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Measuring a Boom and Bust: The Sydney Housing Market 2001-2006

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Abstract: The Sydney housing market peaked in 2003. The period 2001-2006 is, therefore, of particular interest since it captures a boom and bust in the housing market. We compute hedonic, repeat-sales and median price indexes for five regions in Sydney over this period. While the three approaches are in broad agreement regarding the timing of the turning point in the housing market, some important differences also emerge. In particular, we find evidence of sample selection bias in our hedonic and repeat-sales data sets, which in turn seems to generate bias (although in opposite directions) in our hedonic and repeat-sales indexes. The median indexes also may be biased as a result of an apparent decline in the average quality of houses sold in the latter part of the sample. Although in this case the repeat-sales indexes seem to generate the most reliable results, we nevertheless in general favor the hedonic approach. We also find evidence of convergence in prices across regions during the boom and divergence in the subsequent bust.

Keywords: House prices; Price index; Hedonic regression; Repeat-Sales index; Sample selection bias; Convergence

JEL Classification Codes: C23, C43, E31.

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1. Introduction

Movements in the prices of residential housing are important indicators for most economies. Much of household wealth is held in the form of housing. Hence movements in house prices have important implications for national consumption and investment decisions, as has been clearly demonstrated by recent events in the US subprime market. Access to housing is also important for social equity and hence changes in price can have major political implications.

The nature and quality of housing price statistics came under increased scrutiny as housing markets boomed in many countries. For example, in Australia the reliability of official measures of housing prices have been questioned.

> Housing is the biggest asset in the country. Certainly for the household sector it is about 60 to 70 percent of their total wealth. It is an extremely important asset class for most people, yet the information we have on prices is hopeless compared with the information we have on share prices, bond prices, and foreign exchange rates, and even the information we have on commodity prices, export prices, import prices and consumer prices. It really is probably the weakest link in all the price data in the country so I think it is something that I would like to see resources put into. (Ian Macfarlane, Governor of the Reserve Bank of Australia, 4 June 2004).

House price indexes can be based on actual market data or expert surveys. Here we focus exclusively on the former. Such indexes come in three main varieties.[1] The simplest are median indexes that track the change in the price of the median house from one period to the next. Examples include the National Association of Realtors (NAR) index in the US, and the Real Estate Institute of Australia (REIA) and LJ Hooker/BIS Shrapnel indexes in Australia. Median indexes, however, confound changes in prices with quality differences. This is because the median house sold say in 2007 will tend to be of higher or lower quality

[1] Market prices can take the form of asking prices, the price on which a mortgage backed offer is based, the price at which contracts are exchanged, and the actual price that is eventually officially recorded. Index providers trade off timeliness against accuracy depending on which market price they use. See Acadametrics (2009) for a discussion of which market prices are used by index providers in the UK.

than the median house sold in 2008. These quality differences will tend to introduce noise into the index. Some median index providers try to address this problem by computing stratified (or mix adjusted) medians (see for example the Established Homes Price Index published by the Australian Bureau of Statistics 2006).[2]

The other two varieties yield quality-adjusted indexes. A repeat-sales index is computed from repeat-sales data. Restricting the comparison to repeat sales ensures that each price relative compares like with like. One problem with this reasoning, however, is that the same house at two different points in time is not necessarily the same. The best known repeat-sales indexes are the Standard and Poor's/Case-Shiller (SPCS) Home Price Indexes in the US. These are computed for 20 cities (see Standard and Poor's 2008). The Office of Federal Housing Oversight (OFHEO) also computes repeat sales indexes in the US (see Calhoun 1996). Australian Property Monitors and Residex compute repeat-sales indexes for Australian cities, while the UK and Dutch Land Registries compute repeat-sales indexes for the UK and the Netherlands, respectively.

The third variety is hedonic indexes. These utilize information on characteristics (such as number of bedrooms, number of bathrooms, lot size, and location) to compute quality-adjusted indexes. Perhaps the oldest hedonic index is the US Census Department's constant quality index, which dates back to 1964. In the UK, the Halifax house price index and the Nationwide index both date back to the 1980s. More recently, a third UK hedonic index – the Communities and Local Government (CLG) index – was developed by the Office of National Statistics (ONS) (see Acadametrics 2009 for a discussion of the various UK indexes). Conseil Supérieur du Notariat (CSN) and INSEE (the national statistical office of France) compute hedonic indexes for regions in France (see Gouriéroux C. and A. Laferrère 2006). Statistics Finland also computes a hedonic index (see Saarnio 2006), while RPData-Rismark recently started computing hedonic indexes for cities in Australia.

In this study we use a large transactions data set on housing prices and characteristics for Australia's largest city, Sydney, over the period 2001-2006, to examine the effects of quality-adjustment using hedonic and repeat-sales methods on both temporal and spatial house price indexes. To provide a point of reference, we also compute median indexes. We

[2] Stratified medians are discussed in the next section.

split Sydney into five regions, and then compute temporal indexes for each region as well as for Sydney as a whole, and spatial indexes that compare prices across the five regions.[3]

The period 2001-2006 is particularly well suited to such comparisons since it includes both a boom and bust. We find that some of our results change as we move from boom to bust. For example, we find evidence of systematic bias in our median indexes during the bust, although less clearly so in the boom. We also pay particular attention to the problem of sample selection bias in the hedonic and repeat-sales data sets. Both appear to be biased, the former focusing more on better quality properties, and the latter doing the reverse. Sample selection bias seems to generate a downward bias in our hedonic indexes, and an upward bias (although less clearly so) in our repeat-sales indexes. We also compare the volatility of hedonic, repeat-sales and median indexes, and consider whether house prices are converging or converging over time across regions. We find evidence of convergence during the boom and divergence since the beginning of the bust.

Our main findings are summarized in the conclusion.

2. Methodologies for Constructing House Price Indexes

(i) Median House Price Indexes

A median house price index tracks changes in the price of the median house sold from one period to the next. The main attraction of median indexes are that they are easy to compute and easy to understand. Their main disadvantage is that they will provide very noisy estimates of the change in the cost of housing. For example, suppose there are two regions in a city denoted by A and B, and that region A is much richer and hence has more expensive houses than region B. Suppose further that the median house sold in 2006 and 2008 is from region A, while the median house in 2007 is from region B. It follows that the median index could record a large rise from 2006 to 2007 and then a large fall from 2007 to 2008. Such an index could be a very poor indicator of what is actually happening in the housing market.

Stratification (often alternatively referred to as mix-adjustment) is often used to try and deal with this problem. The simplest form of stratification divides a city into geographical

[3] Repeat-sales indexes are by necessity temporal. However, median and hedonic indexes can be computed either in a spatial or temporal domain.

regions and then computes a separate median for each region. The changes in the median indexes for each region are then averaged, usually by taking an arithmetic or geometric mean to obtain the overall price index for that period. While stratification should reduce the amount of noise in the index, it will not eliminate it. Within each region, it will still be the case that the median house sold in one period will tend to be of either superior or inferior quality to the median sold in the previous period. These differences will not necessarily offset each other from one region to the next. More sophisticated median indexes stratify by structural attributes of dwellings within regions, the physical location of the dwelling, and neighborhood characteristics of regions. The Established Homes Price Index published by the Australian Bureau of Statistics (ABS) is an example of such an index (see Australian Bureau of Statistics 2006).

