathrooms*Year1982	0.0469	Logarea*Year1988	0.0760***
Year1976	1.3763***	Postcode2069	-0.2219***	Postcode2164	-1.0131***	Postcode2747	-0.9287***	Bathrooms*Year1983	-0.0063	Logarea*Year1989	-0.0433**
Year1977	0.5188***	Postcode2070	-0.2610***	Postcode2165	-1.0465***	Postcode2748	-0.7320***	Bathrooms*Year1984	-0.0545	Logarea*Year1990	-0.0202***
Year1978	0.0656	Postcode2071	-0.1847***	Postcode2166	-1.0601***	Postcode2749	-0.8970***	Bathrooms*Year1985	-0.0009	Logarea*Year1991	0.0017*
Year1979	0.2270**	Postcode2072	-0.2742***	Postcode2167	-1.0392***	Postcode2750	-0.7650***	Bathrooms*Year1986	0.0142	Logarea*Year1992	0.0522
Year1980	0.7668***	Postcode2073	-0.3581***	Postcode2168	-1.1081***	Postcode2752	-0.9093***	Bathrooms*Year1987	0.0488	Logarea*Year1993	0.0714
Year1981	0.8846***	Postcode2074	-0.4230***	Postcode2170	-1.0002***	Postcode2753	-0.7667***	Bathrooms*Year1988	-0.0058	Logarea*Year1994	-0.0444
Year1982	0.8524***	Postcode2075	-0.4023***	Postcode2171	-0.8838***	Postcode2754	-0.6717***	Bathrooms*Year1989	-0.0563**	Logarea*Year1995	-0.0281
Year1983	0.7463***	Postcode2076	-0.4712***	Postcode2172	-0.8303***	Postcode2756	-0.9250***	Bathrooms*Year1990	0.0219**	Logarea*Year1996	0.0030**
Year1984	0.8193***	Postcode2077	-0.7781***	Postcode2173	-1.0152***	Postcode2757	-0.6445***	Bathrooms*Year1991	0.0094*	Logarea*Year1997	0.0442***
Year1985	0.6571***	Postcode2079	-0.9029***	Postcode2174	-0.5838**	Postcode2758	-0.5715***	Bathrooms*Year1992	0.0583	Logarea*Year1998	0.0539
Year1986	0.6715***	Postcode2080	-0.9002***	Postcode2175	-0.5707***	Postcode2759	-0.9470***	Bathrooms*Year1993	-0.0142*	Logarea*Year1999	-0.0478
Year1987	0.9447***	Postcode2081	-0.8809***	Postcode2176	-0.9291***	Postcode2760	-1.0602***	Bathrooms*Year1994	-0.0494**	Logarea*Year2000	-0.0431*
Year1988	1.1782***	Postcode2082	-0.8622***	Postcode2177	-1.0210***	Postcode2761	-1.0665***	Bathrooms*Year1995	0.0290**	Logarea*Year2001	0.0028***
Year1989	1.5736***	Postcode2083	-0.8485***	Postcode2178	-0.8372***	Postcode2762	-0.9785***	Bathrooms*Year1996	0.0057***	Logarea*Year2002	0.0488***
Year1990	1.4840***	Postcode2084	-0.5356***	Postcode2179	-0.9354***	Postcode2763	-0.9806***	Bathrooms*Year1997	0.0714***	Logarea*Year2003	0.0529***
Year1991	1.5718***	Postcode2085	-0.5954***	Postcode2190	-0.9517***	Postcode2765	-0.9675***	Bathrooms*Year1998	-0.0161***	Logarea*Year2004	-0.0391***
Year1992	1.7182***	Postcode2086	-0.6718***	Postcode2191	-0.8269***	Postcode2766	-1.0517***	Bathrooms*Year1999	-0.0553***	Logarea*Year2005	-0.0484***
Year1993	1.8053***	Postcode2087	-0.6264***	Postcode2192	-0.8808***	Postcode2767	-1.0722***	Bathrooms*Year2000	0.0612***	Logarea*Year2006	0.0033***
Year1994	2.0575***	Postcode2088	0.0359	Postcode2193	-0.7672***	Postcode2768	-0.9751***	Bathrooms*Year2001	0.0059**	Logarea*Year2007	0.0491**