A median index may also be subject to systematic bias. Suppose for example that the average quality of housing improves over time. A median index will ignore this fact, and hence in this case will be an upward biased measure of the quality-adjusted price of housing. Stratification is of little use for dealing with this problem. Bias can also arise if say better quality houses sell more frequently than worse quality houses, and also rise in price faster than worse quality houses. In this case, the bias would act in the opposite direction. This second problem is applicable to varying degrees to any house price index based on actual transactions (including hedonic and repeat-sales indexes), since transacted houses are only a small and not necessarily representative part of the overall housing stock.

(ii) Repeat-Sales House Price Indexes

The repeat sales method is usually attributed to Bailey, Muth and Nourse (1963), although Shiller (2008) traces back its origins to Wyngarden (1927) and Wenzlick (1952). The method was extended by Case and Shiller (1987, 1989) to better account for heteroscedasticity. Here we use the weighted repeat sales (WRS) methodology as used by the Office of Federal Housing Oversight (OFHEO) in the US, and described in Calhoun (1996).

Case and Shiller (1987, 1989) argue that the change in house prices includes components whose variances increase with the interval of sales. They estimate this heteroscedastic variance by regressing the square of the ordinary least squares (OLS) error on a constant and the time interval between sales. Calhoun (1996), however, argues that the heteroscedastic variance can be expected to be non-linear in time intervals. Hence he proposes estimating the square of the error as a function of a constant, the time interval and the square of the time interval. The difference between the Case and Shiller (1989) and Calhoun (1996) approaches is, therefore, mainly in the inclusion of the quadratic term of the time intervals in estimating the variance of the error.

Calhoun's WRS method begins by estimating the following regression model by OLS:

$$\ln p_{th} - \ln p_{sh} = \sum_{\tau=0}^{T} \beta_\tau D_{\tau h} + \varepsilon_h, \tag{1}$$

where h indexes a particular house, s and t denote time periods, ε_h an error term, and $D_{\tau h}$ is a dummy variable that takes the value 1 if the price of house k was observed for the second time in period τ, -1 if the price of house h is observed for the first time at time τ, and zero otherwise. The OLS estimates of β_t in (1), denoted here by $\hat{\beta}_t$, can be used to predict the price in period t of a property with a transaction price p_{sh} in period s as follows:

$$\ln \hat{p}_{th} = \ln p_{sh} + \hat{\beta}_t - \hat{\beta}_s.$$

These predicted values can in turn be used to calculate squared deviations of observed house prices around the estimated market index:

$$d_h^2 = [\ln p_{th} - \ln \hat{p}_{th}]^2 = [\ln p_{th} - \ln p_{sh} - \hat{\beta}_t + \hat{\beta}_s]^2.$$

These squared deviations are then used as the dependent variable in the following regression:

$$d_h^2 = a + b(t-s) + c(t-s)^2. \tag{2}$$

The predicted squared deviations $\hat{d}_h^2$ obtained from (2), modelled as a function of time between sales and time between sales squared, provide the weights that correct for heteroscedasticity in the generalized least squares (GLS) estimation of β_t.

$$\frac{\ln p_{th} - \ln p_{sh}}{\sqrt{\hat{d}_h^2}} = \sum_{\tau=0}^{T} \beta_\tau \frac{D_{\tau h}}{\sqrt{\hat{d}_h^2}} + \frac{\varepsilon_h}{\sqrt{\hat{d}_h^2}}. \tag{3}$$

The WRS price indexes P_t are obtained by exponentiating the estimated GLS parameters, denoted here by $\tilde{\beta}_t$:

$$P_t = \exp(\tilde{\beta}_t).$$

It can be shown that this index is a biased estimate of the desired population parameter since it entails taking a nonlinear transformation of a random variable (see Garderen and Shah 2002). Goetzmann (1992) suggests the following correction:

$$P_t = \exp(\tilde{\beta}_t + \hat{\sigma}_t^2/2),$$

where $\hat{\sigma}_t^2$ is an estimate of the variance of the house price index (see Calhoun 1996 for further details on how this variance is estimated).

The main advantages of the repeat sales method is that it generates quality adjusted indexes that are easy to compute and allow the provider only limited discretion. Its main disadvantages are that it throws away a lot of data (i.e., the prices of all properties that sell only once in the data set), and that one cannot be sure that one is comparing like with like when comparing the price of the same property at two different points in time. The property may have been renovated, extended, neglected, etc., between the two transaction dates. A further problem is that the data set may suffer from sample selection bias, which may in turn cause bias in the index. For example, suppose it is the case that lower quality properties sell more frequently than better quality properties. Suppose further that better quality properties rise in price on average at a slower rate than worse quality properties. In this case, a repeat sales index will tend to have an upward bias. This seems to be the situation we observe in our data set. We return to this issue when we discuss our empirical results.

(iii) Hedonic House Price Indexes

The hedonic method dates back at least to Court (1939) and Griliches (1961). The conceptual basis of the approach was laid down by Lancaster (1966) and Rosen (1974). The two main approaches which have been used in practice are the time-dummy method and the hedonic imputation method (see International Labour Office 2004 and Triplett 2004). Here we focus on the time-dummy method.[4]

We extend the time-dummy method in a number of ways. First, we make comparisons both across time and space. That is, we pool across all the regions and periods in the sample and estimate the region-time specific fixed effects. We refer to this method as the

[4]The hedonic imputation method as it is applied in a housing context is discussed in detail in Hill and Melser (2008a, 2008b).

region-time-dummy method.[5] We use a semi-log specification for the hedonic equation.[6] The estimated model is as follows:

$$\ln(p_{kth}) = \sum_{c=1}^{C} \beta_c z_{ch} + \sum_{\tau=1}^{T} \sum_{\kappa=1}^{K} \delta_{\kappa\tau} d_{\kappa\tau h} + \epsilon_{\kappa\tau h} \quad \text{for} \qquad \begin{aligned} &h = 1, \ldots, H_{kt}, \\ &k = 1, \ldots, K \\ &t = 1, \ldots, T. \end{aligned} \tag{4}$$

In (4), $k = 1, \ldots, K$ are the regions, $t = 1, \ldots, T$ the periods, $h = 1, \ldots, H_{kt}$ the properties sold in region-period kt, and $c = 1, \ldots, C$ the characteristics, in our case the number of bedrooms, number of bathrooms, lot size (for houses only), lot size squared (for houses only), or dwelling type of a property. In addition we include interaction terms between characteristics. For houses, we include interactions between bedrooms and lot size, bathrooms and lot size, bedrooms and bathrooms. For units, the only interaction is between bedrooms and bathrooms (since we do not have lot size data). All the characteristics are significant at the 5 percent level and the interaction terms are jointly significant.

The dependent variable is the natural logarithm of the price of an observation belonging to region-period kt. The dummy variable d_{kth} takes the value 1 if the observation h is from region-period kt, and zero otherwise. z_{ch} denotes a characteristic or attribute (in our case the number of bedrooms, number of bathrooms, lot size, lot size squared, or dwelling type) of a property. In a housing context, typically most of the characteristics take the form of dummy variables. The primary interest lies in the coefficients δ_{kt} which measure the region-period specific fixed effects on the logarithms of the price level after controlling for the effects of the differences in the attributes of the dwellings. One attraction of the simple region-time-dummy model is that the price index P_{kt} for region-period kt is derived directly

[5]It was first proposed by Aizcorbe and Aten (2004), who refer to it as the time-interaction-country product dummy method.

[6]See Diewert (2003) for a discussion of the advantages of the semi-log model in this context.

from the δ_{kt} coefficient as follows:[7]

$$\hat{P}_{kt} = \exp(\hat{\delta}_{kt}). \tag{5}$$

The simple region-time-dummy model above fails to make use of postcode identifiers for each property, which when included significantly increase the explanatory power of the model (R^2 rises from about 0.56 to 0.76). It also fails to account for spatial correlation in the error terms. In addition, the use of a common vector of characteristic shadow prices β_c for all region-periods may create a bias analogous to substitution bias (see Hill and Melser 2008b). We provide evidence of this bias in the empirical results that follow.

Our extended hedonic model includes postcode dummies, allows the characteristic shadow prices to evolve over time (by estimating the model separately for rolling blocks of five consecutive quarters) and accounts for spatial correlation in the error terms. The estimated extended model is as follows:

$$\ln(p_{kth}) = \sum_{c=1}^{C} \beta_c z_{ch} + \sum_{\kappa=1}^{K} \sum_{m=2}^{M_\kappa} \gamma_{\kappa m} b_{\kappa mh} + \sum_{\kappa=1}^{K} \sum_{\tau=1}^{T} \delta_{\kappa\tau} d_{\kappa\tau h} + u_{kth}, \quad \text{for} \quad \begin{aligned} h &= 1, \ldots, H_{kt}, \\ k &= 1, \ldots, K, \\ t &= 1, \ldots, T. \end{aligned} \tag{6}$$

The additional term in the extended model is the dummy variable $b_{\kappa mh}$, where $b_{\kappa mh} = 1$ if observation h is from postcode m in region κ and zero otherwise.

A spatial correlation adjustment is important because many of the price determining factors shared by neighborhoods are difficult to document explicitly (see Basu and Thibodeau 1998). The influence of these potentially 'omitted' variables are contained in the neighboring prices.

To account for spatial correlation, we first need to find the neighbors of each observation. The nature of the spatial dependence is specified in a spatial weight matrix. Here we construct a matrix of ones and zeros, with 'ones' denoting neighboring observations and 'zeros'

[7] Again, it can be shown that this index is a biased estimate of the desired population parameter since it entails taking a nonlinear transformation of a random variable (see Garderen and Shah 2002). The bias however is very small. Using Kennedy's (1981) correction, we find that to four decimal places the resulting price indexes are the same as in (5). See Syed, Hill and Melser (2008) for further details. In the extended model that follows, to simplify matters, we do not make this correction.

otherwise from the longitudes and latitudes of each property using the 'Delaunay triangle algorithm'.[8] A spatial matrix with binary numbers contains relatively less information but makes econometric estimation computationally less intensive. Also, given that postcode dummies are already included in the hedonic regression equation, we do not lose much by focusing our spatial correlation adjustment on each property's immediate neighbors.[9]

To reduce the dimensions of the spatial weight matrix (and hence further reduce computational intensity), we divide our data set into overlapping blocks of five quarters, and estimate the hedonic model separately for each five quarter block (again see Syed, Hill and Melser 2008 for further details). This also introduces more flexibility by allowing the shadow prices to evolve over time. This rolling estimation approach is similar to the adjacent period method (see Triplett 2004), which, as its name suggests, estimates the time-dummy method on pairs of adjacent periods. Here we re-estimate the model only on an annual basis rather than every quarter.

Once we have defined the spatial weight matrix, spatial correlation between observations is captured in the error term u_{kth} in equation (6) as follows:

$$u_{kth} = \lambda W u_{kth} + \epsilon_{kth}, \tag{7}$$

where $\epsilon_{kth} \sim N(0, \omega_{kth}\sigma^2)$. The variance of ϵ_{kth} is subscripted with kt implying that the model will allow for heteroscedasticity. W is the spatial weights matrix, and the parameter λ measures the average locational influence of the neighboring observations on each observations. For example, $\lambda = 0.30$ means that 30 per cent of the variation of u_{kth} is explained by locational influences of its neighbors.

We use the maximum likelihood estimation (MLE) method developed by Anselin (1988) to estimate the parameters of the hedonic model in (6) including the additional location parameter λ.[10]

The temporal price indexes (i.e., between different periods for the same region) are derived in essentially the same way as in the simple hedonic model by exponentiating the estimated δ parameters. The one additional complication is that when the quarters do not

[8]Matlab 6.5 has an in-built Delaunay triangle algorithm routine.

[9]An elaborate discussion of alternative ways of constructing a spatial weights matrix is provided in Kelejian and Robinson (1995).

[10]Again see Syed, Hill and Melser (2008) for further details.

lie in the same block (i.e., they are not from the same year), it is necessary to chain the results across hedonic models (since the model is estimated in rolling five quarter blocks). The rise in price in region k from quarter s to quarter t (in the same five-quarter block) is determined as follows:

$$\frac{P_{kt}}{P_{ks}} = \exp(\hat{\delta}_{kt} - \hat{\delta}_{ks}).$$

The derivation of the spatial indexes now, however, is slightly more complicated as a result of the inclusion of postcode dummies. That is, the spatial indexes depend on both the estimated δ and γ parameters as follows:

$$\frac{P_{kt}}{P_{jt}} = \exp(\hat{\delta}_{kt} - \hat{\delta}_{jt}) \times \exp\left[\sum_{m=1}^{M_k}\left(\frac{H_{ktm}}{H_{kt}}\right)\hat{\gamma}_{km} - \sum_{n=1}^{M_j}\left(\frac{H_{jtn}}{H_{jt}}\right)\hat{\gamma}_{jn}\right],$$

where H_{jt} denotes the number of property sales in region-period jt, and H_{jtn} denotes the number of sales in postcode n in region-period jt.

The main advantages of the hedonic approach is that it explicitly addresses the quality-adjustment issue, while at the same time making full use of the available data (at least when characteristics data are available for all properties). Its main disadvantage is that it requires good data on the characteristics of each property. Often some of the characteristics data are missing for some properties. These missing characteristics can be imputed (see Syed, Hill and Melser 2008) or the comparison could be restricted to those properties with complete data. The latter approach can cause sample selection bias. We return to this issue in the next section. Certainly the quality of the data is improving over time, thus making the computation of hedonic indexes increasingly feasible. A further criticism of hedonics is that it gives the index provider too much discretion with regard to the choice of explanatory variables, functional form, etc. (see Shiller 2008). This can encourage data mining and a lack of transparency. However, in another sense the flexibility of the hedonic approach can also be viewed as an advantage. Finally, there is almost certainly an omitted variables problem. That is, it is almost impossible to include all the relevant variables in the hedonic regression equation. An important consideration is whether or not the presence of omitted variables causes systematic bias in the resulting hedonic price indexes. To the extent that these omitted variables are locational, the inclusion of postcode dummies and a spatial correlation correction helps to ameliorate this problem.