Year1995	2.0852***	Postcode2089	-0.1141***	Postcode2194	-0.8539***	Postcode2769	-0.8521***	Bathrooms*Year2002	0.0597**	Logarea*Year2008	0.0483**
Year1996	2.2383***	Postcode2090	-0.0669***	Postcode2195	-0.9987***	Postcode2770	-1.2113***	Bathrooms*Year2003	0.0079**	Logarea*Year2009	-0.0476***
Year1997	2.4525***	Postcode2092	-0.3464***	Postcode2196	-0.9362***	Postcode2773	-0.4682***	Bathrooms*Year2004	-0.0546**	Logarea*Year2010	-0.0445***
Year1998	2.4854***	Postcode2093	-0.4144***	Postcode2197	-0.9206***	Postcode2774	-0.5921***	Bathrooms*Year2005	0.0660**	Logarea*Year2011	0.0041
Year1999	2.5586***	Postcode2094	-0.3759***	Postcode2198	-0.8188***	Postcode2775	-1.2048***	Bathrooms*Year2006	0.0065***	DCBD*Year1972	0.0471***
Year2000	2.6509***	Postcode2095	-0.2884***	Postcode2199	-0.9612***	Postcode2776	-0.6003***	Bathrooms*Year2007	0.0667***	DCBD*Year1973	0.0530***
Year2001	2.9111***	Postcode2096	-0.5447***	Postcode2200	-0.9177***	Postcode2777	-0.6276***	Bathrooms*Year2008	0.0298***	DCBD*Year1974	-0.0416***
Year2002	3.1098***	Postcode2097	-0.5622***	Postcode2203	-0.7317***	Postcode2778	-0.6470***	Bathrooms*Year2009	-0.0525***	DCBD*Year1975	-0.0507***
Year2003	3.2619***	Postcode2099	-0.6713***	Postcode2204	-0.7807***	Postcode2779	-0.6528***	Bathrooms*Year2010	0.0497***	DCBD*Year1976	0.0056***
Year2004	3.3210***	Postcode2100	-0.6799***	Postcode2205	-0.8582***	Postcode2780	-0.3240***	Bathrooms*Year2011	0.0027***	DCBD*Year1977	0.0613***
Year2005	3.2038***	Postcode2101	-0.6628***	Postcode2206	-0.7216***	Postcode2782	-0.3592***	Garages*Year1972	0.0443***	DCBD*Year1978	0.0531***
Year2006	3.2132***	Postcode2102	-0.6683***	Postcode2207	-0.7813***	Postcode2783	-0.5940***	Garages*Year1973	0.0210	DCBD*Year1979	-0.0487***
Year2007	3.2364***	Postcode2103	-0.5950***	Postcode2208	-0.7239***	Postcode2784	-0.6041***	Garages*Year1974	-0.0594***	DCBD*Year1980	-0.0422***
Year2008	3.3203***	Postcode2104	-0.4190***	Postcode2209	-0.7647***	Postcode2785	-0.3049***	Garages*Year1975	0.0946	DCBD*Year1981	0.0054***
Year2009	3.4502***	Postcode2105	-0.4787***	Postcode2210	-0.7470***	Postcode2786	-0.3722***	Garages*Year1976	-0.0021	DCBD*Year1982	0.0537***
Year2010	3.5380***	Postcode2106	-0.5329***	Postcode2211	-0.8826***	Postcode2787	-0.0434	Garages*Year1977	0.0504	DCBD*Year1983	0.0695***
Year2011	3.5612***	Postcode2107	-0.5366***	Postcode2212	-0.9185***	Bedrooms*Year1972	0.0369*	Garages*Year1978	0.0452***	DCBD*Year1984	-0.0510***
Postcode2007	-0.4419***	Postcode2108	-0.1928***	Postcode2213	-0.8394***	Bedrooms*Year1973	-0.0238	Garages*Year1979	-0.0629**	DCBD*Year1985	-0.0418***
Postcode2008	-0.5484***	Postcode2110	-0.1150***	Postcode2214	-0.7949***	Bedrooms*Year1974	-0.0545**	Garages*Year1980	0.0407***	DCBD*Year1986	0.0049***
Postcode2009	-0.4297***	Postcode2111	-0.4984***	Postcode2216	-0.7504***	Bedrooms*Year1975	-0.0879**	Garages*Year1981	0.0071***	DCBD*Year1987	0.0491***
Postcode2010	-0.3057***	Postcode2112	-0.6737***	Postcode2217	-0.6513***	Bedrooms*Year1976	0.0140	Garages*Year1982	0.0397***	DCBD*Year1988	0.0950**
Postcode2011	-0.0884***	Postcode2113	-0.6997***	Postcode2218	-0.7724***	Bedrooms*Year1977	0.0281	Garages*Year1983	0.0536***	DCBD*Year1989	-0.0592***
Postcode2015	-0.6515***	Postcode2114	-0.6784***	Postcode2219	-0.5773***	Bedrooms*Year1978	-0.0074***	Garages*Year1984	-0.0656***	DCBD*Year1990	-0.0356***
Postcode2016	-0.5839***	Postcode2115	-0.8686***	Postcode2220	-0.7346***	Bedrooms*Year1979	-0.0158***	Garages*Year1985	0.0518***	DCBD*Year1991	0.0035***
Postcode2017	-0.6839***	Postcode2116	-0.8853***	Postcode2221	-0.4907***	Bedrooms*Year1980	-0.0084***	Garages*Year1986	0.0073***	DCBD*Year1992	0.0419***
Postcode2018	-0.6328***	Postcode2117	-0.7888***	Postcode2222	-0.7192***	Bedrooms*Year1981	0.0065***	Garages*Year1987	0.0642***	DCBD*Year1993	0.0896***
Postcode2019	-0.7607***	Postcode2118	-0.6644***	Postcode2223	-0.6368***	Bedrooms*Year1982	0.0447***	Garages*Year1988	0.0397***	DCBD*Year1994	-0.0599***
Postcode2020	-0.7465***	Postcode2119	-0.4622***	Postcode2224	-0.5385***	Bedrooms*Year1983	-0.0597***	Garages*Year1989	-0.0612***	DCBD*Year1995	-0.0380***
Postcode2021	-0.0188	Postcode2120	-0.6534***	Postcode2225	-0.7666***	Bedrooms*Year1984	-0.0978***	Garages*Year1990	0.0284***	DCBD*Year1996	0.0026***
Postcode2022	-0.2707***	Postcode2121	-0.5836***	Postcode2226	-0.8191***	Bedrooms*Year1985	-0.0662***	Garages*Year1991	0.0077***	DCBD*Year1997	0.0491**
Postcode2023	0.2457***	Postcode2122	-0.5920***	Postcode2227	-0.7726***	Bedrooms*Year1986	0.0206***	Garages*Year1992	0.0664***	DCBD*Year1998	0.0791
Postcode2024	-0.2264***	Postcode2125	-0.5808***	Postcode2228	-0.7575***	Bedrooms*Year1987	0.0696***	Garages*Year1993	0.0274***	DCBD*Year1999	-0.0564*
Postcode2025	0.1085***	Postcode2126	-0.6810***	Postcode2229	-0.6528***	Bedrooms*Year1988	-0.2372***	Garages*Year1994	-0.0476***	DCBD*Year2000	-0.0582***
Postcode2026	-0.2962***	Postcode2127	-0.5973***	Postcode2230	-0.6136***	Bedrooms*Year1989	-0.0380***	Garages*Year1995	0.0155***	DCBD*Year2001	0.0032***
Postcode2027	0.1922***	Postcode2128	-0.9359***	Postcode2231	-1.1303***	Bedrooms*Year1990	-0.1214**	Garages*Year1996	0.0052***	DCBD*Year2002	0.0426***
Postcode2028	0.2130***	Postcode2130	-0.5950***	Postcode2232	-0.7954***	Bedrooms*Year1991	0.0158***	Garages*Year1997	0.0535***	DCBD*Year2003	0.0789***
Postcode2029	-0.0035	Postcode2131	-0.6408***	Postcode2233	-0.8612***	Bedrooms*Year1992	-0.0176***	Garages*Year1998	0.0366***	DCBD*Year2004	-0.0540***
Postcode2030	0.1459***	Postcode2132	-0.6313***	Postcode2234	-0.8148***	Bedrooms*Year1993	-0.0826***	Garages*Year1999	-0.0476***	DCBD*Year2005	-0.0465***