3. An Empirical Comparison: Sydney 2001-2006

(i) The Data Set

Our data set was obtained from Australian Property Monitors and consists of prices and characteristics of houses and units sold in 198 postcodes in Sydney for the years 2001-2006. The characteristics we have for each property are sale price, time of sale (quarter/year), postcode, dwelling type (i.e., house or apartment), number of bedrooms, number of bathrooms and lot size (for houses only). In addition, given we have exact addresses, we were also able to compute the longitude and latitude of each property.

Our data set consists of 436,985 observations (i.e., property sales). Of these, 226,021 are for houses and 210,964 for units. Complete data on all our hedonic characteristics are available for 172,000 observations (102,629 for houses and 69,371 for units). A total of 336,483 observations are single sales. That is, these observations are excluded when calculating a repeat-sales index. Of a total of 100,502 sales observations relating to properties that sell at least twice, 53,822 are for houses and 46,680 for units.

We divide Sydney into five regions, which we refer to as Central, Eastern, Southern, Western and Northern, and then compute quarterly hedonic, repeat-sales and median quarterly price indexes separately for houses and units in each region, and for Sydney as a whole. The hedonic indexes are calculated using both the simple and extended model outlined above. The changes in the hedonic indexes for Sydney from one quarter to the next are obtained from the indexes for the five regions (here P_{kt} denotes the price index for region k in period t) using the Törnqvist formula with weights determined by the number of sales in each region:

$$\frac{P_{t+1}}{P_t} = \prod_{k=1}^{K} \left(\frac{P_{k,t+1}}{P_{kt}}\right)^{(s_{kt}+s_{k,t+1})/2},$$

where

$$s_{kt} = \frac{H_{kt}}{\sum_{j=1}^{K} H_{jt}},$$

and H_{kt} denotes the total number of properties sold in region-period kt.

(ii) The Problem of Sample Selection Bias

The fact that radically different samples were used to compute each of our three types of indexes makes comparisons between them problematic. It is, however, possible to compute median indexes over all three data sets (i.e., over all 436,985 observations, over the 172,000 observations used by the hedonic indexes, and over the 100,502 observations used by the repeat-sales indexes). Such a comparison provides some indication of whether the data samples used by the hedonic and repeat-sales data sets are representative of the whole population of housing transactions.[11]

Median indexes computed over the full sample, hedonic sample and repeat-sales sample for each region and for Sydney as a whole, with the price index for each region normalized to one in 2001_1, are shown in Figure 1 for houses and in Figure 2 for units. Focusing on the results for houses in Sydney as a whole (i.e., Figure 1(f)), the median index computed over the hedonic sample rises at a much slower rate (about 28 percent over the whole period) than the median indexes computed using either the whole sample or the repeat-sales sample (about 50 percent over the whole period). A similar pattern is observed for units, although the difference between the hedonic median and the other medians is much smaller. The main source of this difference between the median indexes for houses seems to be the Northern region (see Figure 1(e)). Also, the median house price for Sydney for the hedonic sample is \$589,750 as compared with \$526,500 and \$509,750 for the whole sample and repeat-sales samples, respectively. Again, the biggest contributor to this difference is the Northern region. For units, the corresponding figures are \$397,500 (hedonic sample), \$389,000 (whole sample), and \$370,000 (repeat-sales sample).

Insert Figure 1 Here

Insert Figure 2 Here

A Wilcoxon signed-sum test can be used to determine whether these differences in median prices (not median price indexes) are significant. The results for comparisons between full sample and hedonic sample medians and between full sample and repeat-sales sample medians are shown in Table 1. The difference between the hedonic sample median house price and the full sample median price is significant for Sydney at the 1

[11] It is important to distinguish between the population of housing transactions and the overall housing stock. In each period, only a small fraction of the total stock of houses are sold. Here we focus exclusively on the issue of whether the hedonic and repeat-sales samples are representative of the population of housing transactions, and not of the housing stock itself. This latter issue is addressed by Gatzlaff and Haurin (1997, 1998).

percent significance level, and for the Northern region at the 5 percent level. However, the difference between the repeat-sales and full sample median is not significant, even at the 10 percent level. For units, the median price obtained from the full sample is found to be significantly different from the hedonic and repeat-sale medians at the 5 percent and 1 percent significance levels, respectively.[12]

Insert Table 1 Here

The results in Table 1 suggest that the hedonic sample seems to be biased in its coverage towards more expensive properties, particularly with respect to houses and particularly in the Northern region. This might be because more expensive properties receive more attention and hence the characteristics of these properties are more likely to be recorded.[13] Conversely, Clapp and Giaccotto (1992) argue that a repeat-sales sample has a "lemons" bias, since starter homes sell more frequently as a result of people upgrading as their wealth rises. This lemons bias has also been documented by Meese and Wallace (1997) and Steele and Goy (1997). The results in Table 1 likewise support this hypothesis, particularly for the case of units.

Whether these sample selection biases translate into biased price indexes is another matter. This would require that more and less expensive properties follow differing price change paths. The results in Figure 1 suggest that this may be the case. More expensive properties on average may have risen less in price between 2001 and 2006 than less expensive properties. By implication, sample selection may be causing a downward bias in our hedonic indexes and an upward bias in our repeat-sales indexes.

One way of overcoming this problem for the case of hedonic indexes is to impute missing characteristics in the data set using the multiple imputation method developed by Rubin (1976, 1987), see also Schafer (1997), and applied first in a housing context by Syed, Hill and Melser (2008).

(iv) The Simple and Extended Hedonic Models Compared

Simple and extended hedonic prices indexes are graphed in Figures 3 and 4 for houses

[12] This last finding might seem surprising given the visual evidence in Figure 2(f). It must be remembered, however, that the Wilcoxon test compares median prices not median price indexes.

[13] The APM data set is privately constructed. Such a pattern is probably less likely to be observed in a public data set constructed directly from officially recorded transactions.

and units, respectively. For houses, for every region in Figure 3 except the Southern region, the extended hedonic index is higher than the simple hedonic index. A similar although less pronounced pattern is observed for units in Figure 4. This is consistent with the findings of Hill and Melser (2008b), who argue that the failure of the simple hedonic index to allow the shadow prices of characteristics to evolve over time creates a bias akin to substitution bias in the resulting price indexes. A similar pattern emerges in the results of Clapham, Englund, Quigley and Redfearn (2006), where their hedonic imputations index (which is not affected by substitution bias) in their Figure 2 rises faster than their time-dummy (i.e., simple hedonic) index.[14] Clapham et al. do not attempt to explain this finding.

Insert Figure 3 Here

Insert Figure 4 Here

(iv) Hedonic, Repeat Sales and Median Indexes Compared

From Figure 5 it can be seen that the increase in house prices in Sydney as a whole and in each of the five regions from 2001 to 2006 was larger according to the repeat-sales index than according to the hedonic index. For units, in Figure 6 we do not find any clear pattern. Clapham, Englund, Quigley and Redfearn (2006) and Bourassa, Hoesli and Sun (2006) also find that their repeat-sales indexes rise faster than their corresponding hedonic indexes, although a number of earlier authors cited by Bourassa et al. observe the opposite pattern. Hansen (2006), by contrast, using data also for Sydney, does not observe any systematic difference.[15]

Insert Figure 5 Here

Insert Figure 6 Here

One possible explanation for the systematic difference in the repeat-sales and hedonic results for houses is the sample selection bias in the hedonic sample discussed in the previous section. The nature of this sample selection bias may change over time and from one city or country to the next (depending on whether prices are converging or diverging), thus explaining the lack of consensus on this issue in the literature.

[14] They refer to the former as a chained Fisher index and the latter as a longitudinal hedonic index.

[15] Hansen's time horizon is significantly longer than ours (from about 1993 to 2004). Also, his data set for Sydney consists of about 642,000 observations spread over 12 years as compared with our 436,985 observations spread over six years.

The results in Figure 1 certainly suggest that the repeat-sales sample may be more representative than the hedonic sample of the total population of houses sold in Sydney.[16]

There is little difference between the hedonic and median results for houses. If the hedonic results are biased downwards, the same therefore must be true of the median results.

A better indication of the difference between the hedonic and median results is obtained by comparing the former with the hedonic sample median results. It can be seen in Figure 5 that the hedonic indexes rise systematically faster than their corresponding hedonic sample median indexes. One possible explanation of this difference is that the average quality of houses traded decreases over time. Since median indexes fail to quality adjust, such a trend would impart a downward bias to a median index. A comparison between the repeat-sales index and its corresponding sample median again in Figure 5 confirms this pattern, in that the former is also consistently higher than the latter. This apparent decrease in quality seems to be particularly concentrated in the latter part of our sample. This could be because of an increase in the number of distressed sales concentrated predominantly in the lower half of the house price distribution.

(v) Index Volatility

The volatility V of a price index can be measured as follows:

$$V = \left(\frac{1}{T-2}\right) \sum_{t=1}^{T-1} \left[\ln(P_{t+1}/P_t) - \overline{\ln(P_{t+1}/P_t)}\right]^2,$$

where

$$\overline{\ln(P_{t+1}/P_t)} = \left(\frac{1}{T-1}\right) \sum_{t=1}^{T-1} \ln(P_{t+1}/P_t).$$

V is the standard deviation of the natural logarithm of price changes (i.e., $\ln(P_{t+1}/P_t)$) across the whole time series. This volatility measure is invariant to rescaling of the index and treats price rises and declines symmetrically. The volatility of the extended hedonic, repeat-sales and median indexes is shown in Table 2. For 11 of 12 cases (i.e., the five regions plus Sydney for houses and units), the hedonic index is the least volatile. Volatility in median indexes is to be expected due to their failure to quality adjust. That is, the

[16]Determining which sample is most representative of the housing stock is another matter (again see Gatzlaff and Haurin 1997, 1998).

quality of the median house will fluctuate over time and hence impart volatility to the index. Greater volatility of repeat-sales indexes as compared with hedonic indexes can probably at least partly be attributed to the smaller sample of properties over which the repeat-sales indexes are calculated in our data set.[17]

Insert Table 2 Here

(vi) Convergence

So far, we have focused only on temporal price indexes. It is also possible, however, to compute spatial median and hedonic indexes (although not repeat-sales indexes). To investigate whether differences in price levels across regions are rising or falling over time, we calculate σ-convergence coefficients for the 5 regions in each of the 24 quarters in our data set. σ-convergence measures the variance of the cross-section of price parities and then examines whether this has declined or increased over time (see for example Sala-i-Martin 1996). That is, we calculate and compare the following:

$$\sigma_t^2 = \left(\frac{1}{K-1}\right)\sum_{k=1}^{K}\left[\ln(P_{kt}) - \overline{\ln(P_t)}\right]^2, \quad \overline{\ln(P_t)} = \left(\frac{1}{K}\right)\sum_{k=1}^{K}\ln(P_{kt}), \quad t = 1,\ldots,T.$$

Applying this formula to the full-sample median price indexes in Figures 1 and 2 and the extended hedonic and repeat-sales indexes in Figures 3 and 4, we find evidence of convergence (i.e, a falling sigma coefficient over time) until early 2004 (when house prices stopped rising) followed by divergence thereafter (when house prices were falling) for both houses and units. The convergence turning point appears to lag the change in direction of the housing market by one or two quarters. The results are presented in Figure 7.

Insert Figure 7 Here

This pattern of convergence followed by divergence implies that prices in the poorer regions (Southern, Western and Northern) rose faster than in the richer regions (Central and Eastern) during the boom, but that this pattern has reversed since the end of the boom. By comparison, as has already been discussed above, the differences in the median indexes in Figure 1(f) suggest that within each region the price difference between better and worse quality houses may have narrowed throughout the period 2001-2006.

[17]It should be noted that the proportion of single-sale observations in a data set will decrease as the time horizon of the data set lengthens and hence the sample coverage of the repeat-sales method will improve.

Also, striking in Figure 7(a) is the lower level of price dispersion across regions for houses according to the hedonic indexes as compared with the median indexes. The explanation for this finding lies in the fact that houses in richer regions (here the Central and Eastern regions) tend to be of higher quality. A failure to make this quality adjustment causes spatial median indexes to systematically overstate the difference in prices across regions.

4. Conclusion

We have identified a number of possible biases in house price indexes. The biases in median indexes arise when average quality changes over time or space in a systematic way as a result of their failure to quality adjust. Both hedonic and repeat-sales data sets are vulnerable to sample selection bias. The bias in the hedonic data set can be attributed to an apparent tendency of data gatherers to focus on better quality properties when gathering characteristics data. Repeat-sales data sets, by contrast, may focus disproportionately on lower quality properties since they seem to sell more frequently. The sample selection problem seems to be causing a downward bias in our hedonic indexes and an upward bias in our repeat-sales indexes. This problem is more apparent in the hedonic indexes. This is somewhat ironic given that in our case the repeat-sales method throws away more data than the hedonic method.

Overall, we still in general favor the hedonic approach on the grounds that it has more potential for addressing the quality adjustment problem. However, our findings clearly demonstrate the importance of addressing the sample selection bias problem when constructing hedonic indexes. We show how this can be done in Syed, Hill and Melser (2008).

A second theme that emerges from our analysis is how the results can change as the housing market moves from boom to bust. For example, we find that the bias in a median index arising from its failure to quality adjust is rather more of a problem in the bust than in the boom. We also find convergence in prices across regions during the boom and divergence in the bust. It remains to be seen whether this finding is specific to our data set, or whether it is more generally applicable.

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Table 1: Non-Parametric Test for the Difference in Median Prices by Region and for Sydney

Regions		Wilcoxon Test Statistic	
		FS vs. HS	FS vs. RS
Houses:			
	Central	1.05	-0.41
	Eastern	1.65*	1.77*
	Southern	1.65*	-0.23
	Western	1.23	-1.01
	Northern	2.33**	1.73*
	Sydney	4.43***	-1.07
Units:			
	Central	-0.52	-1.28
	Eastern	1.05	0.82
	Southern	-0.25	-2.10**
	Western	-1.01	-3.20***
	Northern	1.11	-1.20
	Sydney	2.39**	-2.58***

Notes: (1) FS, HS and RS denote full sample, hedonic sample and repeat-sales sample, respectively.