Postcode2031	-0.3083***	Postcode2133	-0.7616***	Postcode2250	-1.1843***	Bedrooms*Year1994	-0.0245***	Garages*Year2000	0.0086***	DCBD*Year2006	0.0018***
Postcode2032	-0.4907***	Postcode2134	-0.4560***	Postcode2251	-1.1137***	Bedrooms*Year1995	-0.1663***	Garages*Year2001	0.0055***	DCBD*Year2007	0.0199***
Postcode2033	-0.2747***	Postcode2135	-0.2754***	Postcode2256	-1.1040***	Bedrooms*Year1996	0.0134***	Garages*Year2002	0.0460**	DCBD*Year2008	0.0675***
Postcode2034	-0.2967***	Postcode2136	-0.7162***	Postcode2257	-1.1166***	Bedrooms*Year1997	0.0356***	Garages*Year2003	0.0482***	DCBD*Year2009	-0.0800***
Postcode2035	-0.4742***	Postcode2137	-0.5136***	Postcode2258	-1.2190***	Bedrooms*Year1998	-0.1003**	Garages*Year2004	-0.0520**	DCBD*Year2010	-0.0227**
Postcode2036	-0.6876***	Postcode2138	-0.6043***	Postcode2259	-1.2993***	Bedrooms*Year1999	-0.0041**	Garages*Year2005	-0.0115***	DCBD*Year2011	0.0011

Note: ***,** and * indicate significance at the 1%, 5% and 10% level, respectively.

D Estimation Results of the Hybrid Model

Parameter	Estimate	Parameter	Estimate	Parameter	Estimate	Parameter	Estimate	Parameter	Estimate	Parameter	Estimate
Intercept	0.1471***	Postcode2037	-0.3781***	Postcode2140	-0.6382***	Postcode2260	-0.6427***	Bedrooms*Year2000	-0.0433***	Garages*Year2006	0.0049***
Bedrooms	-0.0282	Postcode2038	-0.4876***	Postcode2141	-0.9600***	Postcode2261	-0.8782***	Bedrooms*Year2001	0.0120***	Garages*Year2007	0.1100***
Bathrooms	0.1448***	Postcode2039	-0.4640***	Postcode2142	-1.0482***	Postcode2262	-1.0084***	Bedrooms*Year2002	0.1088***	Garages*Year2008	-0.0470***
Garages	0.1255***	Postcode2040	-0.5889***	Postcode2143	-0.9838***	Postcode2263	-0.9564***	Bedrooms*Year2003	-0.0973***	Garages*Year2009	-0.0698***
Age/100	0.5414***	Postcode2041	-0.2424***	Postcode2144	-0.9892***	Postcode2555	-1.6974***	Bedrooms*Year2004	-0.0629***	Garages*Year2010	-0.0782***
$Age^2/1,000$	-45.1111***	Postcode2042	-0.5894***	Postcode2145	-0.9140***	Postcode2556	-0.9629***	Bedrooms*Year2005	-0.1295***	Garages*Year2011	0.0053***
$Age^3/10,000$	1,035.0502***	Postcode2043	-0.6524***	Postcode2146	-1.0189***	Postcode2557	-0.8635***	Bedrooms*Year2006	0.0238***	Logarea*Year1972	0.1134***
$Age^4/100,000$	-6,397.3342***	Postcode2044	-0.8239***	Postcode2147	-1.0480***	Postcode2558	-1.1846***	Bedrooms*Year2007	0.1027***	Logarea*Year1973	-0.0420
Built60s	0.2143***	Postcode2045	-0.4006***	Postcode2148	-1.1129***	Postcode2559	-1.3634***	Bedrooms*Year2008	-0.0995***	Logarea*Year1974	-0.0670***
Built70s	0.1907***	Postcode2046	-0.4439***	Postcode2150	-0.8367***	Postcode2560	-1.1205***	Bedrooms*Year2009	-0.0352***	Logarea*Year1975	-0.0801
Built80s	0.1613***	Postcode2047	-0.3257***	Postcode2151	-0.7483***	Postcode2563	-0.6617***	Bedrooms*Year2010	-0.1168***	Logarea*Year1976	0.0049**