(2) The Wilcoxon signed-sum test statistic follows approximately the standard normal distribution for large samples. Two sided tests are conducted. Average scores are used for ties.

(3) Significance levels: *=significant at 10%, **=significant at 5% and ***=significant at 1%.

Table 2: Volatility of Price Indexes

HOUSES	Ext Hed	R-S	Med(Hed)	Med(R-S)	Med(Full)
Central	0.032	0.053	0.037	0.052	0.042
Eastern	0.038	0.070	0.048	0.070	0.065
Southern	0.032	0.033	0.036	0.039	0.035
Western	0.030	0.033	0.041	0.039	0.032
Northern	0.027	0.032	0.041	0.041	0.037
Sydney	0.027	0.027	0.052	0.055	0.046

UNITS	Ext Hed	R-S	Med(Hed)	Med(R-S)	Med(Full)
Central	0.041	0.050	0.034	0.053	0.027
Eastern	0.032	0.044	0.057	0.059	0.047
Southern	0.033	0.046	0.039	0.031	0.028
Western	0.036	0.050	0.045	0.045	0.039
Northern	0.028	0.032	0.049	0.055	0.030
Sydney	0.024	0.027	0.029	0.032	0.025

Note: Ext Hed = Extended Hedonic; R-S = Repeat Sales; Med(Hed) = Median (Hedonic Sample); Med(R-S) = Median (Repeat-Sales Sample); Med(F-S) = Median (Full Sample).

Figure 1: Median Price Indexes for Houses by Regions and for Sydney

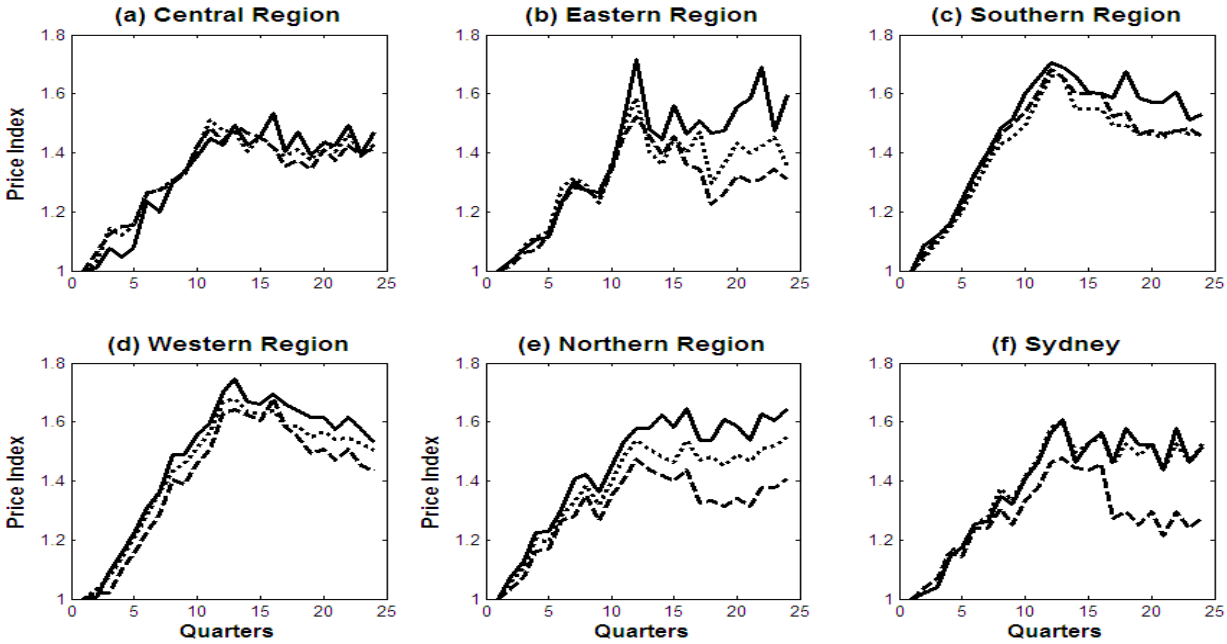
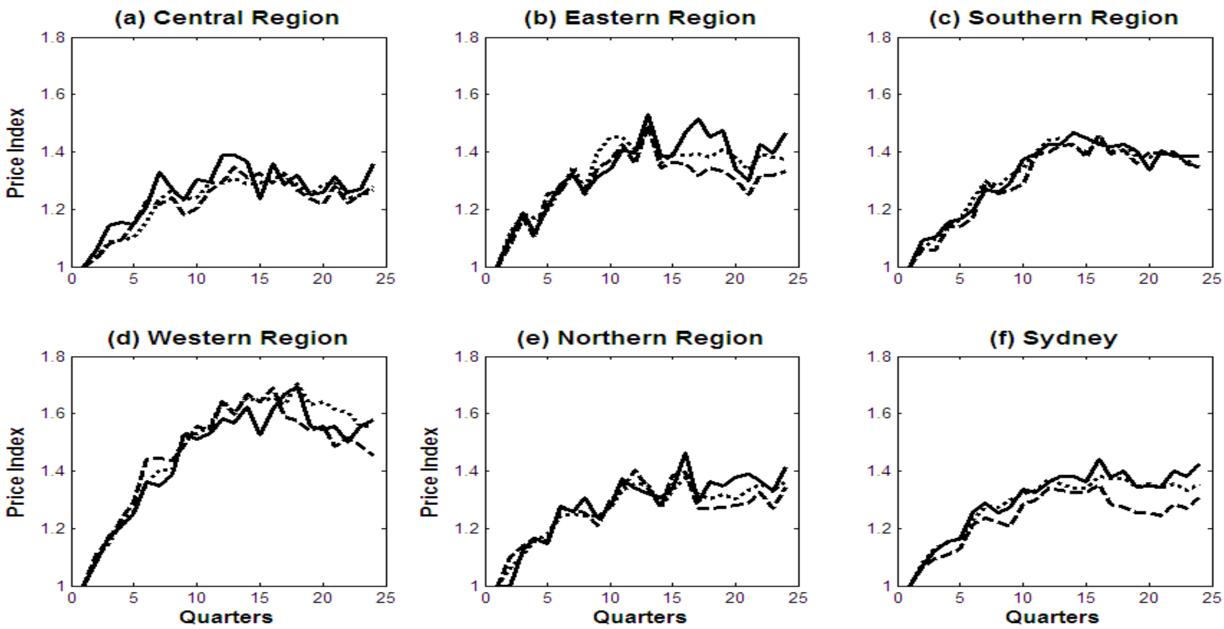


Figure 2: Median Price Indexes for Units by Regions and for Sydney



…… Full sample	**— — Hedonic sample**	**—— Repeated sales sample**

Figure 3: Hedonic Price Indexes for Houses by Regions and for Sydney

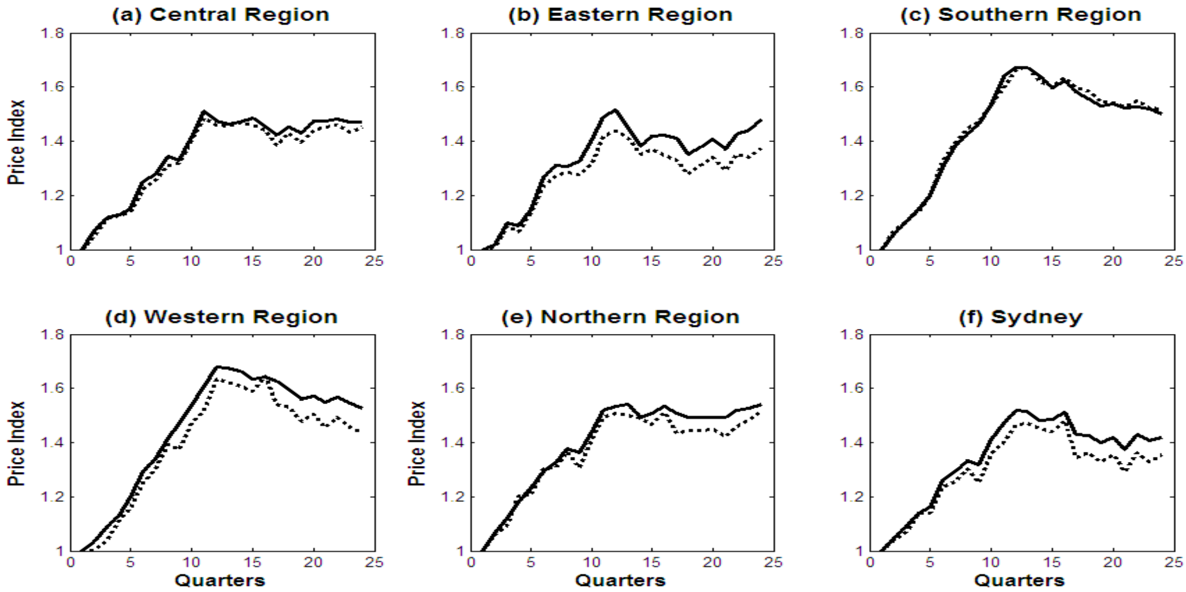
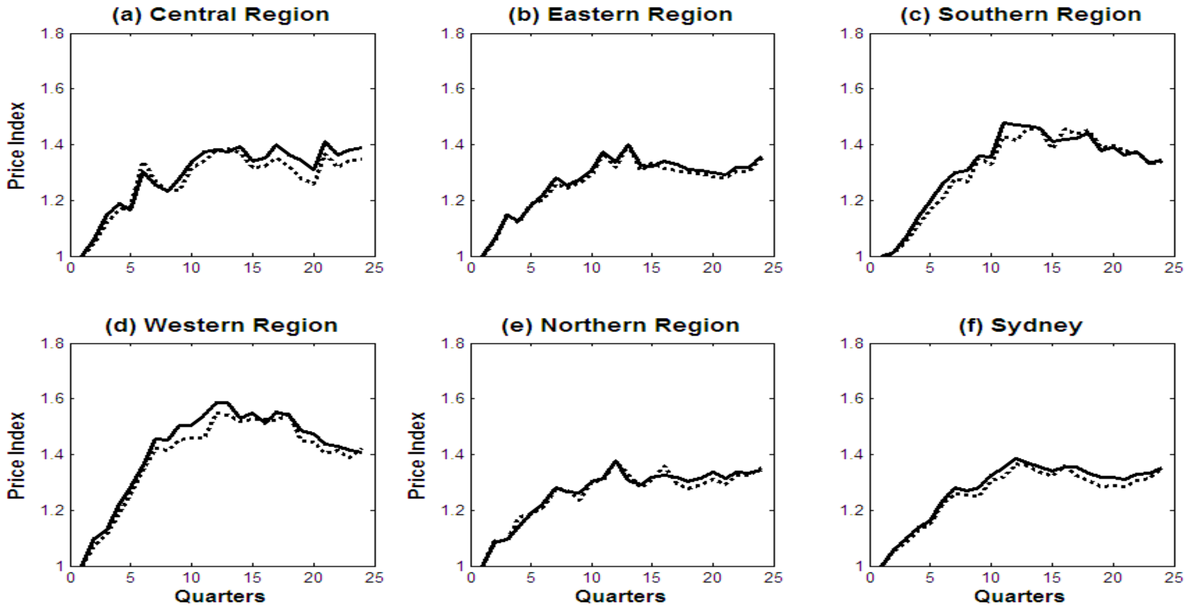


Figure 4: Hedonic Price Indexes for Units by Regions and for Sydney



…… Simple hedonic index	**—— Extended hedonic index**

Figure 5: Median, Hedonic and Repeat Sales Price Indexes for Houses by Regions and for Sydney