Built90s	0.1411***	Postcode2048	-0.5773***	Postcode2152	-0.8666***	Postcode2564	-1.1873***	Bedrooms*Year2011	0.0198***	Logarea*Year1977	0.1167***
Built00s	0.1102***	Postcode2049	-0.6025***	Postcode2153	-0.7683***	Postcode2565	-1.0391***	Bathrooms*Year1972	0.1070**	Logarea*Year1978	-0.0333***
Built09-11	0.0862***	Postcode2050	-0.5733***	Postcode2154	-0.6440***	Postcode2566	-1.1524***	Bathrooms*Year1973	-0.0946***	Logarea*Year1979	-0.0756***
Log area	0.2233***	Postcode2060	-0.0572**	Postcode2155	-0.8148***	Postcode2567	-1.0619***	Bathrooms*Year1974	-0.0597***	Logarea*Year1980	-0.0729***
DCBD	-0.0155***	Postcode2061	0.1501***	Postcode2156	-0.6728***	Postcode2568	-0.9639***	Bathrooms*Year1975	-0.1060***	Logarea*Year1981	0.0031***
$DCBD^2$	0.0000***	Postcode2062	-0.1918***	Postcode2157	-0.7393***	Postcode2569	-1.0443***	Bathrooms*Year1976	0.0162***	Logarea*Year1982	0.1082***
Longitude	0.0640***	Postcode2063	-0.0664**	Postcode2158	-0.6966***	Postcode2570	-0.9062***	Bathrooms*Year1977	0.1123***	Logarea*Year1983	-0.0413***
Latitude	0.0130	Postcode2064	-0.2488***	Postcode2159	-0.7959***	Postcode2571	-0.9743***	Bathrooms*Year1978	-0.0933***	Logarea*Year1984	-0.0657***
Year1972	0.2668***	Postcode2065	-0.2741***	Postcode2160	-0.9882***	Postcode2572	-0.9546***	Bathrooms*Year1979	-0.0733***	Logarea*Year1985	-0.0631***
Year1973	0.3258***	Postcode2066	-0.3084***	Postcode2161	-1.0631***	Postcode2573	-1.0038***	Bathrooms*Year1980	-0.1031***	Logarea*Year1986	0.0021***
Year1974	0.4188***	Postcode2067	-0.3365***	Postcode2162	-1.0126***	Postcode2574	-1.0611***	Bathrooms*Year1981	0.0149***	Logarea*Year1987	0.0953***
Year1975	0.3928***	Postcode2068	-0.2803***	Postcode2163	-1.1578***	Postcode2745	-0.9620***	Bathrooms*Year1982	0.0955***	Logarea*Year1988	-0.0175***
Year1976	0.3982***	Postcode2069	-0.1763***	Postcode2164	-1.0601***	Postcode2747	-1.0835***	Bathrooms*Year1983	-0.1079***	Logarea*Year1989	-0.0636***
Year1977	0.5337***	Postcode2070	-0.2201***	Postcode2165	-1.0811***	Postcode2748	-0.9079***	Bathrooms*Year1984	-0.0564***	Logarea*Year1990	-0.0621***
Year1978	0.7493***	Postcode2071	-0.1449***	Postcode2166	-1.0922***	Postcode2749	-1.0616***	Bathrooms*Year1985	-0.1011***	Logarea*Year1991	0.0026***
Year1979	0.9169***	Postcode2072	-0.2429***	Postcode2167	-1.0228***	Postcode2750	-0.9495***	Bathrooms*Year1986	0.0169***	Logarea*Year1992	0.1119***
Year1980	1.2100***	Postcode2073	-0.3265***	Postcode2168	-1.1360***	Postcode2752	-1.0794***	Bathrooms*Year1987	0.1044**	Logarea*Year1993	-0.0232***
Year1981	1.3547***	Postcode2074	-0.3902***	Postcode2170	-1.0085***	Postcode2753	-0.9611***	Bathrooms*Year1988	-0.1096***	Logarea*Year1994	-0.0661***
Year1982	1.3517***	Postcode2075	-0.3433***	Postcode2171	-0.9031***	Postcode2754	-0.8825***	Bathrooms*Year1989	-0.0569*	Logarea*Year1995	-0.0758***