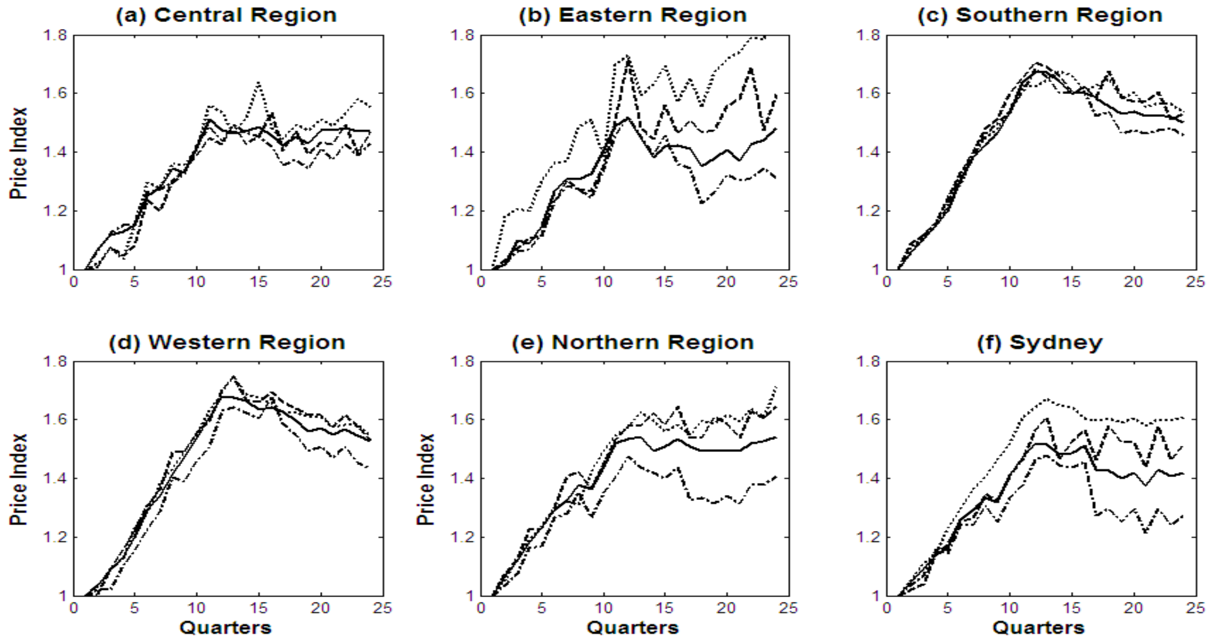
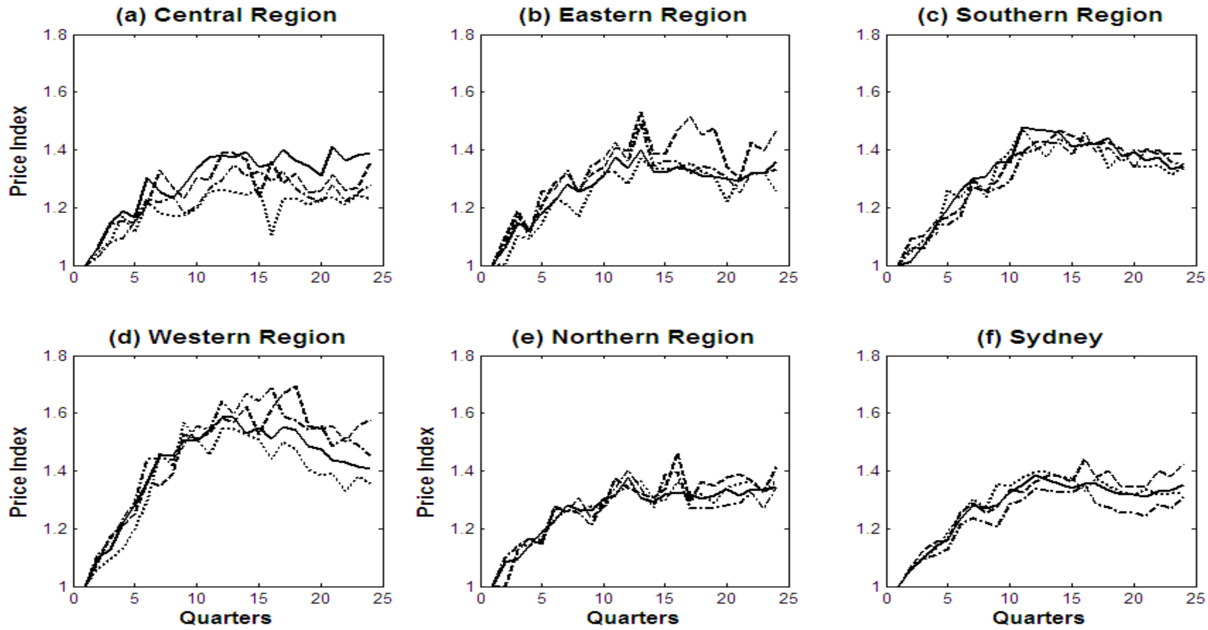
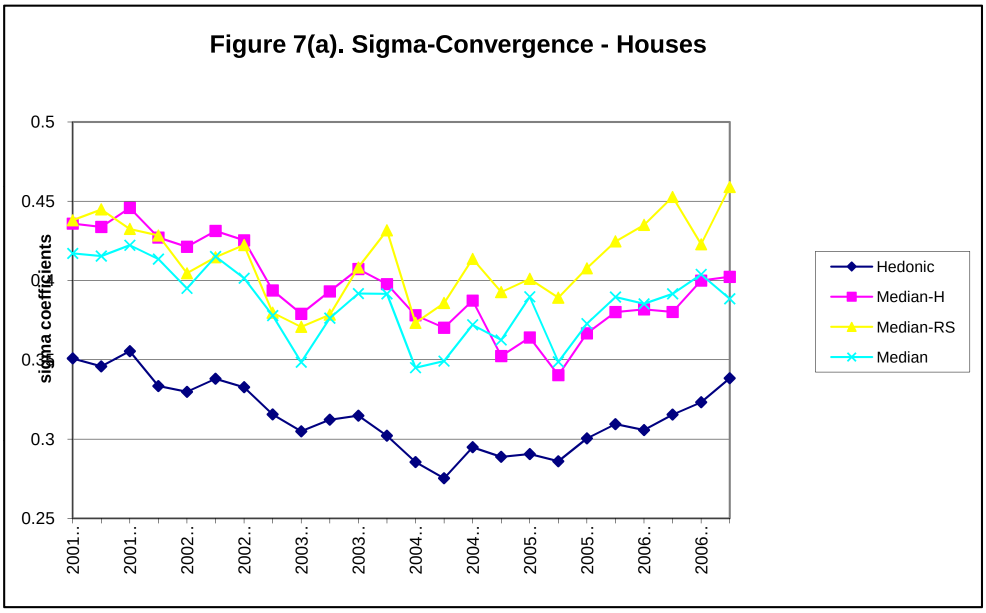
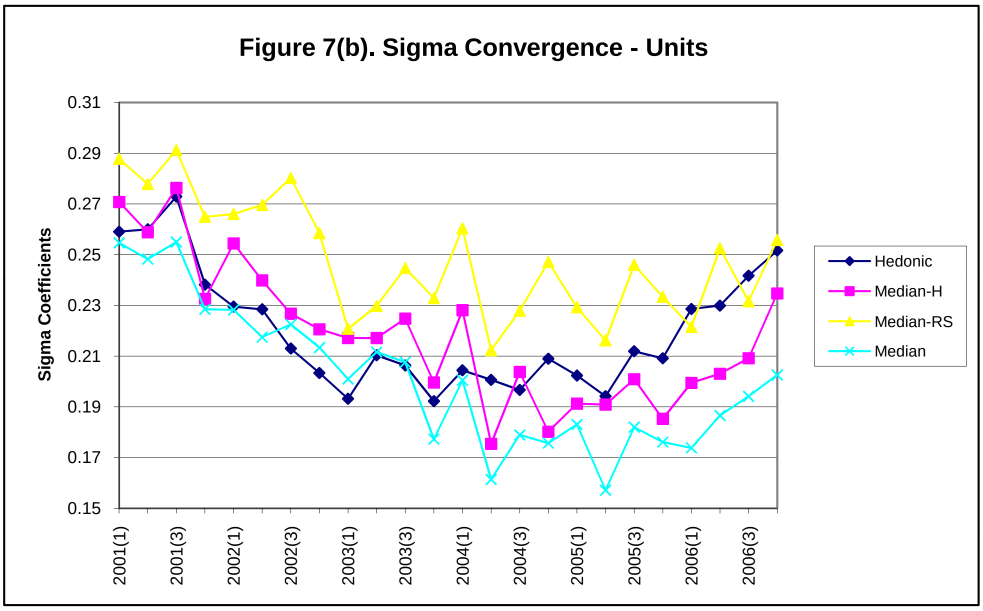


Figure 6: Median, Hedonic and Repeat Sales Price Indexes for Units by Regions and for Sydney



—.—. Median index (Hedonic sample)	**—— Extended hedonic index**	**— — Median index (Repeat sales sample)**	**…… Repeat sales index**





Note: Hedonic = Extended Hedonic; Median-H = Median (Hedonic Sample);
Median-RS = Median (Repeat-Sales Sample); Median = Median (Full Sample).