Year1983	1.3117***	Postcode2076	-0.4432***	Postcode2172	-0.7800***	Postcode2756	-1.0537***	Bathrooms*Year1990	-0.0937	Logarea*Year1996	0.0040***
Year1984	1.3815***	Postcode2077	-0.7582***	Postcode2173	-0.9905***	Postcode2757	-0.8429***	Bathrooms*Year1991	0.0125*	Logarea*Year1997	0.1010***
Year1985	1.4509***	Postcode2079	-0.8586***	Postcode2174	-0.6802***	Postcode2758	-0.8392***	Bathrooms*Year1992	0.1138**	Logarea*Year1998	-0.0424***
Year1986	1.5086***	Postcode2080	-0.8432***	Postcode2175	-0.7402***	Postcode2759	-1.0514***	Bathrooms*Year1993	-0.1102**	Logarea*Year1999	-0.0706***
Year1987	1.6545***	Postcode2081	-0.8075***	Postcode2176	-0.9721***	Postcode2760	-1.1855***	Bathrooms*Year1994	-0.0562*	Logarea*Year2000	-0.0655***
Year1988	1.9743***	Postcode2082	-0.7993***	Postcode2177	-1.0546***	Postcode2761	-1.1586***	Bathrooms*Year1995	-0.0821	Logarea*Year2001	0.0037***
Year1989	2.2671***	Postcode2083	-0.7228***	Postcode2178	-0.8518***	Postcode2762	-1.0649***	Bathrooms*Year1996	0.0077	Logarea*Year2002	0.1015***
Year1990	2.2146***	Postcode2084	-0.4259***	Postcode2179	-0.9481***	Postcode2763	-1.0443***	Bathrooms*Year1997	0.1194	Logarea*Year2003	-0.0393***
Year1991	2.2184***	Postcode2085	-0.5107***	Postcode2190	-0.9368***	Postcode2765	-1.0742***	Bathrooms*Year1998	-0.1163	Logarea*Year2004	-0.0589***
Year1992	2.2394***	Postcode2086	-0.5785***	Postcode2191	-0.8079***	Postcode2766	-1.1488***	Bathrooms*Year1999	-0.0464	Logarea*Year2005	-0.0697***
Year1993	2.2572***	Postcode2087	-0.5590***	Postcode2192	-0.8550***	Postcode2767	-1.1429***	Bathrooms*Year2000	-0.0847	Logarea*Year2006	0.0042***
Year1994	2.3201***	Postcode2088	0.0871***	Postcode2193	-0.7427***	Postcode2768	-1.0151***	Bathrooms*Year2001	0.0079	Logarea*Year2007	0.1062***
Year1995	2.3431***	Postcode2089	-0.0751***	Postcode2194	-0.8334***	Postcode2769	-0.8751***	Bathrooms*Year2002	0.1092	Logarea*Year2008	-0.0462***
Year1996	2.3805***	Postcode2090	-0.0165	Postcode2195	-0.9697***	Postcode2770	-1.3259***	Bathrooms*Year2003	-0.0894	Logarea*Year2009	-0.0746***
Year1997	2.4678***	Postcode2092	-0.2646***	Postcode2196	-0.9079***	Postcode2773	-0.6817***	Bathrooms*Year2004	-0.0480	Logarea*Year2010	-0.0695***
Year1998	2.5677***	Postcode2093	-0.3114***	Postcode2197	-0.9223***	Postcode2774	-0.8142***	Bathrooms*Year2005	-0.0888	Logarea*Year2011	0.0050***
Year1999	2.6752***	Postcode2094	-0.2596***	Postcode2198	-0.8216***	Postcode2775	-1.2715***	Bathrooms*Year2006	0.0090	DCBD*Year1972	0.1000***
Year2000	2.7932***	Postcode2095	-0.1619***	Postcode2199	-0.9533***	Postcode2776	-0.8963***	Bathrooms*Year2007	0.1138	DCBD*Year1973	-0.0387***
Year2001	2.8965***	Postcode2096	-0.4117***	Postcode2200	-0.9023***	Postcode2777	-0.8884***	Bathrooms*Year2008	-0.0626	DCBD*Year1974	-0.0640***
Year2002	3.0896***	Postcode2097	-0.4063***	Postcode2203	-0.7098***	Postcode2778	-0.9680***	Bathrooms*Year2009	-0.0517	DCBD*Year1975	-0.0748***
Year2003	3.2676***	Postcode2099	-0.5312***	Postcode2204	-0.7509***	Postcode2779	-0.9902***	Bathrooms*Year2010	-0.0820	DCBD*Year1976	0.0064***
Year2004	3.3253***	Postcode2100	-0.5639***	Postcode2205	-0.7950***	Postcode2780	-0.7847***	Bathrooms*Year2011	0.0045	DCBD*Year1977	0.1101***
Year2005	3.2810***	Postcode2101	-0.4966***	Postcode2206	-0.6829***	Postcode2782	-0.7708***	Garages*Year1972	0.0972***	DCBD*Year1978	-0.0397***
Year2006	3.2665***	Postcode2102	-0.4775***	Postcode2207	-0.7158***	Postcode2783	-0.9488***	Garages*Year1973	-0.0839	DCBD*Year1979	-0.0758***
Year2007	3.2979***	Postcode2103	-0.4059***	Postcode2208	-0.6773***	Postcode2784	-0.9666***	Garages*Year1974	-0.0588***	DCBD*Year1980	-0.0761***
Year2008	3.3067***	Postcode2104	-0.2316***	Postcode2209	-0.7173***	Postcode2785	-0.8226***	Garages*Year1975	-0.0539***	DCBD*Year1981	0.0064***
Year2009	3.3330***	Postcode2105	-0.3039***	Postcode2210	-0.6912***	Postcode2786	-0.9506***	Garages*Year1976	0.0004***	DCBD*Year1982	0.1058***
Year2010	3.4323***	Postcode2106	-0.3296***	Postcode2211	-0.8351***	Postcode2787	-1.0181***	Garages*Year1977	0.1049	DCBD*Year1983	-0.0227***
Year2011	3.4380***	Postcode2107	-0.3237***	Postcode2212	-0.8817***	Bedrooms*Year1972	0.0743***	Garages*Year1978	-0.0502***	DCBD*Year1984	-0.0804***
Postcode2007	-0.4254***	Postcode2108	0.0132	Postcode2213	-0.8022***	Bedrooms*Year1973	-0.0895**	Garages*Year1979	-0.0720	DCBD*Year1985	-0.0729***
Postcode2008	-0.5169***	Postcode2110	-0.1043***	Postcode2214	-0.7737***	Bedrooms*Year1974	-0.0714***	Garages*Year1980	-0.0922***	DCBD*Year1986	0.0059***
Postcode2009	-0.4328***	Postcode2111	-0.4992***	Postcode2216	-0.6744***	Bedrooms*Year1975	-0.0668***	Garages*Year1981	0.0094***	DCBD*Year1987	0.1012***
Postcode2010	-0.2594***	Postcode2112	-0.6795***	Postcode2217	-0.5519***	Bedrooms*Year1976	0.0125***	Garages*Year1982	0.0897**	DCBD*Year1988	0.0046
Postcode2011	-0.0626*	Postcode2113	-0.7016***	Postcode2218	-0.6842***	Bedrooms*Year1977	0.0677***	Garages*Year1983	-0.0426**	DCBD*Year1989	-0.0913***
Postcode2015	-0.6210***	Postcode2114	-0.6924***	Postcode2219	-0.4560***	Bedrooms*Year1978	-0.1565***	Garages*Year1984	-0.0709**	DCBD*Year1990	-0.0693***
Postcode2016	-0.5481***	Postcode2115	-0.8870***	Postcode2220	-0.6608***	Bedrooms*Year1979	-0.0091***	Garages*Year1985	-0.0867**	DCBD*Year1991	0.0044***
Postcode2017	-0.6364***	Postcode2116	-0.9106***	Postcode2221	-0.3914***	Bedrooms*Year1980	-0.0201***	Garages*Year1986	0.0101**	DCBD*Year1992	0.0905***
Postcode2018	-0.5534***	Postcode2117	-0.8133***	Postcode2222	-0.6521***	Bedrooms*Year1981	0.0060***	Garages*Year1987	0.1139**	DCBD*Year1993	-0.0026***
Postcode2019	-0.6502***	Postcode2118	-0.6842***	Postcode2223	-0.5627***	Bedrooms*Year1982	0.1144***	Garages*Year1988	-0.0560***	DCBD*Year1994	-0.0912***
Postcode2020	-0.6645***	Postcode2119	-0.4739***	Postcode2224	-0.4071***	Bedrooms*Year1983	-0.1310***	Garages*Year1989	-0.0728***	DCBD*Year1995	-0.0587***
Postcode2021	0.0363	Postcode2120	-0.6545***	Postcode2225	-0.6610***	Bedrooms*Year1984	-0.1347***	Garages*Year1990	-0.0952***	DCBD*Year1996	0.0035***
Postcode2022	-0.1809***	Postcode2121	-0.5941***	Postcode2226	-0.7135***	Bedrooms*Year1985	-0.1163***	Garages*Year1991	0.0102***	DCBD*Year1997	0.0985***
Postcode2023	0.3343***	Postcode2122	-0.6021***	Postcode2227	-0.6197***	Bedrooms*Year1986	0.0230***	Garages*Year1992	0.1206**	DCBD*Year1998	-0.0060*
Postcode2024	-0.1094***	Postcode2125	-0.5911***	Postcode2228	-0.6060***	Bedrooms*Year1987	0.1949***	Garages*Year1993	-0.0687**	DCBD*Year1999	-0.0898**
Postcode2025	0.1837***	Postcode2126	-0.6756***	Postcode2229	-0.4784***	Bedrooms*Year1988	-0.4194***	Garages*Year1994	-0.0535***	DCBD*Year2000	-0.0639***
Postcode2026	-0.1761***	Postcode2127	-0.5897***	Postcode2230	-0.4123***	Bedrooms*Year1989	-0.0796***	Garages*Year1995	-0.0897***	DCBD*Year2001	0.0039***
Postcode2027	0.2403***	Postcode2128	-0.9484***	Postcode2231	-0.9248***	Bedrooms*Year1990	0.0061***	Garages*Year1996	0.0068***	DCBD*Year2002	0.0885***
Postcode2028	0.2903***	Postcode2130	-0.5750***	Postcode2232	-0.6653***	Bedrooms*Year1991	0.0086***	Garages*Year1997	0.1101***	DCBD*Year2003	-0.0143***
Postcode2029	0.1090***	Postcode2131	-0.6306***	Postcode2233	-0.7301***	Bedrooms*Year1992	0.1276***	Garages*Year1998	-0.0584***	DCBD*Year2004	-0.0827***
Postcode2030	0.2712***	Postcode2132	-0.6284***	Postcode2234	-0.7113***	Bedrooms*Year1993	-0.1532***	Garages*Year1999	-0.0581***	DCBD*Year2005	-0.0536***
Postcode2031	-0.1971***	Postcode2133	-0.7508***	Postcode2250	-0.9322***	Bedrooms*Year1994	-0.1090***	Garages*Year2000	-0.0853***	DCBD*Year2006	0.0028***
Postcode2032	-0.3861***	Postcode2134	-0.4562***	Postcode2251	-0.8133***	Bedrooms*Year1995	-0.0353***	Garages*Year2001	0.0069***	DCBD*Year2007	0.0820***
Postcode2033	-0.1939***	Postcode2135	-0.2675***	Postcode2256	-0.8783***	Bedrooms*Year1996	0.0080***	Garages*Year2002	0.1037***	DCBD*Year2008	-0.0211***
Postcode2034	-0.1722***	Postcode2136	-0.7077***	Postcode2257	-0.8836***	Bedrooms*Year1997	0.1054***	Garages*Year2003	-0.0506***	DCBD*Year2009	-0.1012***
Postcode2035	-0.3338***	Postcode2137	-0.5190***	Postcode2258	-0.9368***	Bedrooms*Year1998	-0.1532***	Garages*Year2004	-0.0704***	DCBD*Year2010	-0.0375**
Postcode2036	-0.5218***	Postcode2138	-0.6134***	Postcode2259	-0.9480***	Bedrooms*Year1999	-0.0193***	Garages*Year2005	-0.0723***	DCBD*Year2011	0.0025**

Note: ***,** and * indicate significance at the 1%, 5% and 10% level, respectively.